Sustainable Approaches for Highway Runoff Management During Construction and Operation

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Preface

Sustainable development in urban areas directly necessitates building infrastructure (e.g., highways) and also employing sustainable water management techniques. In this regard, managing highway runoff and protecting the quality of roadside water bodies are of great importance. This Ph.D. project focuses on the effects of road runoff on water quality and seeks environmentally friendly measures to manage such runoff during construction and operation. These approaches include the characterization and treatment of tunneling wastewater, vulnerability assessment of water quality due to road construction, optimization of water quality monitoring networks, and the application of remote sensing technology to monitor roadside water quality.

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Acknowledgments

A Ph.D. career is a unique experience for interaction with scientists, researchers, and students. It is an excellent opportunity to share ideas and broaden scientific and cultural horizons.

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Abstract

Environmentally friendly approaches for highway runoff management during construction and operation are considered in this project. First, the state of the art in runoff management in terms of characterization, treatment, and modeling approaches were surveyed, and knowledge gaps were identified. Then, the characterization and treatment of tunneling wastewater (by natural and chemical coagulants) was investigated. In the next stage, the vulnerability of water quality to road construction activities was investigated by analyzing field monitoring data. In addition, two different approaches, involving information theory and gamma test theory, were suggested to optimize the water quality monitoring network during road construction. Lastly, the application of satellite data (i.e., Sentinel-2 Multi-Spectral Imager satellite imagery products) for water quality monitoring was examined.

Based on the results, it can be shown that site-specific parameters (e.g., climate, traffic load) cause spatiotemporal variation in the characterization of highway runoff and performance of best management practices (BMP) to protect water quality. There is a knowledge gap regarding the characterization of highway runoff under different climatic scenarios, as well as the continuous monitoring and assessment of roadside water bodies.

Analysis of the field monitoring data indicates that blasting, area cleaning, and construction of water management measures have the highest impact on surface water quality during road construction. Additionally, the application of information theory and gamma test theory indicate that the primary monitoring network assessed here is not optimally designed. The number and spatial distribution of monitoring stations could be modified and reduced, as the construction activities vary over time.

Additionally, the suggested remote sensing techniques applied in this project are able to estimate water quality parameters (i.e., turbidity and chlorophyll-a) in roadside water bodies with a reliability consistent with field observations, reflecting the spatiotemporal effects of road construction and operations on water quality.

Finally, an efficient two-step treatment strategy (15 min sedimentation followed by chemical coagulation and 45 min sedimentation) is suggested for the treatment

of tunneling wastewater. The optimum coagulant dosages in the jar test exhibit high treatment efficiency (92-99%) for both turbidity and suspended solids (SS), especially for particle removal in the range of 10-100 μm, which is hard to remove by sedimentation ponds and may pose serious threats to the aquatic ecosystem.

It is hoped the knowledge generated by this project will help decision-makers with management strategies and support UN Sustainable Development Goals (SDGs). The proposed approaches directly contribute to managing highway runoff and achieving SDG 6 (clean water and sanitation) and especially target 6.3 (water quality).

Sammendrag

Miljøvennlige tilnærminger for håndtering av avrenning fra veianlegg i anleggsfase og i driftsfase ble studert i dette prosjektet. Innledningsvis ble dagens kunnskap innen håndtering av overvann fra veianlegg kartlagt, med vekt på karakterisering, behandling og modellering, og kunnskapshull ble identifisert. Deretter ble det gjort studier av avløpsvann fra tunneldriving, hvor vann ble karakterisert og renset ved hjelp av en biopolymer og kjemiske koagulanter. Videre ble det vist hvordan ulike aktiviteter i anleggsfasen påvirker omkringliggende vannforekomster ved å benytte overvåkingsdata fra et gjennomført veiprosjekt. For å optimalisere nettverk for overvåking av vannkvalitet i omkringliggende vannforekomster i anleggsfase ble to tilnærminger foreslått. Disse tok i bruk informasjonsteori og gamma-teori. Avsluttningsvis ble det gjennomført en studie hvor satelittdata fra Sentinel-2 ble benyttet for overvåkning av vannkvalitet.

Basert på resultatene ble det vist at stedspesifikke parameter knyttet til f.eks. klima og trafikktetthet resulterer i kvalitative og kvantitative variasjoner i avrenningen, og hvordan dette påvirker funksjonen av rensetekniske tiltak for å beskytte omkringliggende vannforekomster. Det ble identifisert kunnskapshull knyttet til karakteriseringen av veiavrenning under ulike klimatiske scenarier, og ulike metoder for kontinuerlig overvåking og måling av vannkvaliteten i nærliggende vannforekomster.

Analyse av overvåkingsdata indikerte at anleggsaktiviteter som sprengningsarbeid, rydding av areal og gravearbeid, og konstruksjon av vannbehandlingsanlegg hadde størst negative effekt på omkringliggende vannforekomster. Ved å benytte informasjonsteori og gamma-teori ble det vist at nettverkene for overvåking av vannforekomster kunne optimaliseres. Antallet og fordelingen av overvåkingstasjoner kunne modifiseres og reduseres, da de ulike anleggsaktivitetene endres over tid. Teknikkene for fjernovervåking som ble foreslått i dette prosjektet viste seg å kunne estimere vannkvalitetsparametre som turbiditet og klorofyll-a, og derved reflektere den miljømessige effekten av anleggsvirksomheten på omkringliggende vannforekomster. De estimerte verdiene ble verifisert ved hjelp av feltmålinger.

En effektiv to-trinns strategi for behandling av avløpsvann fra tunneldriving ble lansert, basert på 15 min sedimentering fulgt av kjemisk koagulering og 45 min

sedimentering. Ved optimal koagulantdose ble det oppnådd en renseeffekt på 92-99% med hensyn på turbiditet og suspendert stoff (SS), og god fjerning av små partikler med diameter 10-100 µm, som er vanskelige å fjerne i tradisjonelle sedimenteringsdammer, og som kan skade akvatiske økosystemer.

Forhåpentligvis vil kunnskapen som er generert i dette prosjektet kunne hjelpe beslutningstakere med forbedredede strategier for håndtering av veiavrenning og beskyttelse av vannforekomster i tråd med FNs bærekraftsmål, spesielt bærekraftsmål 6 (clean water and sanitation).

Publications

The following papers have been published or submitted for publication in peer-reviewed international conference proceedings and journals.

A. Current European approaches in highway runoff management: a review, Journal of Environmental Challenges, https://doi.org/10.1016/j.envc.2022.100464

B. Spatiotemporal assessment of surface water vulnerability to road construction, Journal of Environment, Development and Sustainability, https://doi.org/10.1007/s10668-021-01763-9

C. Assessing optimal water quality monitoring network in road construction using integrated information-theoretic techniques. Journal of Hydrology, https://doi.org/10.1016/j.jhydrol.2020.125366

D. Design of a surface water quality monitoring network in a road construction project using gamma test theory, Journal of Water Resources and Industry, https://doi.org/10.1016/j.wri.2021.100162

E. Roadside water quality monitoring and assessment by integrating remote sensing and field measurement, Submitted to remote sensing of environment (under review)

F. Characterization and Treatment of Tunneling wastewater Using Natural and Chemical Coagulants, Submitted to Journal of Water Process Engineering (under review)

Contents

Abbreviations

AHP	analytical hierarchy process
BOD	biochemical oxygen demand
CCME	Canadian Council of Ministers of the Environment
DO	dissolved oxygen
EDS	X-ray energy dispersive spectrometer
EO	earth observation
GEE	Google Earth Engine
GTT	gamma test theory
MSI	MultiSpectral Imager
PAH	polycyclic aromatic hydrocarbons
PROMETHEE	preference ranking organisation method for enrichment evaluations
PSD	particle size distribution
SEM	scanning electron microscope
SDGs	Sustainable Development Goals
SS	suspended solids
TE	transinformation entropy
TOPSIS	technique for order preference by similarity to ideal solution,
VOI	value of information
WFD	water framework directive
WQI	water quality index
WQMN	water quality monitoring network

Chapter 1

1.1 Introduction

Roads are an integral part of urban development and have a vital role in the quality of life (Commission, 2011; Meland, 2015). Highway construction and operation may reduce the quality of receiving waters by increasing the concentration of suspended solids, metals, and hydrocarbons such as oil and polycyclic aromatic hydrocarbons (PAHs). Highway runoff is one of the most significant non-point sources of pollution for the terrestrial and aquatic environment, with biological, physical, and chemical effects (Angermeier et al., 2004). It may cause cumulative or acute impacts on the ecological condition of the receiving water bodies (Barbosa and Fernandes, 2021).

During construction, the nature of the runoff is highly dependent on the type of construction activities and site-specific geographical features. During road operation, runoff includes a mix of exhaust and wear products from breaks, tires, and asphalt (Meland, 2010, 2015). A vast spectrum of road runoff pollutants has been reported. In addition to those already mentioned (Helmreich et al., 2010; Lee et al., 2011; Brenčič et al., 2012; Kayhanian et al., 2012; Zhao et al., 2016), microplastics (Carr et al., 2016; Horton et al., 2017; Siegfried et al., 2017; Zhang et al., 2018; Li et al., 2018), nitrogen, carbon and sulfur oxides, nitrogen and phosphorus nutrients, as well as oil and grease may all contribute to the mix (Helmreich et al., 2010; Kayhanian et al., 2012).

According to the EU Water Framework Directive (WFD), all countries should have achieved “good status” for their water bodies by 2015 or finally by 2027. But 47 percent of the EU's surface waters still did not achieve these standards by the first of these dates (Meland, 2015). Although not documented, runoff from roads probably contributes significantly to this shortcoming. Therefore, studies on highway runoff characteristics and suitable treatment technologies should be encouraged. In particular, sustainable approaches must be applied for runoff management when it comes to more efficient and environmentally friendly road construction and operation. There are different aspects that could be considered to achieve comprehensive road runoff management.

Understanding the impacts of road runoff (a non-point source of pollution with spatiotemporal variation) and their control is critical for the accomplishment of the EU WFD regarding a good ecological status for all water bodies and overall environmental sustainability goals. In this regard, water quality monitoring is an effective tool (Barbosa and Fernandes, 2021). Also, the characterization of road runoff and measuring the vulnerability of water bodies helps support decision-makers in adopting and implementing the best approaches for runoff management. (Barbosa and Fernandes, 2021). Notably, the source control policies that minimize the presence of pollutants in receiving water bodies are cost-effective management tools. Hence, there is a strong need to study such pollution control tools (Müller et al., 2020). The sedimentation ponds used for the treatment of tunneling wastewater are an example of such source control policies and investigating the treatment process in such ponds is of great importance.

This Ph.D. project focuses on environmentally friendly highway runoff management approaches during construction and operation. These include assessing the spatiotemporal variation of water quality in roadside water bodies due to road construction, optimizing the networks that monitor surface water quality during road construction, applying remote sensing technology to monitor roadside water quality, and assessing methods for characterizing and treating tunneling wastewater.

1.2 Motivation and Problem Statement

The spatiotemporal variation of surface water quality due to the construction of highways and related structures (e.g., bridges and tunnels) has not been properly investigated. For example, a set of activities such as the construction of tunnels, bridges, and culverts, blasting, as well as factors such as runoff treatment, mineral leakage during concrete and asphalt preparation, and accidental spills of chemicals, may all contaminate surrounding surface water. One study (Moretti et al., 2018) has shown that construction of an embankment and a trench road cross-section (both sections were 1 m long and 4 m high) can cause 1.08 kg and 2.61 kg phosphate ($PO4^{3-}$) eq, respectively.

Depending on the size and type of construction activities, various pollutants may be produced and transported to surface waters (Licbinský et al., 2012). Fig. 1

shows a construction site in the project for a new 22 km highway, E18 Arendal-Tvedestrand in southern Norway (Af-Grouppen, 2021). Despite the importance of the construction phase on the quality of the roadside water bodies, there is a considerable gap in assessing the spatiotemporal effects of the road construction on the surface water quality and the effect of each activity on surface water quality. Therefore, a practical approach was developed as part of this Ph.D. for assessing the spatiotemporal vulnerability of surface water to road construction by analyzing water quality data from the environmental monitoring during the construction of the new highway (2017–2019).

Fig. 1 The Stølen site in E18 Arendal-Tvedestrand May 2018

In the next phase of the Ph.D. project, the water quality monitoring network (WQMN) during road construction was optimized. WQMNs generate sufficient qualitative data over time to provide a basis for appropriate measures in the shortest possible time and control pollution risks. Additionally, the information from an WQMN can be used to evaluate the aquatic environment in terms of the quality required for the habitat, the identification of pollution sources and pollution levels, and management of clean-up operations (Telci et al., 2009; Xiaomin et al., 2016). The data provided by WQMNs can be applied by decision-makers for reliable assessments of water quality and to support policies for protecting water resources (Alfonso and Price, 2012; Behmel et al., 2016).

In road construction projects, sometimes after a long monitoring period, it becomes clear that the number of monitoring stations is unnecessarily large, and that consequently a great deal of time and money has been wasted. Conversely, the number of stations may be insufficient, with the collected information giving only a rudimentary understanding of the environmental impact of the construction works. Therefore, finding a method to determine the optimal number and location of stations after the initial monitoring period can be valuable to local authorities in helping manage both costs and the environment (Mooselu et al., 2020b).

The WQMN on roadside water bodies is established based on experts' knowledge and local priorities, such as the protection of main streams, drinking water resources, and specific species (e.g., sea trout). However, it does not necessarily follow that the monitoring stations available provide the best information. The number of stations, their location, and the value of the data provided by the primary network should therefore be assessed, and the network should be optimized accordingly. This optimization process is a key step towards a comprehensive program in which the effective elements of the existing water quality monitoring network are evaluated (Behmel et al., 2016; Pourshahabi et al., 2018a). Hence, after the initial design of the WQMN and a few periods of data collection, the monitoring network can be modified for the number and location of stations, based on the quality of data provided and design constraints such as the project budget.

In this project, the WQMN during the process of road construction was first investigated based on information theory (the value of provided information and the amount of information redundancy in the primary network). In addition, the primary network was optimized by the gamma test theory (GTT) for finding the minimum number of stations and the best combination of stations.

Due to the importance of water quality monitoring and assessment, the feasibility of remote sensing (RS) to provide supplementary data for ground-based observation of surface water quality was evaluated. The lack of a comprehensive monitoring system for spatiotemporal assessment of roadside water bodies on a regional scale and for longer stretches of road is felt keenly. The physical, chemical, and biological indicators of water quality are usually evaluated by field sampling and laboratory analyses. However, in-situ measurements alone cannot provide sustainable data for water quality assessments or long-term water resource management plans (Ritchie et al., 2003). Such sampling is a time-consuming, labor-intensive, costly, and unproductive method for regional-scale assessments (Duan et al., 2013; Gholizadeh et al., 2016). However, recent advances in RS techniques provide valuable methods and data resources to monitor environmental issues in real time (Gholizadeh et al., 2016). RS techniques efficiently evaluate water quality problems on a regional scale and assess the complex interactions of environmental processes in time and space (Hassanien et al., 2020). Satellite-based sensors can measure almost all hydrological parameters (Lettenmaier et al., 2015; Zhang et al., 2016; Mccabe et al., 2017), deliver fundamental management data, and track the contaminants transported in water bodies (Sheffield et al., 2018).

Relying on the abilities of RS technology to monitor environmental systems and aquatic ecosystems, the Sentinel-2A sensor was applied to determine the spatiotemporal variation of turbidity and chlorophyll-a parameters in roadside water bodies. Turbidity indirectly reveals anthropogenic effects, such as the variation of land use and cover, soil erosion, weather, and the development of urban areas and infrastructure, on water quality (Mccarthy et al., 2018; Ma et al., 2021). Thus, regular turbidity monitoring is an efficient management approach to protect water resources.

Tunneling is a critical activity in road construction, which may generate several manufactured and natural water-borne pollutants for receiving water bodies (Petersen et al., 2016). The tunneling wastewater is generally known for characteristics such as high concentrations of suspended solids (SS), turbidity (Lee et al., 2014; Liltved, 2014), and high pH values (Yi-Wen et al., 2012). However, the quality and chemical composition of tunneling wastewater are site-specific and depend on the geological features of each construction site (Rustøen, 2015). The bedrock, weather, and applied machinery are the most prominent site-specific factors that specify the characteristics of tunneling wastewater. Particles reduce light penetration, can change both temperature and spawning conditions, reduce the fish foods (e.g., benthic invertebrates), and damage fish gill tissues (Bilotta and Brazier, 2008). According to the European Inland Fisheries Advisory Commission (EIFAC), 400 mg/L of suspended solids will cause poor fishing (Vikan and Meland, 2013). Particle-bound contaminants such as heavy metals, oil, and PAH are another concern related to suspended particles in tunneling wastewater.

Additionally, particles from drilling and blasting might be edgier and sharper than rounded particles such as clay, and thus more harmful for biota. Despite the importance of tunneling construction for the deterioration of surface water quality, little research has been published on the characterization and treatment of tunneling construction wastewater (Yi-Wen et al., 2012; Lee et al., 2013; Lee et al., 2014). Therefore, in the last section of this Ph.D. project, both the characterization and treatment of tunneling wastewater are investigated, and the feasibility of using precipitating agents for particle removal are explored by experimental work.

1.3 State of the Art

Erosion runoff during the construction and operation of roads is a significant issue for water quality (Malamataris, 2014). Road runoff can influence aquatic ecosystems by pollution within 50 m, by hydrological effects within 200 m, and by sediments more than 1 km downstream (Forman and Alexander, 1998). Regarding the impacts of the road industry on surface water quality, most previous studies have focused on the effects of highway operations (Meland et al., 2010; Licbinský et al., 2012; Vieira et al., 2013; Malamataris, 2014; Banerjee et al., 2018) and especially the impact of road salt on water quality (Corsi et al., 2010; Kelly et al., 2012; Vitale et al., 2017; Arnott et al., 2020). However, in the construction phase, due to the variety of activities and related pollutants involved and the prolonged periods of some projects, irreversible damage may be posed to water resources. For instance, (Restrepo et al., 2019) have examined the water quality in a river system during and after road construction. Physicochemical analysis shows an increase in qualitative parameters such as oils and greases, biochemical oxygen demand (BOD), and a decrease in dissolved oxygen (DO). Due the fact that there are few published research works on the project phase of roads (Houser and Pruess, 2009; Chen et al., 2009; Restrepo et al., 2019), the knowledge gap on the spatiotemporal assessment of road construction effects on surface water quality is quite apparent.

Water quality monitoring programs often provide considerable time-series data, including many water quality variables, which are challenging in terms of analyzing and understanding for decision-makers (Mooselu et al., 2020a). A water quality index (WQI) is a useful managerial tool for interpretation of qualitative data (Munna et al., 2013), classification of water quality (Boyacioglu, 2010; Nikoo and Mahjouri, 2013), and water management (Khan et al., 2005). A WQI is applicable for investigating the effects of construction projects on the quality of water resources (Sikder et al., 2015; Mgbenu and Egbueri, 2019; Mooselu et al., 2020a). During road construction, a WQI can determine the impact of natural factors and anthropogenic activities on water resources (Mgbenu and Egbueri, 2019). In studies, this type of index has been used to evaluate the quality of surface water, groundwater, and sediments under the influence of various industrial pollutants (Abrahão et al., 2007), drilling and mining (Madzin et al., 2017), and in-operation highways (Banerjee et al., 2018).

Monitoring the quality of roadside water bodies can accurately reflect the impact of road construction on aquatic ecosystems (Vieira et al., 2013; Barbosa and Fernandes, 2021). However, the optimal design of a WQMN is a complicated process. Firstly, an uneven distribution of monitoring stations, or an insufficient number, may provide a limited understanding of the surface water system of the study area. On the other hand, if the number of monitoring stations is too large, the additional information obtained can make the monitoring process costly and inefficient (Ayvaz and Elçi, 2018). The optimization of WQMNs has been investigated using methods such as fuzzy clustering (Karamouz et al., 2009; Wang et al., 2012; Lee et al., 2020), genetic algorithms (Park et al., 2006; Telci et al., 2009; Puri et al., 2017; Asadollahfardi et al., 2018), the value of information (Pourshahabi et al., 2018b; Khorshidi et al., 2020; Mooselu et al., 2020b), and entropy (Mahjouri and Kerachian, 2011; Memarzadeh et al., 2013; Pourshahabi et al., 2018a; Mooselu et al., 2020b). The type and number of water quality parameters, number and location of stations (Alilou et al., 2018; Alilou et al., 2019), and sampling frequency (Karamouz et al., 2009; Zeng et al., 2016; Khorshidi et al., 2018) have been widely investigated for surface water monitoring. A small number of works have been published using a combination of information theory techniques. In these, optimum sensor placement (Khorshidi et al., 2018) and optimum WQMN in reservoirs (Pourshahabi et al., 2018a; Pourshahabi et al., 2018b; Maymandi et al., 2018) were explored. However, the lack of an integrated method capable of taking advantage of the value of information (VOF) and transinformation entropy (TE) in terms of surface water quality is quite apparent. In addition, one of the most significant challenges related to applying information theory to surface water quality monitoring is the type of applied data used for computing prior and posterior probabilities.

A review of previous studies indicates a lack of knowledge on optimizing the WQMN for surface water during road construction. Also, the optimization of WQMN during road construction, considering the spatiotemporal variation of activities in terms of the type and size of activities, is barely considered. Hence, in this project, which uses sampling data from the field, two different techniques, including a hybrid form of information theory techniques (Pourshahabi et al., 2018a; Khorshidi et al., 2020) and a gamma test theory (Koncar, 1997), were separately used to optimize the WQMN design for a road construction project (the same case study, Fig. 3).

Regarding the application of RS as a supplementary tool for ground-based observation, it is notable that the Sentinel-2 MultiSpectral Imager (MSI) has three near-infrared (NIR) (i.e., 865 nm) bands that can be used with appropriate algorithms for detecting chlorophyll-a concentrations (Pahlevan et al., 2019). Sentinel-2A data has been applied in previous research for water quality monitoring, especially for turbidity (Liu et al., 2017; Sebastiá-Frasquet et al., 2019; Page et al., 2019; Niroumand-Jadidi et al., 2020; Ma et al., 2021) and chlorophyll (Vanhellemont and Ruddick, 2016; Gernez et al., 2017; Watanabe et al., 2017; Caballero et al., 2019; Vanhellemont and Ruddick, 2021). Sentinel-2 has a different spectral resolution and spectrum range than other sensors (e.g., Operational Land Imager, Thematic Mapper, and Enhanced Thematic Mapper Plus sensors), which necessitates exploring the MSI applicability in turbidity mapping (Ma et al., 2021). Nonetheless, the MSI products' capability for spatiotemporal assessment of road effects on water quality by analyzing the time-series data records over monitoring stations in lakes has not been considered in the literature. Therefore, in the next part of this Ph.D. project, the turbidity and chlorophyll in roadside water bodies are estimated using Sentinel-2 spectral reflectance, with the aim of improving spatiotemporal monitoring of roadside water bodies on a regional scale.

Particle removal from wastewater has been widely investigated, and different methods such as sedimentation, coagulation-flocculation (Yang et al., 2012; Gupta et al., 2012; Kim et al., 2015), and some secondary treatment methods such as membrane filtration (Liu et al., 2007; Yi-Wen et al., 2012; Lee et al., 2014; Kim et al., 2015; Cho et al., 2016) and reverse osmosis (Lee et al., 2014) have been applied for the removal of high SS concentrations in tunneling wastewater.

A conventional combination of sedimentation with the coagulation-flocculation process is an environmentally friendly and efficient approach for particle removal. Coagulation, which is based on the destabilization of the colloidal fraction (Bratby, 2016) has been widely utilized in the treatment of drinking water (Fabris et al., 2010; Zemmouri et al., 2013; Muthuraman and Sasikala, 2014; Choy et al., 2016), stormwater and highway runoff (Trejo-Gaytan et al., 2006; Kang et al., 2007; Sansalone and Kim, 2008; Rounce et al., 2012; Lee et al., 2014; Rustøen, 2015; Nyström et al., 2019, 2020). The most common coagulants for water treatment are aluminum and iron salts, e.g., aluminum sulfate, ferric chloride, ferric sulfate (Kang et al., 2007; Choy et al., 2016). However, excessive sludge and disposal problems should be considered before using chemical coagulants (Renault et al., 2009). Besides these factors, elevated aluminum concentrations in the aquatic environment may cause toxic effects for biota and humans (Mclachlan, 1995; Forbes et al., 1997). Recently, environmentally friendly coagulants such as biopolymers, which are biodegradable and non-toxic to human health (Muthuraman and Sasikala, 2014), have been proposed as an alternative. Biopolymers are efficient in low dosages and reduce sludge volume (Bina et al., 2009; Choy et al., 2016); their impact on pH and alkalinity is also insignificant (Zemmouri et al., 2013).

Notably, sedimentation ponds alone can purify tunneling water to approximately 400 mg/L SS (Vikan and Meland, 2013), and limited removal of the finer (<20 μm) particles is a serious concern regarding sedimentation basins (Li et al., 2006). Finer particles may pose a risk to the receiving waters (Nyström et al., 2020). Particle contents below 100 mg/L can be removed by adding coagulants, often in combination with acid (HCl), at the inlet of the sedimentation pond (Vikan and Meland, 2013). Thus, after analysis and characterization of tunneling wastewater, a two-step treatment process consisting of pre-sedimentation (15 minutes of sedimentation) followed by chemical coagulation, flocculation, and precipitation is proposed for particle removal tunneling wastewater.

1.4 Methodology and Research Design

This section shows how data from a full-scale construction project was used in different approaches to generate valuable knowledge. The selected case study was the E18 Tvedestrand-Arendal highway, which involved construction of a new 22-km, four-lane road. Work began in 2017 and the road opened publicly in July 2019. This road, with a total catchment area of 7,180 hectares, includes multiple catchments such as Storelva (#1), Vennevann (#2), Langangselva (#3), Sagene (#4), Mørfjær (#5), Songebekken (#6), and Longum/Barbu (#7). Regarding the topography of the area, several monitoring stations were established on the main and side streams of each catchment area to monitor spatiotemporal changes in the physical and chemical parameters of surface water during road construction (Fig. 2). In Fig. 2, the first digit in the number of each station indicates the catchment number. The monitoring data was provided by Nye Veier and obtained from 48 water quality monitoring stations distributed spatially over seven catchments (Fig. 2). This is the main source of data for this Ph.D. project.

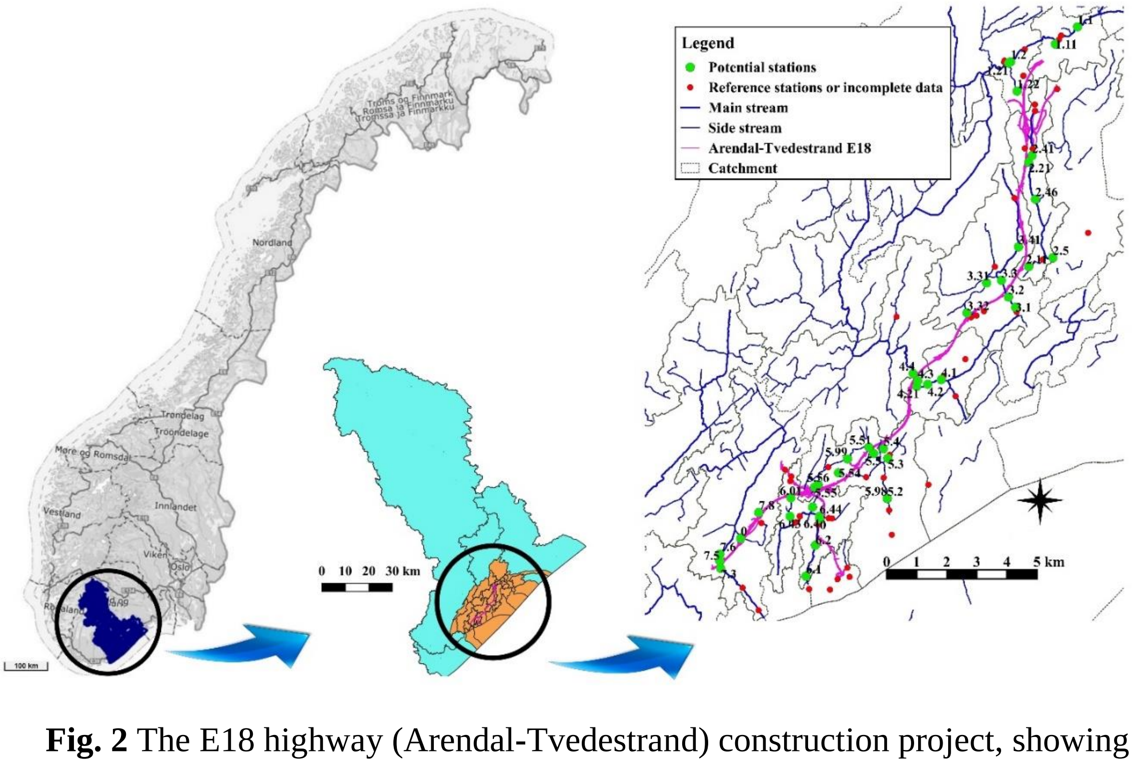

Fig. 2 The E18 highway (Arendal-Tvedestrand) construction project, showing established monitoring stations

In this study, six time periods of one month each, divided by intervals of four months, were considered during the construction phase from 2017 to 2019.

Regarding the parameter selection for calculation of the WQI, the principal component analysis (PCA) was performed on the present dataset to reduce its dimensionality while retaining as much as possible the variability present in the data (Uddin et al., 2021). Accordingly, 28 parameters with the highest importance and a complete time series for the monitoring periods were selected for the WQI calculation. The proposed WQI in this part takes advantage of a relative weighting method (Kangabam et al., 2017) based on previous studies to achieve a feasible balance among water quality parameters (see Appendix–Paper 3).

In order to investigate the temporal impact of road construction on surface water quality, using the field observation data, the WQI was computed for monitoring stations in all selected periods. Using the calculated WQI, the surface water quality was classified for the six selected times (Yadav et al., 2018). Then, for comparing the vulnerability of water resources to different sections of the road, the average of the WQI for the monitoring stations of each catchment area was calculated (spatial view). Lastly, to investigate the vulnerability of surface water quality to each specific construction activity, the variety of activities performed in each part of the project during the selected time periods was extracted. Considering the average value of WQI for each operation in all catchments, and during all selected time sections, the vulnerability of surface water bodies to various activities was calculated.

For the next part of this project, two different approaches were investigated to optimize the established water quality monitoring network during road construction. In the first approach, using the Canadian Council of Ministers of the Environment (CCME)-WQI (Nikoo et al., 2011) the water quality index was computed for each potential monitoring station during construction. The CCME-WQI incorporates three variance values (scope, frequency, and amplitude) to achieve the overall water quality state in the form of a unitless number between 0 and 100 (with 100 representing best quality). These values are classified based on five categories, including poor (≤44), marginal (45‑64), fair (65‑79), good (80‑94), and excellent (95‑100), as prior and posterior probabilities in monitoring stations. Then, the integrated form of the information-theoretic techniques consists of the value of information (VOI), and the transinformation entropy (TE), which were calculated for each pair of stations. VOI theory evaluates the importance of new information and updates the earlier probability about the state of a system

(Alfonso and Price, 2012; Pourshahabi et al., 2018a). The concept of TE is employed to achieve the amount of mutual information between stations and help to identify essential and unnecessary stations (Alizadeh and Mahjouri, 2017).

To achieve the optimal WQMNs in this approach, the optimization models NSGA-II and NSGA-III, based on nondominated sorting genetic algorithms (NSGAs) were developed, considering three objective functions: a) minimizing the number of stations, b) maximizing the VOI in the selected network, and c) minimizing redundant information for the selected nodes. The optimization models deliver a Pareto front (trade-off curve) between objectives, which consists of the right answers for the optimization problem. Finally, three multi-criteria decision-making models, including Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Preference Ranking Organisation Method for Enrichment Evaluations (PROMETHEE), and Analytical Hierarchy Process (AHP), were utilized for choosing the best alternative among Pareto optimal solutions, considering various weighing scenarios assigned to criteria.

In the second approach, gamma test theory (GTT) was applied to achieve the optimal number of stations (M_{min}) and the best combination of stations. In GTT, data analysis is conducted based on the calculation of a statistic number, named the gamma statistic (GT). The higher the GT value, the weaker the modeling performance, which is mainly due to: a) too much noise in measured data, b) a low number of datasets, and c) the low number of independent variables in the model (Kemp et al., 2004). In this method, an M-test, as a GTT tool, determines the minimum required number of training datasets (M_{min}) in a given dataset to achieve a model with maximum reachable accuracy, directly from the dataset (Lafdani et al., 2013; Marquez and Coimbra, 2011). The moving window test (MW-test) is another tool in GTT, which indicates the variation of the GT value for different subsets of the datasets displaying the same size (Pitcher, 2017). In an MW-test, a virtual window with the length of M_{min} is moved along the datasets with a special order, and the GT value is computed for the datasets in the window. Here, the datasets with the lowest GT value are selected as the best training set for modeling (Pitcher, 2017).

To put this theory into practice, the relative weighting method was applied to calculate the WQI for all 48 monitoring stations and monitoring periods. By randomizing the total datasets, M_{min} was determined by the M-test tool, in which GT was computed for an increasing number of datasets, and GT was then plotted against the number of datasets. As the number of datasets reaches the M_{min}, the graph is stabilized to an asymptote (Iturrarán-Viveros and Parra, 2014). Then, the MW-test was conducted with the M_{min} to specify a group of datasets (stations) with the least GT value. The selected group was located at the beginning of the rest of the datasets. This process was repeated by randomizing the datasets and changing their initial order. Lastly, the group of datasets (stations) with the lowest GT value was selected as the optimal group.

The monitoring dataset was also applied to investigate the application of remote sensing data for water quality monitoring in roadside water bodies as well as detecting the effects of road construction and operation on water quality. Accordingly, Sentinel-2 Multi-Spectral Imager (MSI) satellite imagery products were applied to estimate turbidity and chlorophyll-a in roadside water bodies. For this purpose, an absolute method, known as modified atmospheric correction for inland waters (MAIN), was used to clarify inland waters (Page et al., 2019). Next, we used the Otsu Method (Otsu, 1979) to identify the water pixels and segment the Sentinel-1 images using a threshold with minimum occurrences higher than 90%. We used the Google Earth Engine (GEE) platform to do atmospheric correction and matchup analysis. Accordingly, 602 atmospherically corrected images across Norway were analyzed to match up with in-situ data for 115 ground-based monitoring stations and 2,357 time-series of field observations for turbidity and chlorophyll-a parameters between 2017 and 2021 (late August, Fig. 3). This information is provided by https://vannmiljo.miljodirektoratet.no/. Therefore, water-only pixels with >90 % of occurrences were classified as water and <90 % as land masks. Hence, using the fast distance method on the GEE platform, observation gauges within more than one pixel distance (10 meters of Sentinel-1 data) of shorelines were excluded from matchup analysis. Finally, 18 observations matched up for turbidity and 49 matched up for chlorophyll-a with gauge observations across Norway were used for the calibration process.

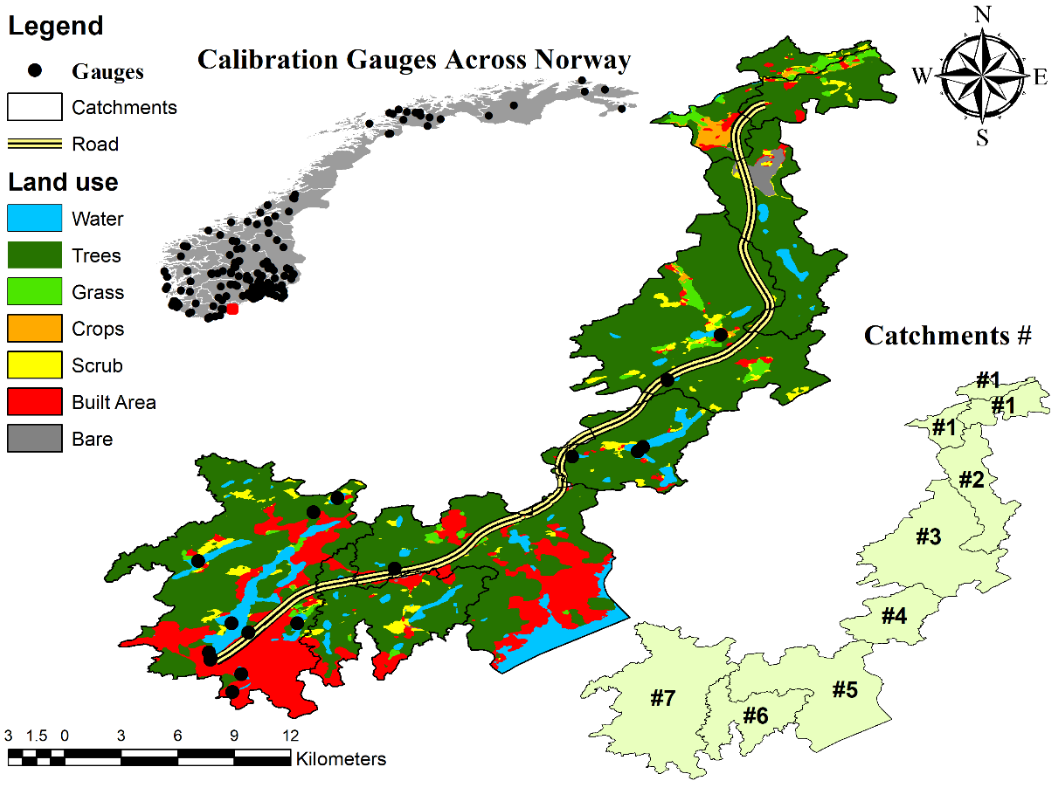

Fig. 3 The calibration gauges, and catchment areas

We applied the B3/B2 band combinations to calibrate turbidity observations in 18 gauges in Norway. Also, a normalized difference chlorophyll index (NDCI) (Mishra and Mishra, 2012) was used to calibrate chlorophyll-a estimations with the gauge observations. Two performance metrics, including root mean square error (RMSE) and R-squared (R^2) were applied in the calibration section to fit an empirical equation between Sentinel-2 image reflectances and gauge observations.

In the last part of this project, characterization and treatment of tunneling wastewater were investigated. Wastewater samples targeted in this study were collected from the tunneling project during drilling operations at the new E39 road from Kristiansand to Mandal in southern Norway. The chemical characteristics of the three tunneling wastewater samples before and after 15 min sedimentation were measured by Eurofins Environment Testing Norway AS (Kr.Sand).

Chemical coagulation and precipitation were implemented to remove small residual particles with low settling velocity. For efficient treatment and substantially lower chemical dosages, we introduced a two-step treatment process, with 1) pre-sedimentation to remove the majority of the suspended solids (here 15 minutes of sedimentation), followed by 2) chemical coagulation, flocculation, and precipitation to remove the finer solids. To assess particle removal efficiency, a flocculation and sedimentation were performed with conventional jar-test apparatus (Fig. 4) using both natural (i.e., chitosan) and chemical coagulants, including ferric chloride sulfates (PIX-318) and polyaluminium chloride solution (PAX-XL-3103D). Each jar test had a protocol consisting of an initial 45 second rapid mixing phase (200 rpm) in which coagulant was added, followed by 10 minutes of slow mixing (30 rpm) and finally sedimentation for 45 min. After completing the jar-test cycle (rapid mixing, flocculation, and sedimentation), 500 ml samples were carefully siphoned from the clear phase for analysis.

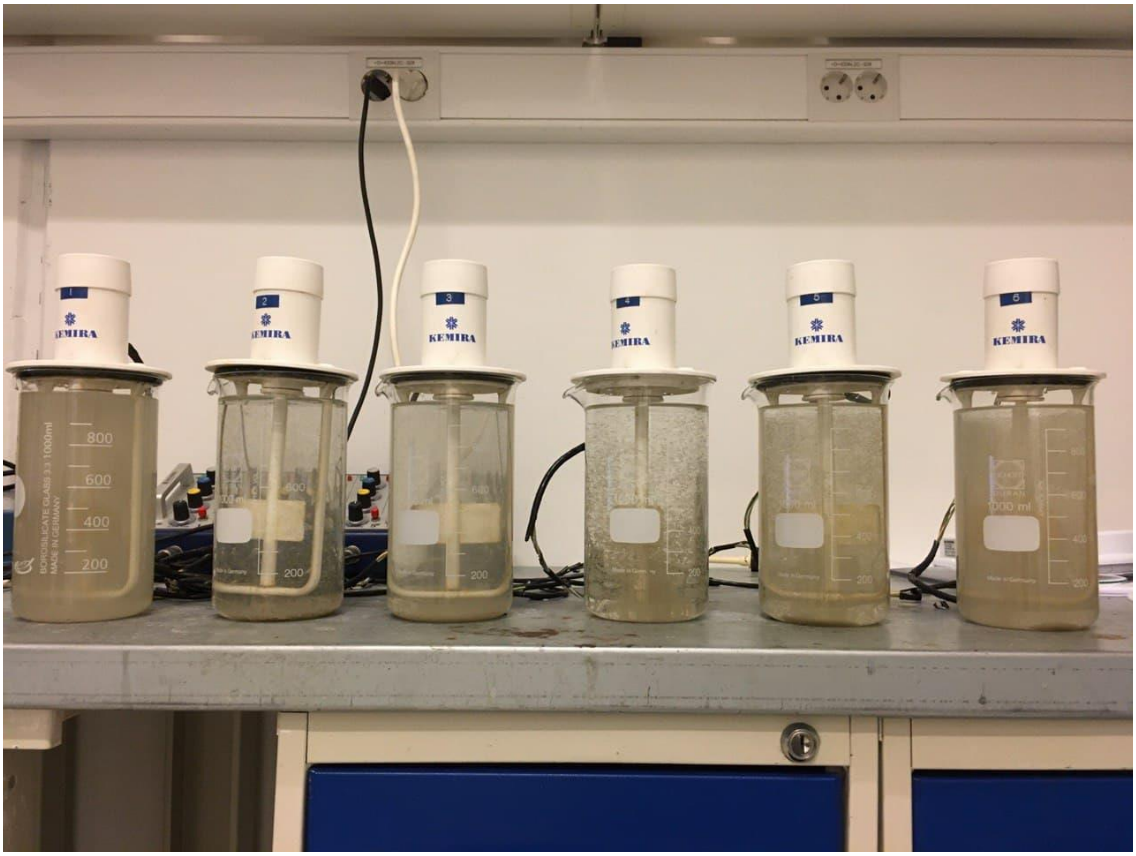

Fig. 4 The applied Jar-test for tunneling wastewater treatment

Several analyses were performed before and after the jar tests to characterize the different tunnel waters and evaluate the treatment efficiency. Electrical conductivity (EC), pH, turbidity, suspended solids (SS), and particle size distribution (PSD) were measured in the laboratory of the University of Agder according to Norwegian and European standards. Particle size distribution was analyzed by light scattering using a Mastersizer 3000 (Malvern v3.72) instrument. For particle morphology study, a field emission scanning electron microscope (SEM) (JEOL 7200F, Tokyo, Japan) equipped with an energy dispersive X-ray spectrometer (Octane Elect EDS system from EDAX$_{®}$-AMETEK$^{®}$) was employed.

1.5 Outline

The rest of this thesis is divided into two main chapters. Chapter 2 describes the contribution of this project regarding each stage of the project and also towards the realization of the United Nations Sustainable Development Goals (UN SDGs). The last chapter (Chapter 3) concludes the thesis and provides the reader with recommendations for more efficient road construction in Norway.

Chapter 2

The most popular definition of sustainable development is “development that meets the needs of the present without compromising the ability of future generations to meet their own needs” (Brundtland, 1987). In 2015, nations agreed to meet the Sustainable Development Goals (SDGs) set out within the UN’s 2030 Agenda for Sustainable Development. The SDG framework consists of 17 goals and 169 targets focusing on three pillars of sustainability: the economy, society and the environment (Cochran et al., 2020).

While road construction and operation are essential for human societies, the challenge is how to manage the negative physical, chemical, and biological impacts they pose to roadside water bodies and streams (Vörösmarty et al., 2018). The irreplaceable role of water resources in supporting the economy (e.g., energy production and agriculture) and ecosystems (e.g., biodiversity) (Tsani et al., 2020), necessitates sustainable environmental management to protect water quality against urbanization (Vörösmarty et al., 2018). It is also increasingly recognized that water systems must be sustainable with respect to the economy, society and the environment (Sørup et al., 2020; Larsen et al., 2016). Due to the fundamental role of water in the development of human societies, the realization of almost all UN SDGs will depend on its careful management. Thus, if aquatic environments are managed with the aim of sustainability, with a long-time horizon in mind, they will reliably underpin both human well-being and economic development. Fresh water as one of the essential components in the earth system and human water security will be achieved on a truly sustainable basis only through well-functioning quantitative and qualitative management (Vörösmarty et al., 2018). The UN SDGs recommend an interconnection between water management and sustainable development (Tsani et al., 2020).

The aim of this section is to evaluate the role of highway runoff management approaches in achieving UN SDGs and map them to the relevant targets. The review of the UN SDGs shows that there are several goals that can be directly and/or indirectly linked to highway runoff management approaches during road construction and operation. Therefore, this chapter focuses first on the contribution of each approach, then considers its contribution to achieving the UN SDGs. To serve this goal, the importance of water quality monitoring and assessment on achieving UN SDGs is investigated. After that, the role of remote sensing technology in achieving the mentioned SDGs is considered. Finally, the impact of the project on UN SDGs in Norway is explained.

2.1 Contributions

This thesis is based on six papers that have been published or submitted for publication during the project period.

2.1.1 Paper A: Current European Approaches in Highway Runoff Management: A Review

Summary: Highway runoff is one of the most significant non-point sources of pollution for the terrestrial and aquatic environment with biological, physical, and chemical effects. Considering local characteristics, treatment practices, and determining factors are essential for highway runoff management. This paper aims to survey the state of highway runoff management in Europe, with emphasis on runoff characterization, treatment, and modeling approaches, and identify possible knowledge gaps that exist based on our review. The results show that highway runoff has spatiotemporal variation, which is the main factor in the regional selection of best management practices (BMPs). Also, recent studies have assessed the character of highway runoff in different climatic scenarios, determined the performance of the current BMPs, and analyzed uncertainty in modeling approaches. Furthermore, economic and risk analysis, along with decision-making methods, provide an optimum plan for the design and operation of BMPs.

Contributions: This review paper contributes to understanding highway runoff management through attending characterization and treatment of the runoff as well as considering the modeling approaches and current legislation adopted by different countries. Furthermore, this review clarifies the existing knowledge gap in the field of highway runoff management and helps to specify future research directions.

This paper has been submitted as:
Mehrdad Ghorbani Mooselu, Helge Liltved, Atle Hindar, Hamid Amiri, Current European Approaches in Highway Runoff Management, A Review. Journal of Environmental Challenges.

2.1.2 Paper B: Spatiotemporal Assessment of Surface Water Vulnerability to Road Construction.

Summary: Highway construction may generate different pollutants, including suspended solids, metals, and hydrocarbons such as oil and polycyclic aromatic hydrocarbons (PAH's), which can enter water resources and decrease water quality. For assessing the spatiotemporal vulnerability of surface water to road construction, first, the water quality monitoring data during construction of a new 22-km-long highway in southern Norway (2017-2019) were used to assign the relative weights of parameters, and the water quality index (WQI) was computed for all monitoring stations. Then, by defining six time periods, the temporal variation of the WQIs for various stations were determined, and by classification of WQIs according to different levels (i.e., excellent water, good water, poor water, very poor water, and unsuitable for drinking), the temporal changes were analyzed. To assess the spatial variation in surface water quality during road construction, the averages of the WQIs for all monitoring stations of each catchment area were computed, and for each section of the road, a vulnerability map was plotted for all time periods. In addition, evaluating the impact of road construction activities on surface water quality is another innovation of this study. By extracting the activity type of each section of the road over the construction time, the average WQI for each activity was computed for all time periods. The results show that construction activities such as blasting, area cleaning, and water management have the highest impact on surface water. The results deliver practical knowledge to decision-makers for establishing best management practices to control the effects of road construction on surface water bodies.

Contributions: The principal contribution of this study is to develop a practical approach for assessing the spatiotemporal vulnerability of surface water to road construction using a feasible WQI index. Besides this, the paper also evaluates the impact of each construction activity on the quality of surface water resources. The results of this study will make a significant contribution to the selection of best management practices (BMPs) in various construction projects.

This paper was published as:

Mooselu, M. G., Amiri, H., Azadi, S., & Liltved, H. (2021). “Spatiotemporal assessment of surface water vulnerability to road construction.” *Environment, Development and Sustainability*, 1-23.

2.1.3 Paper C: Assessing Optimal Water Quality Monitoring Network in Road Construction Using Integrated Information-Theoretic Techniques.

Summary: The environmental impacts of road construction on the aquatic environment necessitate the monitoring of receiving water quality. This paper suggests a feasible methodology for spatial optimization of the water quality monitoring network (WQMN) for surface water during road construction. First, using the Canadian Council of Ministers of the Environment (CCME) method, the water quality index (WQI) was computed for each potential monitoring station during construction. Then, an integrated form of information-theoretic techniques, consisting of transinformation entropy (TE) and the value of information (VOI), was calculated for the potential stations. To achieve the optimal WQMNs, the NSGA-II and NSGA-III-based multi-objective optimization models were developed considering three objective functions, including a) minimizing the number of stations, b) maximizing the VOI in the selected network, and c) minimizing redundant information for the selected nodes. Finally, three multi-criteria decision-making models, including the technique for order preference by similarity to ideal solution (TOPSIS), the preference ranking organization method for enrichment evaluations (PROMETHEE), and the analytical hierarchy process (AHP), were utilized for choosing the best alternative among Pareto optimal solutions considering various weighing scenarios assigned to criteria. The applicability of the presented methodology was assessed using a 22-km-long road construction site in southern Norway. The results deliver significant knowledge for decision-makers on establishing a robust WQMN for surface water during road construction projects.

Contributions: The paper contributes to filling the knowledge gap in the optimization of WQMN during road construction by proposing a feasible framework consisting of a water quality index, an integrated form of information theory techniques, efficient optimization, and decision-making models for monitoring networks for surface water.

This paper was published as:

Mooselu, M. G., Liltved, H., Nikoo, M. R., Hindar, A., & Meland, S. (2020). "Assessing optimal water quality monitoring network in road construction using integrated information-theoretic techniques." *Journal of Hydrology, 589, 125366*.

2.1.4 Paper D: Network Design for Surface Water Quality Monitoring in a Road Construction Project Using Gamma Test Theory.

Summary: Regarding the importance of continuous monitoring of surface water quality, optimization of the water quality monitoring network (WQMN) is an essential step in supporting the sustainable development of road construction projects. This study introduces gamma test theory (GTT) as a practical method for optimizing the WQMN of surface waters during road construction. The water quality index (WQI) was computed for 48 monitoring stations for six monitoring periods from 2017 to 2019. Data was acquired from a primary monitoring network for a new highway in southern Norway. Based on the results, it is possible to reduce the number of stations by 23% in comparison with the original empirical network. The proposed method could be useful in designing the monitoring networks of projects with a limited construction time and budget, as well as projects lacking enough data.

Contributions: This paper's main contribution is determining the optimal number and location of surface water monitoring stations during road construction by applying the field data in the earliest monitoring periods using GTT. In fact, the suggested method provides a suitable context to modify the primary monitoring network during different phases of construction.

This paper was published as:

Azadi, S., Amiri, H., Mooselu, M. G., Liltved, H., Castro-Muñoz, R., Sun, X., & Boczkaj, G. (2021). "Network design for surface water quality monitoring in a road construction project using gamma test theory." *Water Resources and Industry*, 100162.

2.1.5 Paper E: Evaluating Turbidity and Chlorophyll-a in Roadside Water Bodies During Construction and Operation by Sentinel-2A Images.

Summary: The impact of road construction and operation on roadside water bodies entails continuous monitoring and assessment of such resources. This study evaluates the applicability of Sentinel-2 Multi-Spectral Imager (MSI) satellite imagery products for water quality monitoring of roadside water bodies. In the proposed method, an optimal atmospheric correction for inland water was employed to calibrate the gauge observations (115 ground-based monitoring stations) with water leaving reflectance of Sentinel-2 images. Additionally, the Otsu image segmentation method was used to identify water-only pixels, which is in good agreement with observed water bodies. Accordingly, MSI products assessed turbidity and chlorophyll-a spatiotemporally on a regional scale (10 meters). The applicability of the presented methodology was assessed on a 22-km-long road construction site in southern Norway. The proposed method, which is implemented using Google Earth Engine (GEE), shows a reliable performance for estimation of turbidity by the B3/B2 bands combination (R2 = 0.8 and RMSE = 1.947 FNU) and chlorophyll-a by the NDCI index (R2 = 0.79 and RMSE = 6.869 μg/l). The results are consistent with both field observations and Nye-Veier reports on road construction and operation periods, reflecting the effects of road construction and operation on water quality over time. The knowledge generated in this study provides a better view for decision-makers on finding management strategies to protect roadside water systems and achieve related UN sustainable development goals.

Contributions: The paper contributes to filling the knowledge gap in the following cases:

1) More efficient and sustainable water quality monitoring during construction and operation of roads with proper regional coverage over time

2) Assessing the application of modified atmospheric correction for inland waters (MAIN) for roadside water quality monitoring

3) Trend analysis on the quality of roadside lakes considering construction activities and site-specific climate conditions.

The proposed method generates a permanent satellite-based database on roadside water bodies for future comparisons. The provided dataset is reliable, cost-effective, and systematic, improves our understanding of the environmental impacts caused by road systems, and can be confidently used by decision-makers and delivers proper knowledge for environmental planning and management.

This paper has been submitted as:
Mehrdad Ghorbani Mooselu, Shahab Aldin Shojaeezadeh, Helge Liltved, Nikoo, M. R. "Roadside water quality monitoring and assessment by integrating remote sensing and field measurement. Remote Sensing of Environment."

2.1.6 Paper F: Characterization and Treatment of Tunneling Wastewater Using Natural and Chemical Coagulants.

Summary: Particles and other such contaminants are of environmental concern during the discharge of tunneling wastewater to local water bodies. However, there is a gap in the knowledge related to tunneling water characteristics, particularly regarding heavy metal content and its association to particles. Furthermore, there is a lack of understanding of the link between tunneling wastewater characteristics and the efficiency of coagulants for particle removal. In this research, the characterization of tunneling wastewater was carried out by chemical analysis and a range of techniques to assess factors such as particle size distribution (PSD), the shape and morphology of particles, and the presence of heavy metal pollutants. These were assessed by a laser particle analyzer, scanning electron microscope (SEM), and X-ray energy dispersive spectrometer (EDS), respectively. Based on this characterization, laboratory work was conducted to evaluate the effectiveness of coagulants for the removal of particles and particle-associated contaminants. Both natural (i.e., chitosan) and chemical coagulants, including ferric chloride sulfates (PIX-318) and polyaluminium chloride solution (PAX-XL-3103D), caused a high treatment efficiency (92-99%) for both turbidity and SS. Also, sedimentation alone shifted PSDs from coarser particle size fractions to finer fractions, while chemical coagulation significantly decreased the volume density of particles. Chemicals decreased the sample volume in the range of 10-100 μm, showing that coagulants are highly efficient for particle removal, especially particles smaller than 100 μm.

Contributions: The current study aimed to characterize tunnel construction wastewater and explore the feasibility of using precipitating agents to treat such water. The main contribution of this research lies in suggesting a feasible solution for particle removal from tunneling wastewater. In addition, the suggested method could be applied in a real-case situation for sedimentation ponds that are currently used for the treatment of tunneling wastewater.

This paper has been submitted as:

Mehrdad Ghorbani Mooselu, Helge Liltved, Naureen Akhtar. "Characterization and Treatment of Tunneling Wastewater Using Natural and Chemical Coagulants." *Journal of Water Process Engineering*.

2.2 Water Quality Contribution to UN SDGs

Due to the importance of water in the foundation of sustainable, prolific, and dynamic societies and ecosystems, the UN has prioritized water security and defined specific policy targets for water protection and preservation. Two SDGs, including #6 (clean water and sanitation) and #14 (life below water), directly focus on sustainable water policies (Tsani et al., 2020; Sørup et al., 2020; Gain et al., 2016).

Water quality is strongly related to UN SDGs. The long-term socio-ecological consequences of low water quality have become a global issue of concern (Bhaduri et al., 2016). Water quality is clearly included in the SDGs as Target 6.3: "By 2030, improve water quality by reducing pollution, eliminating dumping and minimizing release of hazardous chemicals and materials, halving the proportion of untreated wastewater and substantially increasing recycling and safe reuse globally" (Alcamo, 2019). All approaches investigated in this project are related to surface water quality monitoring and assessment, aiming to protect freshwater quality during road construction and operation and achieve more sustainable road construction. Assessing the vulnerability of surface water to road construction, optimizing water quality monitoring systems (by remote sensing, in-situ sampling and surveys), and characterization and treatment of tunneling wastewater provide good examples to evaluate the anthropogenic effects on water quality and enhance water quality protection services.

Considering the multiple threats to surface water quality, there are a number of SDGs that are relevant to the sustainable management of water bodies as a natural resource for future generations. In this regard, some targets such as SDG1 (no poverty), SDG2 (zero hunger) and SDG8 (decent work and economic growth) indirectly involve European water resources in the eradication of poverty and hunger and improving welfare and per capita income (Tsani et al., 2020). SDG3 targets good health and well-being and covers ambient pollution such as water pollution. SDG12 aims for sustainable consumption and production patterns in natural resources, including water bodies (Tsani et al., 2020). SDG13 (climate action) calls for taking urgent action to prevent or reduce the effects of climate change. SDG15 (life on land) focuses on the protection, restoration, and sustainable use of terrestrial and inland water ecosystems and their services as well as combating desertification, land degradation, and biodiversity loss. Both SDGs 13 and 15 emphasize the recognition of pressures on water ecosystems to provide a good platform for the implementation of sustainable protection policies. Regarding affordable and clean energy (SDG7), and industry innovation and infrastructure (SDG9), the sustainability of water bodies, including water quality, could be considered in adopted policies (Tsani et al., 2020).

The UN SDGs are defined as individual goals. However, they are related to each other, and the policies adopted for each goal can influence others. Water quality acts as an interlinkage between many of these goals, and the targets and indicators of freshwater quality are directly (Goal 6) or indirectly considered in UN SDGs (Bhaduri et al., 2016). Table 1 reviews the role of water quality as an agent of interlinkages among the SDGs. In this table, a negative interlinkage is defined as a state in which actions to meet one target make it more challenging to reach one or more other targets. Conversely, a positive interlinkage is when actions to meet one target facilitate reaching one or more other targets. Direct interlinkages mean water quality is explicitly referenced in the SDG text, or the concepts are directly related to water quality. Indirect interlinkages can be deduced from evidence in the literature. Notably, the direction of influence is important here. The terms one-sided (unilateral) and two-sided (reciprocal) explain the direction of interlinkage between water quality targets (6.3) and other targets. For example, actions to reduce poverty may have a positive effect (more treatment programs) or negative impact (more pollution) on water quality, depending on economic circumstances. However, improvement in water quality does not necessarily lead to an increase per capita income. Hence, the relationship between SDG 1 (no poverty) and water quality targets (6.3) is a one-sided interlinkage. On the other hand, water quality is expected to be degraded by higher cultivation areas. Better quality of water can increase agricultural production and quality or at least increase the potential for more agricultural activities. This creates a two-sided interlinkage between SDG 2 (zero hunger) and water quality target.

Table 1 Summary of interlinkage between water quality target (6.3) and other targets in SDGs.

UN SDGs		Relationship	Type of interlinkage			Ref
			Direct/Indirect	Positive/Negative	Direction	
1. No poverty		As communities' economic situation (per capita income) improves, the rate of pollutants entering water resources increases up to a certain point. Then this trend is reversed by stabilizing the economic situation and increasing the amount of investment in water treatment and clean water supply. Hence, actions to reduce poverty may have a positive or negative effect on water quality depending on economic circumstances.	Indirect	Undetermined	One-sided	(Sullivan, 2002; Lin and Liscow, 2013; Zhang and Gangopadhyay, 2015)
2. Zero hunger	2.1 2.2	Water quality is expected to be degraded by higher cultivation areas (more food production).	Indirect	Negative	Two-sided	(Mateo-Sagasta et al., 2017)
	2.3	Probably will propose approaches to protect water quality during agricultural activities.		Positive		(Grizzetti et al., 2016)
	2.1 & 2.2	For subsistence fishing, good water quality is a prerequisite.		Positive		(Adeyemo, 2003)
3. Good health and well-being	3.3	Water quality directly influences combating of water-borne diseases.	Direct	Positive	Two-sided	(Prüss-Ustün et al., 2014)
	3.1, 3.3, 3.4, 3.8, 3.b	A growing concern is the overuse of antibiotics and antimicrobial resistance (observable in fresh water). As health care expands due to economic routine, antibiotic use will increase.	Indirect	Negative		
	3.9	Contaminated water is a major source of disease.	Direct	Positive		
4. Quality education	4.7	The education targets will facilitate achieving the water quality target.	Indirect	Positive	One-sided	(Mcdonald et al., 2008; Dietz et al., 2004)
5. Gender equality	5.1	In developing countries, and mostly in rural societies, women have the primary role in the water supply. Hence, their support is necessary to achieve successful quality programs.	Indirect	Positive	One-sided	(Manyanhaire and Kamuzungu, 2009)
	5.4		Indirect	Positive		
	5.c		Indirect	Positive		
6. Clean water and sanitation	6.1	”Access to safe and affordable drinking water for all.”	Direct	Positive	Two-sided	(Alcamo, 2019)
	6.2	To “achieve access to adequate and equitable sanitation and hygiene for all and end open defecation.”	Direct	Positive		
	6.4	To “ensure sustainable withdrawals and supply of freshwater.”	Direct	Positive		
	6.5	To “implement integrated water resources management.”	Direct	Positive		
	6.6	To “protect and restore water-related ecosystems.”	Direct	Positive		
	6.a	To expand international cooperation and support in water-related activities.	Direct	Positive		
	6.b	“Support and strengthen the participation of local communities in improving water and sanitation management indicators.”	Direct	Positive		
7. Affordable & clean energy	7.1	Access to affordable, reliable and modern energy services may increase or decrease water quality depending on service type.	Indirect	Undetermined	One-sided	(Who, 2014; Prüss-Ustün et al., 2014)
	7.2	“Increasing the share of renewable energy” may increase or decrease water quality.	Indirect	Undetermined		
	7.a	“To promote investment in energy infrastructure and clean energy technology” can decrease pollution and improve the water quality.	Indirect	Positive		
	7.b	To “upgrade technology for supplying modern and sustainable energy” can decrease the pollution in water resources.	Indirect	Positive		
8. Decent work and economic growth	8.4	“Improving resource efficiency” leads to the use of fewer materials (per service) and generating less wastewater (per service).	Indirect	Positive	One-sided	(Tsuzuki, 2014)

	8.9	“Promoting sustainable tourism” can highly likely encourage the approaches to reduce pollution.	Indirect	Positive		
	8.a	“Increase aid for trade support” can increase or decrease water quality.	Indirect	Undetermined		
9. Industry, innovation, and infrastructure	9.1 9.2 9.4 9.a	Water pollution could be decreased by “Develop quality, reliable, sustainable and resilient infrastructure” (Target 9.1), “Promote inclusive and sustainable industrialization” (Target 9.2), “Upgrade infrastructure and retrofit industries to make them sustainable” (Target 9.4), and “Facilitate sustainable and resilient infrastructure development in developing countries” (Target 9.a).	Indirect	Positive	One-sided	(Alcamo, 2019)
11. Sustainable cities and communities	11.1, 11.2, 11.3	“Upgrade slums” (Targets 11.1), “expanding public transport” (Target 11.2), and “enhance . . . sustainable urbanization” (target 11.3), can reduce water pollution.	Indirect	Positive	One-sided	(Haddis et al., 2014)
	11.5	If we consider chemical spills in cities, as an example of Target 11.5 (“reducing the deaths and number of people affected by water-related disasters”), then it can reduce water pollution.	Direct	Positive		
	11.6	“Reducing the adverse per capita environmental impact of cities.”	Indirect	Positive		
	11.a	“Supporting positive environmental links between urban, peri-urban and rural areas by strengthening national and regional development planning.”	Indirect	Positive		
	11.b	“Increasing the number of cities adopting integrated policies towards resource efficiency.”	Indirect	Positive		
	11.c	“Sustainable and resilient buildings utilizing local materials”	Indirect	Positive		
12. Responsible consumption and production	12.1	“Implementing the 10-Year Framework.”	Indirect	Positive	One-sided	(Tsuzuki, 2014)
	12.2	Sustainable management and efficient use of natural resources.	Indirect	Positive		
	12.3	“Decreasing global food waste” and consequently reducing the impact of agriculture on water quality.	Direct	Positive		
	12.4	“Achieving environmentally sound management of chemicals and significantly reducing their release to . . . water.”	Indirect	Positive		
	12.5	“Substantially reducing waste generation.”	Indirect	Positive		
	12.6	“Encourage companies to adopt sustainable practices” can decrease wastewater generation.	Indirect	Positive		
	12.7	“Promote sustainable public procurement practices” can reduce the entrance of hazardous material into wastewater.	Indirect	Positive		
	12.8	“Ensure people have relevant information for sustainable development” can highly prevent water pollution.	Indirect	Positive		
	12.a	Supporting developing countries to move towards more sustainable patterns of consumption and production can improve water quality over time.	Indirect	Positive		
	12.b	“Implement tools to monitor sustainable development impacts.”	Indirect	Positive		
13. Climate action		Climate change effects on water quality depend on site-specific features of water systems. Regarding the precipitation changes, the dilution capacity of the river and the pollution load by surface runoff are dominant factors. When it comes to temperature changes, global warming negatively influences aquatic ecosystems.	Indirect	Site-specific	One-sided	(Delpla et al., 2009; Punzet et al., 2012)
14. Life below water	14.1	“Reducing marine pollution of all kinds, in particular from land-based activities, e.g., nutrient pollution.” Nitrogen pollution may produce coastal hypoxia zones and endangers the environmental quality of coastal conservation areas.	Direct	Positive	Two-sided	(Alcamo, 2019)
	14.2, 14.5	Sustainably managing marine and coastal ecosystems (Target 14.2) and “conserving at least 10 % of coastal areas” (Target 14.5).	Indirect	Positive	Two-sided	(Alcamo, 2019)
	14.3	“Reducing ocean acidification” improves water quality (acidity is a water quality). Notably, ocean acidification is mostly because of atmospheric CO2 rather than water pollution.	Direct	Positive	One-sided	(Alcamo, 2019)
	14.7	“Sustainable management of aquaculture and tourism” can improve water quality since, in the coastal zone, aquaculture and tourism are considered as the main source of water pollution.	Indirect	Positive	Two-sided	(Reopanichkul et al., 2010)
15. Life on land	15.1	“Ensure the conservation, restoration and sustainable use of terrestrial and inland freshwater ecosystems and their services.”	Direct	Positive	Two-sided	(Alcamo, 2019)
	15.2	“Implementation of sustainable management of all types of forests.”	Indirect	Positive	One-sided	(Croke and Hairsine, 2006)
	15.3	“Combat desertification, restore degraded land and soil” can improve water quality.	Indirect	Positive	One-sided	(Sahrawat et al., 2010)

	15.5	"Prevent the extinction of threatened species."	Indirect	Positive	One-sided	(Borzée et al., 2018)
	15.9, 15.a, 15.b	"Integrate ecosystem and biodiversity values into national and local planning, development processes, poverty reduction strategies and accounts" is related to water quality because water quality is a major ecosystem value.	Indirect	Positive	One-sided	(Keeler et al., 2012)
16. Peace, justice, strong institutions	16.1, 16.3	To "significantly reduce all forms of violence" (Targets 16. 1) and "promote the rule of law" (16.3) can influence water quality. Poor water quality makes the conflict between stakeholders, and water quality can improve peace. On the other hand, supporting water quality targets and supplying enough water with good quality may decrease conflict.	Indirect	Positive	Two-sided	(Evensen and Stedman, 2018; Fischhendler et al., 2016)
17. Partnerships for the Goals		Partnerships provide a suitable context to support and improve successful protective programs	Indirect	Positive	One-sided	(Peckenham, 2006)

2.3 Remote Sensing Contribution to UN SDGs

The application of remote sensing technology as a valuable tool in regional water quality monitoring and assessment was evaluated in this Ph.D. project. Hence, in the second part of this chapter, the application of this technology in achieving SDGs is investigated.

Earth observation (EO) technologies are of great potential to contribute to UN SDGs by monitoring indicators, improving the consistency of SDGs, and supporting management strategies (Kavvada et al., 2020). It is essential to monitor the temporal and spatial SDG indicators (Estoque, 2020). Consistent data for water quality management is often unavailable or incomplete (Connor, 2015). This is partly because the in-situ surface and groundwater quantity observations generate only partial data and fail to reflect the full dimensionality of water problems. Vulnerabilities in evaluating the spatiotemporal variation of water quality and other socio-economic (e.g., populations, biodiversity, and environmental risk) variables on a regional scale may influence decision-making and sustainable management policies (Vörösmarty et al., 2018). In this regard, earth observation can be efficiently applied to obtain reliable information for certain environmental indicators at different scales worldwide and sustainability assessments (Bhaduri et al., 2016). EO data combined with other sources of data (e.g., field measurements, demographics) provide a suitable context for integrated measurements of environmental indicators and SDG indicators (Cochran et al., 2020). Regarding 231 unique indicators for 169 UN SDGs targets, RS directly or indirectly supports 30 (12%) of these indicators by observation data (Estoque, 2020).

Based on the literature, the remote sensing observation effects on UN SDGs are highly related to environmental goals, including Goal 6 (clean water and sanitation), Goal 13 (climate action), Goal 14 (life below water) and Goal 15 (life onland) (Kavvada et al., 2020). However, the application of remote sensing data in measuring Goal 2 (zero hunger) and Goal 11 (sustainable cities and communities) is also considerable (Kavvada et al., 2020; Estoque, 2020). EO data is also employed to achieve sustainable management of the environment and ensure good health and well-being (SDG 3). There are three SDG indicators that could be effectively assessed by remote sensing information: 6.6.1 (water-related ecosystems), 11.3.1 (land-use efficiency), and 15.3.1 (land degradation) (Kavvada et al., 2020; Im, 2020).

In the Ph.D. project, RS technology was applied for water quality monitoring and assessment of roadside water bodies, which is directly related to SDG 6 (clean water and sanitation). Sustainable management in water resources requires reliable data on water resources' content, conditions, and services. Satellite-based information can actively provide such information in the desired scale and time frame (Mulligan et al., 2020; Cochran et al., 2020; Fitoka et al., 2020). In particular, reliable data on the spatiotemporal variation of parameters is vital when it comes to large-scale strategies such as regional or national management plans. To realize targets under SDG 6, priority areas for sustainable management should be determined, and RS data can facilitate this process (Estoque, 2020). Target 6.3 (improving water quality by reducing pollution) and 6.6 (restoring water-related ecosystems) are good examples here. Regular monitoring and analysis of water quality are fundamental to achieving these targets. In this regard, remote sensing can be applied directly or as a complementary tool to measure several different indicators, e.g., 6.3.1 (proportion of wastewater safely treated), 6.3.2 (proportion of bodies of water with good ambient water quality) (Bresciani et al., 2019), and 6.6.1 for “change in the extent of water-related ecosystems over time” (Chirici, 2020; Kaplan and Avdan, 2017). In addition, the application of remote sensing in water quality assessment can explicitly influence other targets and indicators that are related to water quality (see Table 1). Here, some water-related indicators that RS-based measurements can help to determine are listed (Holloway and Mengersen, 2018; Estoque, 2020):

2.4.1 Proportion of agricultural area under productive and sustainable agriculture.

3.d Strengthen the capacity of all countries, in particular developing countries, for early warning, risk reduction, and management of national and global health risks.
6.3.1 Proportion of domestic and industrial wastewater flows safely treated.
6.3.2 Proportion of bodies of water with good ambient water quality.
6.4.1 Change in water-use efficiency over time.
6.4.2 Level of water stress: freshwater withdrawal as a proportion of available freshwater resources.
6.5.1 Degree of integrated water resources management implementation (0–100)
6.6.1 Change in the extent of water-related ecosystems over time.
14.3.1 Average marine acidity (pH) measured at agreed suite of representative sampling stations.
14.4.1 Proportion of fish stocks within biologically sustainable levels.
14.5.1 Coverage of protected areas in relation to marine areas.
15.3.1 Proportion of land that is degraded over total land area.

2.4 Impact of the Project on UN SDGs in Norway

Despite challenges in terms of climate gas emissions, unsustainable consumption patterns, and biodiversity, the current ranking of Norway on the SDG Index is sixth (Unsd, 2021). The status of Norway in SDG 6, which is the most relevant goal to the applied approaches in this Ph.D. project, is acceptable. However, there is still a long way to go to meeting some targets, especially 6.3. A brief explanation of each target in SDG 6 is provided as follow:

6.1 Norway has succeeded in providing safe and affordable drinking water, adequate and equitable sanitation and sewerage for all.

6.2 Norway has also supplied adequate and equitable sanitation and hygiene for all and ended open defecation.

6.3 Despite the general water quality status in Norway (which is good), there are serious challenges regarding wastewater and pollution. In Norway, 35% of the water bodies, including lakes and rivers, are subject to degradation and require environmental action. Additionally, 12% of freshwater resources are strongly modified and do not satisfy environmental objectives. Hence, regular and sustainable monitoring and assessment of the quality of freshwater resources are necessary. More importantly, more investment is required for restoring contaminated or degraded water-related ecosystems (Regjeringen.No, 2021). This point clearly shows the importance of this Ph.D. project for determining the water quality status under the effects of road construction and operation, improving quality monitoring systems by optimizing the current ground-based systems, and evaluating the feasibility of RS technology as a supplementary tool. Therefore, the core idea behind the Ph.D. project directly facilitates achieving target 6.3.

6.4 The fresh water supply is good. However, more investment is required to improve the water and wastewater networks (e.g., 30% water loss in the network before consumption), and to adapt to climate change (e.g., managing increased precipitation, floods, and rising sea levels).

6.5 By implementing the EU WFD, Norway has taken notable steps to achieve integrated water management. This means its knowledge of managing freshwater and coastal resources is considerably improved. In addition, with a higher degree of public participation, more attention and resources are received from the government. However, due to financial constraints and the need to coordinate across state sectors, there is much work to do to fully meet the EU Water Framework Directive.

6.6 Forest protection needs more attention. Protecting water ecosystems (e.g., peatland, wetland and river) should be continued. The role of measures to monitor, analyze, and protect water quality is tangible and significant here (Regjeringen.No, 2021).

Chapter 3

In this project, the central idea behind the sustainable approaches for highway runoff management is the protection of water quality against pollution from road construction and operation. Several sub-topics are presented in this chapter to consider the project's main objective from different perspectives.

3.1 Thesis Findings

The main findings on each part of the project are presented in the following subsections.

3.1.1 Current European Approaches in Highway Runoff Management

Based on the literature review, highway runoff characterization differs between different regions, mainly due to regional traffic load, site-specific characteristics such as climatic factors, and maintenance practices. For highway runoff treatment, the proper treatment system is selected based on site-specific parameters, on the one hand, and cost-efficiency, national and international regulations, and recommendations from local authorities, on the other hand. Therefore, collecting and analyzing proper, consistent, and scientifically valid data from different case studies and considering their site-specific parameters (e.g., geographic and climatic issues) can produce a suitable context to understand the characterization of highway runoff. Notably, some significant topics, such as monitoring network and measurement technology, frequency of data collection, sampling methods, and data analysis, should be further investigated for sustainable highway runoff management. In addition, particle size distribution and the associated pollutants strongly influence runoff toxicity, BMP design, and removal efficiency. The most commonly applied BMPs are grassed swales, retention ponds, sedimentation basins, and wetland basins. Variation in quantity and quality of contaminant loadings, and climate change effects, such as longer dry periods and increased intensity of heavy rainstorms, are also significant issues in the design of BMPs. When it comes to modeling approaches, the selection of models highly depends on the problem that needs to be solved and the project goal. Besides this, considering different types of uncertainty (e.g., model parameters, model structure, and observation data) in runoff modeling is of great importance.

3.1.2 Surface Water Vulnerability to Road Construction

Analyzing the effects of road construction on water quality facilitates more efficient and environmentally friendly road construction. First of all, such analyses act as an effective tool to simplify the complex and massive qualitative data for decision-makers and to reflect the variation of water quality due to anthropogenic activities over time and space. In addition, this approach provides useful knowledge for decision-makers to achieve the optimum solution for mitigating the pollution of road construction and to select the best management practices. Additionally, considering the impact of each construction activity on surface water quality, activities such as construction of treatment plants for runoff water, paving, and bridge-building have a minor impact on the receiving water bodies. By contrast, blasting, area cleaning, water management, and drilling have the highest deteriorating impact on surface water during road construction (Fig. 5).

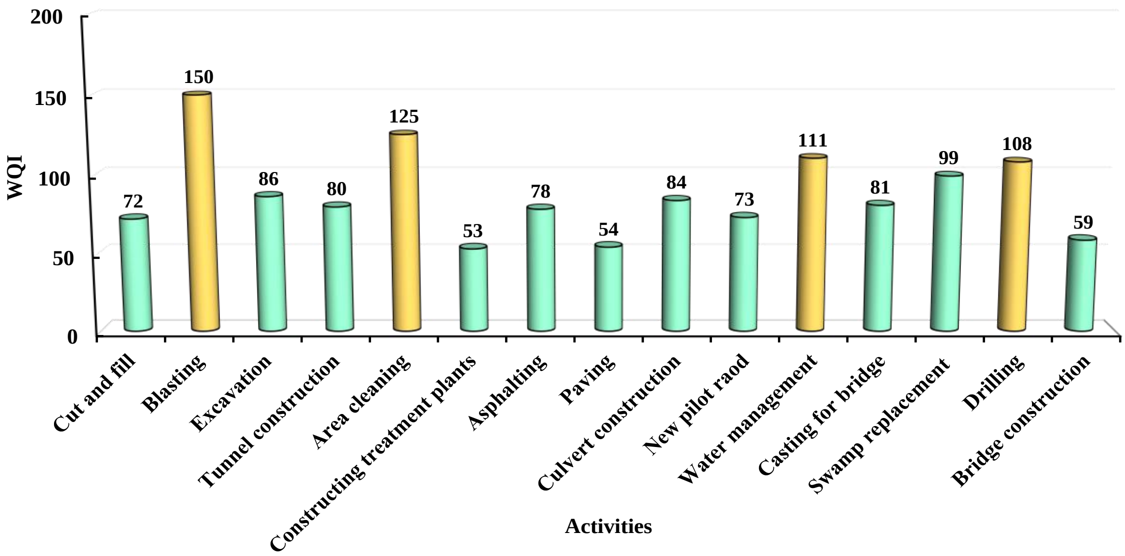

Fig. 5 The vulnerability of water resources to different construction activities of the project. (The larger the obtained WQI, the greater the violation of the standard.)

Therefore, understanding the effects of each construction activity can be applied to calculate the environmental risk of various designs for a road construction project. For example, by assigning a unit (e.g., based on the WQI) to each construction activity and considering the extent of activities along the road, we can compute the overall risk of a specific design to roadside water bodies. The results also show the importance of a water quality index in interpreting water quality data.

3.1.3 Optimizing Water Quality Monitoring Networks

Two different approaches were suggested to achieve the optimized water quality monitoring network during road construction. In the first approach (using information theory), the number of stations in the suggested networks decreased by 25% (in NSGA-II) and 31% (in NSGA-III) compared with the primary network (with 44 stations). In addition, the optimized WQMN minimized the redundancy of information and maximized the value of provided information to understand the qualitative status of the aquatic system over seven catchments along the road path.

In the second approach, the ability of gamma test theory (GTT) to determine the optimal number and location of monitoring stations was investigated. The results reveal that compared with the primary network (containing 48 stations), the GTT method can decrease the number of stations by 23% (to 37 monitoring stations). Additionally, this improved network has an appropriate distribution over seven discharge areas. The results indicate that the optimal number and spatial arrangement of monitoring stations in a road construction project can be modified during the construction period. In particular, some uncertainties, such as large changes in the location and type of construction works or variation in precipitation patterns during different periods, can make a difference to the results. Therefore, the proposed method is feasible to establish a WQMN in short- and medium-term construction projects, such as road construction, tunneling, and mining.

In the first approach, the Canadian Council of Ministers of the Environment (CCME) water quality index was applied to calculate the matrix of VOI and TE between each pair of stations. The universal water quality index (U-WQI) was applied for GTT in the second approach. CCME-WQI requires the same time series for all qualitative parameters in each assessment, which in practice leads to a decrease in the number of parameters examined. Accordingly, in the first approach, four parameters that had the longest time series and a minimum of missing data for 44 potential stations were applied for computing CCME-WQI. By contrast, the universal WQI in the second approach was calculated based on 28 physical, chemical, and biological parameters in 48 monitoring stations.

These optimization approaches indicated that the primary monitoring network was not optimally established, which led to higher monitoring costs and a bigger quality dataset that does not necessarily provide the optimal knowledge for decision-makers. Optimizing the WQMN during road construction decreases the monitoring cost and helps achieve sustainable runoff management. In some cases where local authorities prioritize specific streams and water bodies (e.g., the main streams for sea trout and drinking water resources), the optimization process could be modified based on local conditions and by assigning higher weightings to selected streams.

3.1.4 Application of Remote Sensing for Roadside Water Quality Monitoring

The proposed method applied B3/B2 bands and NDCI combinations to calibrate turbidity (R^2 = 0.8 and RMSE = 1.947 FNU) and chlorophyll-a (R^2 = 0.79, and RMSE = 6.869 μg/l), respectively. Finally, proposed empirical equations were used with atmospherically corrected images of Sentinel-2 to estimate turbidity and chlorophyll-a in various buffer zones along the road, and the results were compared with field observations. Based on the results, the estimated values for turbidity and chlorophyll-a were in good agreement with the field observations and accurately reflect the effects of road construction and operation on water quality.

The estimated seasonality from Sentinel 2 shows that the average turbidity values in fall and winter are higher than those in spring and summer. This is in line with the site-specific climatic conditions, with higher precipitation in fall and winter, that carry highway construction and operation runoff into the roadside water bodies. Another factor is a higher variation of turbidity values in the fall semester, which may be related to higher precipitation events and the “first flush” effect of road pollutants after a dry period. In addition, the turbidity concentrations close to the shore of the water bodies are higher than in central areas (Fig. 6). This may be related to the transport of particles from land in the boundary area and particles dispersed from sediments and shoreside erosion by wind-induced waves and turbulence.

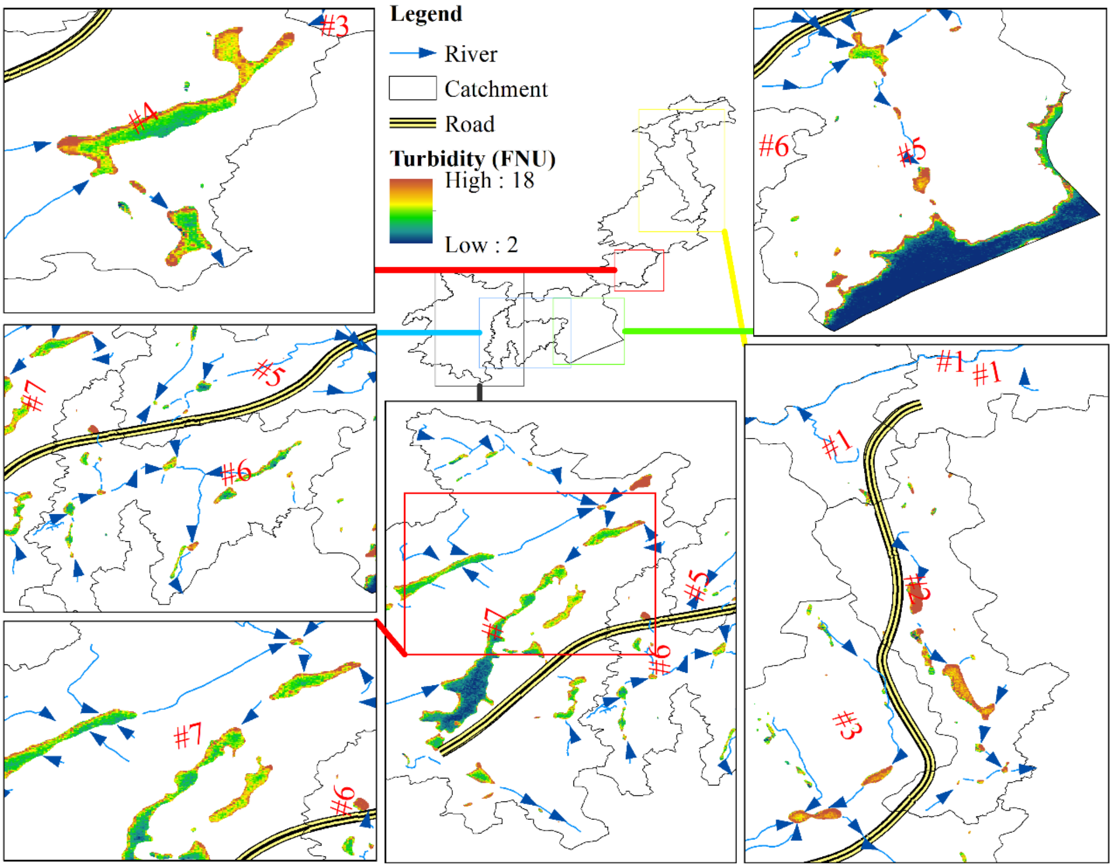

Fig. 6 Spatial map of catchments with average turbidity values in waterbodies derived from Sentinel-2A satellite data (2017-2021) and flow directions

On the other hand, a general trend is detectable for the concentration of chlorophyll-a in roadside water bodies, in which the average chlorophyll-a in warm seasons is higher than that in cold seasons. The highest average chlorophyll-a level in most catchment areas occurs in spring, followed by the second-highest level in summer. The lowest values for chlorophyll-a are related to the autumn season. Variations in temperature and light intensity are the main reasons for the observed variations in chlorophyll-a concentrations. Also, the concentration of chlorophyll-a in the water close to the shorelines is lower than that in central areas of the water bodies (Fig. 7).

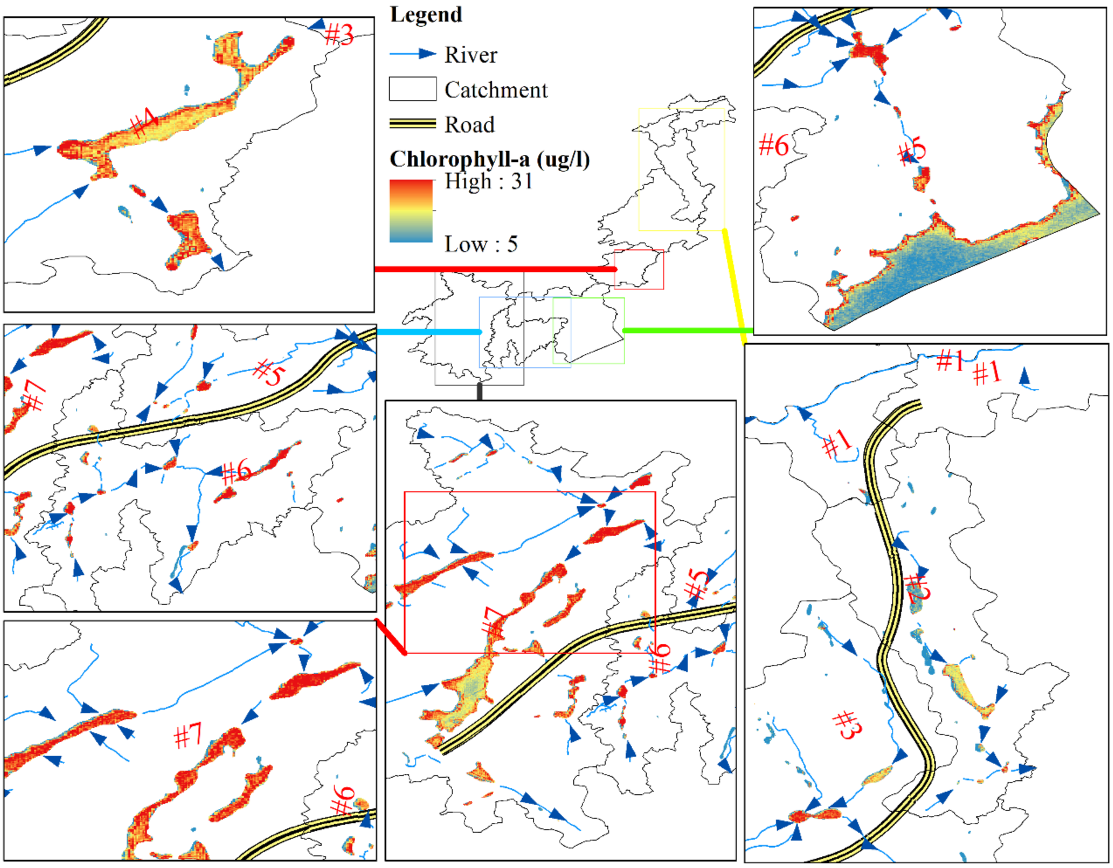

Fig. 7 Spatial maps of average chlorophyll-a values in waterbodies derived from Sentinel-2A satellite data (2017-2021) and flow direction

Using satellite information as a supplement for field observation provides more efficient monitoring of roadside waterbodies during construction and operation. The proposed method facilitates regional-scale assessment (i.e., monitoring roadside water bodies on a long stretch of a road), where in-situ observation methods are time-consuming, costly, or even, in some cases, impossible. Spatiotemporal assessment of water bodies on a regional scale improves management practices. For example, the transport of pollution in time and space can be detected and prevented, or the most vulnerable water bodies during road construction and operation can be determined, and the location of management practices can thereby be defined based on such large-scale analyses.

3.1.5 Characterization and Treatment of Tunneling Wastewater

Analysis shows considerable amounts of heavy metals in all three types of tunneling water. By removing solids by sedimentation, most of the heavy metals were also removed. However, the residual concentrations were still high for some metals, particularly Cu and Cr. The results suggest that the proposed two-step method (15 minutes of sedimentation followed by coagulation and sedimentation) is highly efficient for particle removal in tunneling wastewater and a promising treatment option to comply with discharge regulations. The following conclusions were derived from the chemical and microstructure analysis and the jar test results.

1. In all three types of tunneling waters used in this study, short-time sedimentation alone substantially reduced the particle content (suspended solids and turbidity) and particle-associated pollutants (including heavy metals, in all three types of tunneling waters used in this study. However, based on the jar test results, sedimentation alone is not sufficient as the suspended solid concentration remained higher than the discharge limit of 100 mg/L in all waters. Also, no nitrogen removal was evident, and the concentrations of some heavy metals (e.g., Cu and Cr), severely exceeded the concentrations for acute toxic effects in freshwater bodies. Therefore, it shows that high dilution factors and pH adjustment are required when discharging to local freshwater bodies.

2. Improved removal efficiencies were demonstrated by chemical coagulation followed by sedimentation. The optimum coagulant dosages in jar tests led to high treatment efficiencies (92-99%) for turbidity and SS. The optimum dosages of chitosan, PIX, and PAX for water sample 1 after pre-treatment (15 min sedimentation) were 1 mg/L, 3 mg Fe/L, and 3 mg Al/L, respectively, while a dosage of 2 mg Al/l gave the best results in water sample 3. It was also evident that acid dosage alone (2 mL/Lof 32% HCl) improved particle removal.

3. Fifteen minutes of sedimentation shifted the particle size distribution from coarser-size fractions to finer particles. The size fraction of 10-100 μm were reduced in all three waters, indicating a rapid sedimentation rate for such particles. The application of chemicals for coagulation as an additional treatment step significantly decreased the volume density of the particles. The application of chitosan, PIX, and PAX decreased the particle volume in the range of 10-100 μm by 11.7, 26, and 31%, respectively, showing that coagulants are highly efficient for particle removal, especially particles smaller than 100 μm.

4. Tunneling water without treatment exhibits particles with sharp edges. Sedimentation and chemical treatment seem to remove the majority of these

particles, resulting in waters with smaller and more "rounded" particles. Particle shapes are a critical issue related to negative impacts on aquatic biota, especially fish.

3.2 Conclusion

The Ph.D. project was aimed at assessing environmentally friendly and sustainable approaches for highway runoff management during construction and operation. First, the state of the art in highway runoff management, in terms of characterization, treatment, modeling approaches, and legislation, was surveyed, and the knowledge gaps in this topic were identified. Then, the field monitoring data from environmental monitoring during the construction of a new 22-km-long highway in southern Norway (2017–2019) was applied to evaluate the spatiotemporal effects of road construction on roadside water bodies and determine the effects of each construction activity on water quality. In addition, the monitoring dataset was also applied to optimize the primary water quality monitoring network using two different approaches, which involved information theory and gamma test theory. In the next part of this project, the application of remote sensing data (i.e., Sentinel-2 Multi-Spectral Imager satellite imagery products) for water quality monitoring on a regional scale was investigated. In the final part of the study, the characterization of tunneling wastewater was measured. An efficient two-step method (15 min sedimentation followed by chemical coagulation and 45 min sedimentation) was also suggested for particle removal from tunneling wastewater, and the feasibility of coagulants (both natural and chemical coagulants) was investigated.

Based on the results, it has been shown that highway runoff has spatiotemporal variation, depending on site-specific parameters (e.g., climate, traffic load), which affects the regional selection of best management practices (BMPs). The existing literature shows minimal investigation to date into the characterization of highway runoff in different climatic scenarios, or the performance assessment of the current BMPs, or uncertainty analysis in modeling approaches.

By analyzing the field monitoring data, it was observed that construction activities spatiotemporally affect water quality depending on their type and extent. In this regard, activities such as blasting, area cleaning, and activities to achieve water management during road construction have the highest impact on surface water.

Additionally, the application of two different optimization approaches to field water quality monitoring show that the primary water quality monitoring network can be modified during the construction process, and that the number and location of the monitoring stations can be optimized as the construction activities vary over time. The results also approve the efficiency of satellite-based information and recommend remote sensing techniques as a reliable supplement to ground-based observations for monitoring roadside water bodies. The results are consistent with field observations during construction and operation periods, reflecting the spatiotemporal effects of road construction and operation on water quality.

Considering the treatment of tunneling wastewater, the suggested two-step method for particle removal from tunneling wastewater gave a high treatment efficiency (92-99%) for both turbidity and SS. Sedimentation alone shifted particle size distribution from coarser particle size fractions to finer fractions, and chemical coagulation efficiently decreased the volume density of particles, especially in the range of 10-100 μm, which is hard to remove using sedimentation ponds.

The core idea behind this Ph.D. project is water quality monitoring, assessment, and protection, which directly contributes to UN SDG 6 (clean water and sanitation) and target 6.3 in particular (improving water quality by reducing pollution, eliminating dumping, and minimizing release of hazardous chemicals and materials). This idea could be related to almost all other UN SDGs directly or indirectly. This study improves understanding of the impact of road activities on surface water quality, and introduce tools and measures for improved monitoring and treatment. Hence, the study will be useful for parties involved in planning, construction, and operation of road projects and pollution control authorities responsible for securing the chemical and biological quality of water bodies.

3.3 Recommendations

Based on the results, the following recommendations are suggested to achieve more efficient and sustainable highway runoff management and protect the quality of roadside water bodies.

1. There is a notable lack of documentation on the operation and maintenance of BMPs. If BMPs run without such documentation and control, poor performance or

breakdown may cause undesired environmental effects in downstream water bodies. The performance of existing BMPs under climate change scenarios and for the different forms of pollutants (particle-bound or dissolved) should be investigated. Notably, some significant topics, including monitoring networks and measurement technology, frequency of data collection, sampling methods, and data analysis, should be considered in highway runoff management. Therefore, regular data collection and analysis are suggested.

2. Limited knowledge exists on the buildup/washout of pollutants and mobilization of inorganic and organic compounds by stormwater in the present and future climate. Particle size distribution and associated pollutants will have a strong influence on runoff toxicity, BMP design, and removal efficiency. Another knowledge gap is related to changing pollutant behavior on impervious surfaces over dry and wet periods, particularly during the "first flush" effect. Such uncertainties should be addressed by proper water quality monitoring and assessment.

3. A comprehensive study is required to develop guidelines for the choice of treatment based on site-specific conditions, expected pollutant load, and environmental impact. These guidelines should also give advice on when treatment is necessary.

4. The effect of each type of construction activity on the quality of roadside water bodies should be considered in route design scenarios. This idea can be applied to calculate the environmental impact of different pollution load scenarios for a road construction project. Accordingly, considering the type and size of construction activities, the expected damage to water resources can be calculated, and measures can be implemented to minimize these environmental effects.

5. A water quality monitoring network is established during road construction based on local experts' knowledge, and there are no specific rules. However, it is vital to optimize the number and the location of stations during the construction period. Considering the variation in type and size of construction activities, the modification of the WQMN can decrease the monitoring cost and improve understanding of the transport of pollutants in the water system.

6. To achieve more sustainable water quality monitoring on roadside water bodies, the application of advanced technologies such as remote sensing provides a reliable source of information that can be used to monitor the quality of water bodies on a larger scale and over longer periods. In particular, when it comes to sustainable measures to mitigate or remove the effects of road construction and operation on water quality and select the best management practices, it is highly recommended to consider pollution transport and the hydrological interaction of sub-catchments. Remote sensing techniques provide a valuable tool for assessing such factors in decision-making and understanding the spatiotemporal variation of water quality along the road route.

7. Understanding the characterization of tunneling wastewater and the type of contaminants helps to adopt the right management practices regarding tunneling wastewater. As shown in this study, the application of a two-step treatment method (15 min sedimentation followed by chemical coagulation and 45 min sedimentation) for particle removal is recommended. This is more efficient for particles in the range of 1-100 µm that are among the most problematic particles for aquatic ecosystems and cannot be easily removed during the commonly used sedimentation process.

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Appendices

In this section, six articles from the results of this project that have been published or submitted in peer-reviewed journals are presented.

Paper A

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Current European approaches in highway runoff management: A review

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ABSTRACT

Highway runoff is one of the most significant non-point sources of pollution for the terrestrial and aquatic environment with biological, physical, and chemical effects. Considering local characteristics, treatment practices, and determining factors are essential for highway runoff management. The aim of this paper is to survey the review of highway runoff management in Europe with emphasis on runoff characterization, treatment, and modeling approaches and identifying possible knowledge gaps exists based on our review. The results showed that highway runoff has spatiotemporal variation, which is the main factor in the regional selection of the best management practice (BMP). Also, recent studies have poorly deemed characterization of highway runoff in different climatic scenarios, performance assessment of the current BMPs, and uncertainty analysis in modeling approaches. Furthermore, economic and risk analysis, along with decision-making methods, provide an optimum plan for the design and operation of BMPs.

1. Introduction

Roads are an integrated part of sustainable development and have a vital role in life quality (E.-E. Commission 2011, Meland, 2015). At the same time, road runoff is a pollution source for the aquatic environment (Angermeier et al., 2004). Highway construction and operation may reduce the quality of receiving waters by increasing the concentration of suspended solids (SS), metals and, hydrocarbons such as oil and Polycyclic aromatic hydrocarbons (PAHs). During operation, road runoff is a mix of exhaust and wear products from breaks, tires, and asphalt. Tunnels accumulate these products, and without any cleaning systems, highly contaminated tunnel wash water may impact receiving waters. De-icing salts and asphalt wear due to studded tires may increase the impact during wintertime (Meland, 2015, Meland, 2010). A vast spectrum of road runoff pollutants has been reported. In addition to the already mentioned (Helmreich et al., 2010, Lee et al., 2011, Brenčič et al., 2012, Kayhanian et al., 2012, Zhao et al., 2016), microplastics (such as 1,3-diphenyl guanidine (DPG) (Carr et al., 2016, Horton et al., 2017, Siegfried et al., 2017, Zhang et al., 2018, Li et al., 2018), nitrogen, carbon and sulfur oxides, nitrogen and phosphorus nutrients, oil and grease, hexa (methoxymethyl) melamine (HMMM) (Ma et al., 2021, Zuo et al., 2011, Monira et al., 2021, Wang et al., 2022, Campanale et al., 2020, Johannessen et al., 2021) may contribute (Helmreich et al., 2010, Kayhanian et al., 2012, Brezonik and Stadelmann, 2002, Lee et al., 2004, Chen et al., 2009). Road runoff adversely affects the aquatic environment (Meland, 2010, Hindar and Nordstrom, 2015).

Road runoff can be collected and treated before discharge to water bodies. As the most harmful substances are associated with particulate matter, the primary mechanism for removal is sedimentation. Sedimentation ponds may be efficient if constructed properly based on runoff volumes and particle characteristics and if maintained properly. Supplementary mechanisms for removal of contaminants are enhanced sedimentation by use of coagulants, filtration (smaller particles and colloidal contaminant), adsorption (dissolved contaminant), and microbial processes (degradation, reduction/oxidation) (Andersson et al., 2018).

Best management practices (BMPs) combine ecological and economic advantages and aims at keeping or restoring the chemical and ecological status of downstream water bodies (Poresky et al., 2011, Stagge et al., 2012). According to the above-mentioned removal mechanisms, the most common European BMPs for runoff treatment are: a) infiltration into road shoulders, road embankments and grassed side ditches (e.g., biofiltration systems and sand filters) (Davis, 2005, Hatt et al., 2009, A.A. Bloorchian et al., 2016), b) stormwater ponds and wetlands, c) sedimentation basins and centralized infiltration facilities (Chen et al., 2009, A.A. Bloorchian et al., 2016, Barbosa and Hvitved-Jacobsen, 2001, Hogan and Walbridge, 2007, Houser and Pruess, 2009), and d) combined sedimentation and infiltration facilities (Andersson et al., 2018). The assessments of BMPs typically focus on the

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quantitative and qualitative control of runoff (Bedan and Clausen, 2009, Leroy et al., 2015, A.A. Bloorchian et al., 2016).

Significant highway runoff is associated with precipitation events and, therefore, has considerable spatio-temporal variation (Thomson et al., 1997, Gan et al., 2008) controlled by a set of factors. Most important may be traffic characteristics (vehicle density and composition, speed, fuel type), the intensity of the event and the antecedent dry weather period (Helmreich et al., 2010, Crabtree et al., 2006, Huber et al., 2016, Horstmeyer et al., 2016). Also, data from measuring programs in downstream water bodies may also be affected by chemical and biological processes and the degree of contaminant dilution. Data from different sites may thus be highly variable even if, e.g., the traffic density is similar (Helmreich et al., 2010, Lee et al., 2004, Crabtree et al., 2006, Bulc and Sajn Slak, 2003).

To achieve the desired level of treatment, quantitative and qualitative information of the road runoff and its constituents is inevitable (Brenčič et al., 2012, Kayhanian et al., 2012, Barrett et al., 1998). Such information is particle size distribution, associated pollutants, and the fraction of pollution in the dissolved and bioavailable phase. Consequently, much research has been conducted to evaluate the association of metals and PAHs with particles (Kayhanian et al., 2004, Zhao et al., 2010), and appropriate cleaning systems.

Besides, for decision-making in sustainable highway management, there is a need to predict road runoff quality. This could be done by the use of models that include the most important regulating parameters (Barbosa, 2007, Barbosa and Fernandes, 2009, Chow et al., 2011, Barbosa et al., 2012). Data from monitoring during ordinary conditions and particularly throughout storm events should be the basis for such models (Munoz-Carpena and Parsons, 2004). The lack of detailed physical, chemical, and hydrological understanding of all processes involved has made the modeling approaches as an ideal solution for addressing the challenge of predicting runoff pollutant concentrations (Opher et al., 2009). Understanding through modeling approaches is an effective way to deal with this problem [50, 52]. Changes in the catchment or other input variables may affect the BMPs' effectiveness and runoff variations and may be better understood by running a calibrated model (Barbosa et al., 2012, German et al., 2005, Elliott and Trowsdale, 2007, Abrishamchi et al., 2010).

Considering all of those aspects, this review paper contributes to the understanding of highway runoff management through attending characterization and treatment of the runoff and considering the modeling approaches and current legislation adopted by different countries. Furthermore, this study points to future research challenges for environmentally sound management of highway runoff.

2. Highway runoff characterization

The highway runoff characterization must be performed at a local base because of site-specific and climatic characteristics that may affect the quantity and quality of highway runoff (Barbosa, 2007). Recently, much of the literature pay attention to characteristics of highway runoff (Lee et al., 2011, Kayhanian et al., 2012, Gan et al., 2008, Barrett et al., 1998, Mangani et al., 2005, Kayhanian et al., 2007, Nie et al., 2008, Lee, 2012, Hilliges et al., 2016, Winston and Hunt, 2016, Q. Wang et al., 2017). Proper characterization is dependent on sampling strategy and analytical methods. As road runoff is associated with precipitation events, the sampling should be during such events. Sampling at increasing flow, top flow, and end of event may give rise to event mean concentrations (EMC), and these may be averaged in order to get the site mean concentration (SMC). The SMC may, in turn, be multiplied with annual runoff to get the site-specific annual transport (SAT) of contaminants. By using this approach, it would be easier to compare between sites and also compare data from before and after the establishment of treatment facilities.

Contaminants may or may not be present in measurable concentrations depending on the analytical methods at hand. It could be that the methods produce numbers for heavy metals but not for PAHs due to high detection limits relative to the current concentrations. A pre-study at the site should therefore be performed in order to establish relevant analytical methods (Kayhanian et al., 2003).

Pollutants in highway runoff are known to appear both in particulate and dissolved form. The pollutant form is strongly influenced by the rainfall pH, the solids' characterization (i.e., size, solubility of all substances, and porosity), the surface type, site properties, and pavement residence (Meland, 2010, Andersson et al., 2018, Huber et al., 2016, Meland et al., 2010). Heavy metals like copper, nickel, zinc, and cadmium often can be found in the dissolved phase, while chromium and lead are mostly particle-bound (Huber et al., 2016, Gunawardana et al., 2015). Therefore, due to exchange reactions, cadmium and zinc have more mobility than chromium (Jayarathne et al., 2017). Key inorganic contaminants in road runoff include heavy metals, particularly zinc, copper, and lead (Wicke et al., 2012). While about 50% of the inorganic pollutants are adsorbed to particles with a diameter between 60–200 μm, a fraction of the nutrients is attached to fine particles. The concentration of heavy metals which is bound to the particles (mass of metal per mass of particulate matter) is almost the same in the particle size range of 63–250 μm. The main difference in this regard is related to the particle size distribution in the highway runoff, in which most of the suspended particles in the effluent are less than 63 μm (Baum et al., 2021). Moreover, the removal of fine particles (<63 μm), which is considered 30–40% of the total mass of sediment (<2 mm) is vital (Kayhanian et al., 2012).

The main concerns related to the entry of particulate matters from highway effluents into the environment include increasing water turbidity (Regier et al., 2020), habitat alteration (Gillis et al., 2021), esthetic and recreational problems, and the creation of the erosion banks (Beryani et al., 2021). On the other hand, dissolved pollutants change the surface and groundwater resources quality and make the problems such as algal bloom development (Smith et al., 2020), ammonia and nitrate toxicity, damage to plants, fish mortality, bioaccumulation in the food chain (Karlsson et al., 2010, Du et al., 2017, Luo et al., 2019), and esthetic problems. In addition, the design, operation, maintenance, and effectiveness of treatment approaches highly depend on the pollutant forms (Kayhanian et al., 2012, Huber et al., 2016, Hilliges et al., 2017). For example, the intervening effects of salt-containing effluents are very significant both in the environment and in the treatment process. About 60% of highway salts enter surface water sources and about 40% enter soil and groundwater sources (Perera et al., 2013, Schuler and Relyea, 2018, Green et al., 2008, Szklarek et al., 2021). The entry of salt-containing effluent into groundwater and soil causes the cationic exchange of Na^{+} ion with Ca^{+2} and Mg^{+2} ions (Robinson et al., 2017), thereby lowering the pH, and flushing heavy metals, nutrients, and organic matter, and reducing the retention of water in the soil (Schuler and Relyea, 2018, Green et al., 2008, Szklarek et al., 2021, Rommel et al., 2020). Therefore, the runoff containing road salt reduces the efficiency of biofilter systems in heavy metals treatment (Søberg et al., 2017). In surface water, it reduces the macrophyte biomass, decomposition of highway runoff by micro-organisms and detritivores, and specific denitrifying activity (Szklarek et al., 2021, Lancaster et al., 2016, Tyree et al., 2016, Stoler et al., 2018). Highway runoff characterization is different in diverse regions, mainly due to regional traffic load, site-specific characteristics, climatic factors, and maintenance practices (see Table 1).

The considerable variation in the parameter values is due to site-specific features but probably also to different sampling strategies and analytical methods, as already referred to. ADT, antecedent dry period, drainage area, maximum rain intensity, and land use may represent the most important regulating factors (Kayhanian et al., 2003).

Many of the measured parameters of road runoff correlate (Table 2). The most interesting correlations are those where harmful contaminants (e.g., heavy metals and PAHs) correlate with in-expensive and easily measurable parameters (e.g., turbidity, TSS, and DOC) that are suited for

Table 1
Concentration ranges and mean values of various highway runoff parameters for different vehicle densities.

Constituent	Range & (Mean) values for different ADT (vehicles/day)				
	(Robertson et al., 2019)	(Hilliges et al., 2016)	(Kayhanian et al., 2007)	(Han et al., 2006)	(Kayhanian et al., 2003)
	49,500	< 9690	2000–328,000	> 260,000	1800–259,000
pH (pH unit)		7.11–8.15 (7.83)	4.5–10.1 (7.1)		
Temp. (°C)			4.7–25.4 (12.5)		
Turbidity (NTU)			44–1400 (471)	11–171 (46.8)	
EC (µs/cm)		0.068–21.5 (-)	5–743 (96.1)		
Cl (mg/L)		0.93–7400 (-)	4.3–9000 (1260)		
Hardness (mg/L $CaCO_3$)					2–448 (49.5)
COD (mg/L)	148 ± 49			19–2283 (252.5)	2.4–480 (123.8)
DOC (mg/L)		2.1–21(6.87)	1.2–483 (18.7)	2.9–848.8 (66.9)	
O&G (mg/L)			1–20 (6.6)		
TDS (mg/L)			3.7–1800 (87.3)		
TOC (mg/L)			1.6–530 (21.8)		
TPH (mg/L)			0.12–13 (2.2)		
TSS (mg/L)			1–2988 (112.7)	8.8–466.4 (67.7)	
As* (µg/L)			0.5–20 (1.0)		
Cd* (µg/L)	0 ± 0		0.2–8.4 (0.24)	0.5–17.8 (1.4)	
Cr* (µg/L)	50 ± 37		1–23 (3.3)	0.5 19.3 (2.8)	
Cu* (µg/L)			1.1–130 (14.9)	5.2–735.3 (65.9)	
Fe* (µg/L)			32–3310 (378)		
Ni* (µg/L)	14 ± 7		1.1–40 (4.9)	0.8–229.2 (15.7)	
Pb* (µg/L)	80 ± 45		1–480 (7.6)	0.5–43.4 (4.9)	
Zn* (µg/L)	698 ± 399		3–1017 (68.8)	42.3–8150 (415)	
As** (µg/L)	6 ± 5		0.5–70 (2.7)		
Cd** (µg/L)		<0.1–14 (0.36)	0.2–30 (0.7)	0.4–20.2 (1.8)	
Cr** (µg/L)			1–94 (8.6)	2.3–40.1 (9.7)	
Cu** (µg/L)	143 ± 50	10–273 (67.1)	1.2–270 (33.5)	15.9–920.8 (92.9)	
Fe** (µg/L)			1400–104,000 (18,500)		
Ni** (µg/L)		1.0–67 (12.1)	1.1–130 (11.2)	2.4–253.7 (20)	
Pb** (µg/L)		<1.0–92 (21.4)	1–2600 (47.8)	4.6–151.6 (25.8)	
Zn** (µg/L)		49–1300 (311)	5.5–1680 (187.1)	83.3–8881 (506.3)	
NO3-N (mg/L)			0.01–4.8 (1.07)	0.3–34.7 (2.7)	
Ortho-P (mg/L)			0.01–2.4 (0.11)		
Total P (mg/L)	2.660 ± 2.295		0.03–4.69 (0.29)	0.1–8.2 (0.9)	
TKN (mg/L)			0.1–17.7 (2.06)	0.8–111.3 (9.6)	
Calcium (mg/L)					4.5–66.8 (12.7)
Magnesium(mg/L)					1–21.8 (3.2)
Sodium (mg/L)					1–56 (11)
Sulfate (mg/L)					0.23–57 (4.2)
Total coliform (MPN/100 mL)					2–900,000 (21,970)
Fecal coliform (MPN/100 mL)					2–205,000 (6083)
Oil and grease (mg/L)	144 ± 127			1.5–80.2 (14)	1–226 (10.6)

ADT (mean daily traffic on an annual basis),
* Metals (dissolved),
** Metals (total)

Table 2
Correlations between different road runoff parameters expressed by R^2.

Surrogate pairs	References	
	(Kayhanian et al., 2012)	(Han et al., 2006)
Fe & (Cu, Pb)	0.8	
TSS & (COD)	0.95	0.4
TSS & (DOC, TKN)		0.34, 0.4
COD & (TKN)		0.84
DOC & (TKN, COD, O&G)	0.8	0.92, 0.81, NA*
TOC & (DOC)	0.96	
TPH & (O&G)	0.86	
TSS & (Turbidity)	0.8	
Fe & (Total Pb, Cr, Cu, Zn, Pb)	0.8–0.9	
TDS & (EC, Cl)	0.8, 0.9	
DOC & (Total PAHs, pesticides)	0.8	
O&G & (COD, DOC)	0.8	
TSS & (Particulate metals, Total PAHs)	0.8	NA, 0.52–0.61
TSS & (Particulate Cu, Ni, Zn, Pb)	0.85	0.58–0.61

COD (chemical oxygen demand), DOC (dissolved organic carbon), O&G (oil and grease), TKN (total Kjeldahl nitrogen), TPH (total petroleum hydrocarbons), TDS (total dissolved solids), TOC (total organic carbon).

continuous measuring. After the correlation at a site is established this may be used to 1) reduce the analytical cost by measuring less expensive parameters than the actual target parameters (Kayhanian et al., 2012), and to 2) measure a suitable proxy parameter on a continuous basis to document variability and get a more robust basis for further calculations. Determining such correlations may also provide an improved basis for pollutant source identification as well as modeling efforts (Lee et al., 2004, Gan et al., 2008).

In this table, the value of the correlation between different constituents of road runoff is provided. For example, based on Han et al. (Han et al., 2006), the correlation between DOC and TKN, COD, and O&G are 0.92, 0.81, and not available (NA), respectively. While Kayhanian et al. (Kayhanian et al., 2012) give 0.8 as the correlation between DOC and each of the three parameters of TKN, COD, and O&G.

Three aggregate parameters (TSS, TDS, and TOC) along with iron (Fe) make the most reliable correlations with 13 other water quality parameters, including turbidity, DOC, O&G, TKN, TPH, EC, Cl, Cd, Ni, Cr, Cu, Zn, Pb. This shorter list as surrogate parameters consequently reduces the overall monitoring and analyzing cost (Kayhanian et al., 2012).

An essential but rarely described part of highway runoff is from tunnel washing. Tunnels are washed on a regular basis with detergents to clean walls for accumulated dirt. The wash water is highly polluted with contaminants, especially metals and PAH's (Meland, 2010, Vikan and Meland, 2013), from the exhaust, asphalt wear and tire wear, and demands adequate handling. This is not always the case, however, and the practice differs between countries (Meland et al., 2010). As with road runoff, the characteristics of tunnel wash water may vary significantly due to different tunnel use, traffic, and maintenance practices (Barbosa et al., 2007).

The consumption of road salt for traffic safety produces highly soluble and mobile chlorides, which may have an impact on the physical and biological status of water bodies. Road runoff with high salt concentrations may leach to lakes, accumulate in the bottom waters due to its weight, and cause meromixis. Meromixis means that the lake does not go through complete mixing in spring and autumn. Deicing salt is a growing environmental concern not only in the Nordic countries but also in other European countries (Meland, 2015).

3. Highway runoff treatment

Treatment approaches to reduce pollution loads have been assessed widely (Helmreich et al., 2010, Pontier et al., 2004, Starzec et al., 2005, Vollertsen et al., 2007, Stephansen et al., 2012, Hilliges et al., 2013, Leroy et al., 2016, Gang et al., 2016, Sun, 2017). Generally, the governing factor for the decision to treat runoff or not is traffic density defined as the mean daily traffic on an annual basis (AADT) (Horstmeyer et al., 2016). However, due to the weak correlation between ADT and pollution concentration, caused by several governing factors as already described, other approaches for decisions on treatment should be sought. The Highways Agency Water Risk Assessment Tool (HAWRAT), developed and used in the UK, can compensate for the weaknesses of ADT as a basis. The tool requires a comprehensive understanding of quantitative and qualitative characteristics, treatment level, and the local conditions available for the design of BMPs (Barbosa et al., 2012).

Treatment systems during construction and operation may differ depending on the anticipated pollutants. We, therefore, prefer to split the presentation according to this. European countries have somewhat different priorities when it comes to BMP's and treatment systems; see below

The current practice in European countries may illustrate the variation in both the basis for and the implementation of BMP's. In Austria, the NRA develops smaller and less space-demanding units, which focus on collecting and treating the first flush by sedimentation and filtration. This is in contrast to the situation in Switzerland, where the NRA develops larger treatment plants to receive runoff from larger areas. They claim that this is more cost-efficient than smaller treatment facilities (Meland, 2015). Our opinion is rather that the best technology should be selected site-specifically. Soil filters for retaining particles are currently the most common treatment in Austria (Andersson et al., 2018).

In tunnels, water from the surrounding rock is often separated from the polluted tunnel runoff for monitoring and pH adjustment (Meland, 2015). The clogging of soil filters is a common problem, and no electronic control systems are in use as far as we have seen. However, regular sampling of the inlet and outlet, as well as studies on the load and condition of the soil filter, are mandatory. In some countries, the result of the analysis is reported to the authorities to follow up and control.

In Switzerland, road runoff is handled depending on soil type, hydrogeological situation, ADT, and runoff flow rates (Andersson et al., 2018). Three solutions for treating road runoff are approved, including a) infiltration over the road edge, b) collection and transportation to infiltration/filtration facilities, and c) discharge into the municipal drainage/sewage network. The NRA has started to use new centralized treatment plants consisting of storing, sedimentation, and filtration. The current practice for tunnel wash water is to use sedimentation basins. Separation of leaked water from surrounding rock and polluted runoff is mandatory (Meland, 2015).

In Ireland, all new road projects have a drainage system that directs the runoff to the nearest wastewater treatment plant. Ireland has only three tunnels, in which the wash water is collected and transported/or directed to an approved wastewater treatment plant (WTP). In Italy, the NRA has established small tanks to retain first-flush runoff, comparable with the practice in Austria. Tunnel wash water used to be discharged untreated to the surroundings but is now collected and transported to an approved WTP. In Sweden, road runoff and drainage from road construction are commonly infiltrated via road shoulders, embankments, and open trenches. When infiltration is not possible, road runoff is collected via culverts and open trenches for treatment (Andersson et al., 2018). Since the 1990s, sedimentation ponds and wet infiltration ponds have been used frequently as treatment methods. The tunnel wash water is generally discharged untreated, but runoff from larger tunnels is directed to a sedimentation basin inside the tunnel combined with chemical treatment such as flocculation and/or pH adjustment (Meland, 2015). Modern treatment facilities for roads with high ADT are inspected and include sampling several times per year according to an approved control plan. In Germany, the treatment of road runoff in 90% of all roads in rural areas is local infiltration in the road shoulder and embankment. The most common treatment facilities consist of a concrete basin for the removal of coarse sediments along with an oil separation wall, followed by soil infiltration (Meland, 2015, Andersson et al., 2018). The frequency of inspections is not regulated in Germany, but the recommendations in H-KWES (control and maintenance of drainage systems on roads outside of closed local areas) are in widespread use (FGSV 2012). Control of sediment accumulation levels and sampling is often neglected, and the removal of accumulated sediments is infrequent. In Poland, the use of small sedimentation tanks, oil interceptors, and infiltration/wet ponds is growing (Meland, 2015).

Infiltration basins combined with a forebay (as a pre-sedimentation pond) are widely applied in Austria and Germany and should be interesting for other countries. They improve the quality of the discharged water by providing better retention than in ponds and are more cost-effective. Further testing in colder climates is, however, recommended (Andersson et al., 2018).

In Denmark and England, ponds are considered as the best practice. Due to vast agricultural activities, controlling the water quality at peak flows are prioritized as pollution control in Denmark (Meland, 2015).

In Norway, sedimentation ponds are the most frequently used treatment system, but also wetlands, infiltration ponds/ditches are utilized (Meland, 2015). Tunnel wash water from today's' tunnels is discharged to the surrounding terrain untreated. Mandatory treatment facilities for new tunnels have been recommended (Meland et al., 2010), and sedimentation basins have been implemented in many cases. Regular maintenance of stormwater facilities includes cleaning and mowing of grass, sediment removal, cutting vegetation two times a year, clearance, and maintenance of access roads to the facility and control of security (locks and fences). Monitoring programs to document the performance of treatment facilities are not generally used, but it is mandatory to build access roads for service vehicles to allow for proper maintenance. There is a general need in Norway to assess the performance of treatment systems (Meland, 2015, Andersson et al., 2018).

Pollutants of bridge runoff are like normal road runoff. Thus, for most of the European NRAs, bridge runoff has the same requirements as for normal road runoff. This may cause problems for streams and rivers receiving road runoff not only directly from the bridge through openings but also from the part of the road that drains to the bridge. This review shows that Switzerland, Germany, and Austria have a wide range of BMPs, while tunnel wash water is typically controlled using sedimentation basins/ponds (Meland, 2015).

In most cases, proper treatment system is determined based on site-specific parameters on one hand and cost-efficiency, national and

Table 3
Estimated removal efficiency (%) in various types of treatment systems.

Best Management Practice	Tot-P	Tot-N	Tot-Cu	Tot-Zn	SS	Oil	PAH-16	Reference
Grassed swale	7.5	5.3			49			(Luell et al., 2021)
	30	40	65	65	70	80	60	(Andersson et al., 2018)
	3–78	-62–86*			1–94			(Yu et al., 2013)
	29–99	14–61		68–93	30–97			(Ahiablame et al., 2012)
	20–40	10–35						(Troitsky et al., 2019)
	3–78	-62–86			1–94			(Yu et al., 2013)
	53	74	75	73	54	91		(Barrett et al., 1998)
Vegetated Filter Strip	40–50	40–50						(Troitsky et al., 2019)
	-19–75	-18–68			5–96			(Yu et al., 2013)
Bioretention systems	-3–99	32–99	43–99	62–97	47–99	83–97		(Ahiablame et al., 2012)
Pond	50	35	60	65	80	80	70	(Andersson et al., 2018)
	8.4	18.7			67.8			(Yazdi et al., 2021)
	50–75	30–40						(Troitsky et al., 2019)
					97			(Charters et al., 2015)
Wetland	50	35	60	65	85	90	70	(Andersson et al., 2018)
Constructed	50–75	25–55						(Troitsky et al., 2019)
Wetland	0–93	-40–48			5–97			(Yu et al., 2013)
Sedimentation Basin	55	15	60	65	75	65	60	(Andersson et al., 2018)
Centralized infiltration facilities (soil infiltration)	65	40	65	85	80	80	85	(Andersson et al., 2018)
Infiltration trenches	-29–74	-54–59			27–89			(Yu et al., 2013)
Sand Filter/Filtration Basin	50–65	30–45						(Troitsky et al., 2019)
Combined sedimentation and infiltration facilities	≥65	≥40	≥65	≥85	≥80	≥80	≥85	(Andersson et al., 2018)
permeable	10–78		20–99	73–99	58–94			(Ahiablame et al., 2012)
pavements	59–81	59–81						(Troitsky et al., 2019)
Media filters	-8–91	-59–99			3–100			(Yu et al., 2013)

* the minus sign (-) shows negative removal efficiency

international regulations, and recommendations from local authorities on the other hand.

Typical removal efficiencies for a set of contaminants in different treatment systems are summarized in Table 3. The most commonly applied BMPs are grassed swales, retention ponds, sedimentation basins, and wetland basins. While these approaches are of great potential to reduce runoff pollution, the literature reveals that BMPs show low removal efficiency for many pollutants (e.g., < 40% for total N, total P, and COD). Moreover, the lack of information about the ability of these systems to remove other contaminants such as organic compounds and the variety in the type and number of reported sites pose a challenge to fully understanding the performance of BMPs (Okaikue-Woodi et al., 2020). A part of the variation is probably due to inadequate sampling strategies and site-specific features (Tedoldi et al., 2016). Another issue related to BMPs is the nature of pollutants, seasonal variations, and the intervening effects of pollutants on each other (J. Wang et al., 2017). In winter, de-icing salt-containing effluents greatly reduce the removal efficiency of sedimentation systems due to density differences (Rommel and Helmreich, 2018). Also, biological treatment systems may have reduced performance in colder climatic conditions and should not be adopted without further considerations.

One of the key factors in the variation of results is the sampling protocol. The sampling process typically includes grab and composite methods depending on the rainfall patterns. Composite samples could be time or flow proportional. While a flow-weighted composite sample could be equated using a series of grab samples summed with flow reflecting weights, the programmable automatic flow weighted samplers are much better than grab sampling collections and provide more accurate results for EMCs and mass first flush ratios (Ma et al., 2009).

Variation in quantity and quality of contaminant loadings are significant issues in the design of BMPs. Average daily traffic, hydraulic and hydrological conditions, together with characteristics of the receiving water body, are essential factors (Li and Barrett, 2008, Sharma et al., 2016). Climate change effects, such as longer dry periods and increased intensity of heavy rainstorms are demanding (Field et al., 2012). With an increase of 1.5 °C and 2 °C due to global warming, the load of heavy metals increase by more than 90% and 50% on urban surfaces and stormwater runoff, respectively (B. Wijesiri et al., 2020). Longer dry weather periods increase the accumulation of pollutants. More intense precipitation events and retaining particles in treatment systems will necessitate further cleaning, which is already a demanding issue and will be an even larger challenge in the future (Sharma et al., 2016, Zhang et al., 2019). The climatic change effects on runoff quantity have been studied (Semadeni-Davies et al., 2008, Arnbjerg-Nielsen et al., 2013), but the impacts of climatic change on road runoff quality and treatment performance is less considered. A study by Sharma et al. (Sharma et al., 2016) in Denmark showed that under climate change scenarios, there is little change in retention pond performance for TSS removal. In contrast, its effect on the removal of soluble materials (such as Cu) and slowly biodegradable organic matters is significant. Therefore, it is necessary to investigate further the performance of existing BMPs in climate change scenarios and for the different forms of pollutants (particle-bound or dissolved). Another knowledge gap is related to changing pollutant behavior on impervious surfaces in rainfall and dry periods, particularly for the first flush phenomenon (B. Wijesiri et al., 2020).

Appropriate technologies for runoff treatment are site-specific, governed by the recipients' vulnerability (Chen et al., 2009, Petersen et al., 2016), and should be part of highway planning (Stagge et al., 2012, Fassman, 2012). Efficient environmental protection is a united part of sustainable highways design and maintenance (Bulc and Sajn Slak, 2003).

4. Modeling approaches

The main goals of highway runoff quality modeling are to characterize the highway runoff (spatio-temporal variation of pollutants), provide input to receiving water analysis as well as the basis for decisions on cost-effective BMP's (Tsihrintzis and Hamid, 1997, Sutherland et al., 2006). The basic components of present-day water models are a) rainfall-runoff modeling and b) transport modeling. There is a need to establish a relationship between water chemistry parameters and runoff and how this relationship varies with regulating parameters. Hence, it is essential to have realistic hydraulic or hydrologic models, which have the appropriate spatial and temporal resolution required for the problem (Zoppou, 2001). Accordingly, site-specific hydraulic and hydrological datasets are utilized for calibration and verification of the model. Calibrated models may then be applied to assess different scenarios, such as the fate and transport of contaminants over time and for future conditions (Sutherland et al., 2006). Proper time-series for calibration/verification, as well as for estimating model uncertainty, are of great importance (Barbosa et al., 2012). A variety of modeling techniques capable of simulating water quality and quantity in urban catchments has been developed to assess the effectiveness of BMPs in highway runoff management. These may be categorized into two major groups, empirical and mechanistic models.

4.1. Empirical methods

The empirical methods based on direct observation and measurement applies past and present extensive data series to derive the probable outcomes of future events. Empirical models involve a practical relationship between a dependent variable and variables that are considered germane to the process, chosen from the knowledge of the physical processes and empirical measurements and reflect the current behavior of a catchment at a particular site. Regarding highway runoff modeling, empirical models focus on predicting the event mean concentration (EMC). Highway runoff quality models attempt to incorporate the buildup and wash-off process using an empirical exponential *wash-off* and the *buildup functions* (Zoppou, 2001).

Over the past few decades different empirical modeling approaches have been developed such as multiple regression (Barbosa, 2007, Kayhanian et al., 2007), artificial neural network (ANN) (Park and Stenstrom, 2006, MASOUDIEH and KEYHANIAN, 2008, Trenouth and Gharabaghi, 2016), data-driven models (Barrett et al., 1998, Opher et al., 2009, Ha and Stenstrom, 2008, MASOUDIEH and KEYHANIAN, 2008), optimization models (Pack et al., 2004, Lee et al., 2010, Ciou et al., 2012, Baek et al., 2015, Liu et al., 2016, Khatavkar and Mays, 2017), GIS-based models (A.A. Bloorchian et al., 2016, Ha and Stenstrom, 2008, Viavattene et al., 2010), and Bayesian Networks (Park and Stenstrom, 2006).

Statistical models for estimating flow and water quality loads are usually based on regression models, which are counted in the stochastic modeling approach. These may include climatic characteristics and catchment parameters. The most significant limitation of statistical models is their spatial arrangement, which means for any spatial patterns or processes, new data, and the statistical relationship must be developed (Zoppou, 2001). Notably, most statistical techniques, such as multiple regression, involve mathematical statements about the data generating process and are, therefore, also mechanistic. Regression models explain the relationships between road runoff quality (or water quality) variations and also through some mathematical equations illustrate the significant changes in the variables that control the process. The regression models for stormwater quality utilize concentrations or pollutant loads as variables dependent on traffic intensity, flow volume, interevent dry period, and adjacent land use (Barbosa, 2007). Regression models have been widely used to describe event mean concentrations EMC and total storm event load (Zoppou, 2001).

ANNs as the less input data-intensive assessment tool compared to either empirically- or physically-based modeling approaches are highly useful in the design process by finding the relationships between the input and output of environmental conditions (MASOUDIEH and KEYHANIAN, 2008). Furthermore, ANNs are useful for modeling highly complex, nonlinear environmental phenomena for which knowledge of input parameters and sensitive initial conditions remains poorly understood (Trenouth and Gharabaghi, 2016). Despite the success with which ANNs have been applied, there are some disadvantages, including the structure of the model itself, particularly their "black box" internal nature, as well as the input and output parameters and their selection method (e.g., trial and error approach, which require sensitivity analysis). The challenge is to select model input parameters that have a direct influence on the interested output parameter (Trenouth and Gharabaghi, 2016). Data-driven models are lately used in water and environmental research and have provided an effective, accurate, and easily calibrated predictive model for EMC of highway runoff pollutants (Opher et al., 2009). Also, other models, such as risk-based models (Lundy et al., 2012), were successfully developed in highway runoff management.

Given a large number of alternative management strategies and constraints that must be satisfied, some models include an optimization technique. Optimization is used to determine optimum values for a given set of decision variables that will maximize or minimize an objective function, usually cost. The coupling of a stormwater model with an optimization technique (linear, nonlinear, and dynamic programming) represents an influential tool for highway runoff management (Zoppou, 2001).

Besides, simulation models and optimization techniques as an integrating process has been explored to select (Lee et al., 2005, Reichold et al., 2009), locate (Perez-Pedini et al., 2005), design and analyze the treatment efficiencies (Lee et al., 2010, Zhen et al., 2004, Wong et al., 2006) of various types of BMPs. There is no comprehensive modeling system available in the public domain for systematically evaluating the location, type, and cost of stormwater BMPs (Lee et al., 2012).

Furthermore, the GIS-based models are intended to support a range of local authority/municipal, federal/state regulatory agencies, drainage engineers/consultants, and other interested stakeholders in the development and evaluation of stormwater drainage infrastructure contained within stormwater management plans (Viavattene et al., 2010).

Highway runoff management sometimes requires an intermediate process to overcome the monitoring and computational difficulty of the direct approach. For example, Park and Stenstrom (Park and Stenstrom, 2006) developed a model based on the Bayesian networks and an AI algorithm to predict stormwater pollutant loads through land-use data, which comes from satellite imagery. Despite numerous research projects in this field, there are still open questions regarding the identity and mutual influences of the many factors affecting pollutant concentrations in road runoff (Solomatine and Ostfeld, 2008, Opher and Friedler, 2009).

4.2. Mechanistic models

Mechanistic models are based on an understanding of the behavior of a system's components. For example, a mathematical, mechanistic model that uses the laws of physics to predict tides. These models are applied to simulate the physical flow and transport processes, including advective-dispersive transport and mass exchange between the runoff and pavement surface (L.-H. Kim et al., 2005, L.-H. Kim et al., 2005, Kang et al., 2006, Massoudieh et al., 2008, Bentzen et al., 2009, Bentzen, 2010) and are mostly designed to predict the variation of concentration during a rain event (Abrishamchi et al., 2010). The overall idea of the mechanistic models is to develop physical/numerical models through historical time series of the pollutant discharges in which variation of pollutants removal by a BMP can be identified (Bentzen, 2010). Most models use buildup and wash-off equations for runoff, algorithms for solid transport in the sewers, proportional relationships between the suspended solids and their attached pollutants and pollutant decay or transformation equations (Barbosa et al., 2012). Mechanistic models were utilized for different purposes, including pollutographs prediction in highway runoff (Abrishamchi et al., 2010, Massoudieh et al., 2008), highway runoff modeling (German et al., 2005, Abrishamchi et al., 2010, Park and Stenstrom, 2006, Trenouth and Gharabaghi, 2016), and pollutant load estimation (Brezonik and Stadelmann, 2002, Opher et al., 2009, Massoudieh et al., 2008, Kim et al., 2006, Zhang et al., 2014). Furthermore, a wide range of such models was applied by researchers to evaluate the performance of BMPs under different site-specific circumstances. Table 4 presents a list of recent studies in detail.

Table 4
Mechanistic models used in highway runoff research.

Model	Application in highway runoff	Features	Reference
CREAMS[1]	Investigate the effectiveness of grass strips for various geometrical scenarios	It considers land use (agricultural, forest/natural, chemical application), hydrology (surface runoff, subsurface runoff), water quality (sediments, nutrients, pesticides/toxics), and time frame (event load, continuous simulation) (Tsihrintzis and Hamid, 1997).	(Williams and Nicks, 1988)
WEPP[2]	Predicting the movement of sediment in grass strips	It does not track backwater, has a non-symmetric behavior for fine and medium particles (under-predict and over-predict, respectively), which may cause uncertainties given the associated pollutants (Akram et al., 2015).	(Flanagan and Nearing, 2000)
PHREEQC-2	Simulating pollution transport processes and chemical reactions	Excellent for mixing, speciation, mineral equilibration, surface complexation, ion-exchange, and reaction modeling	(Bäckström et al., 2003)
RPM[3]	Predicting the sediment trapping efficiency in riparian buffers	Simple conceptualization and accurate surface runoff estimation. However, the detachment process, as well as size distribution for inflow sediment, are not considered. So, the prediction of water pollution is not applicable (Akram et al., 2015).	(Newham et al., 2005)
VFSMOD [4], VFSMOD-W	Studying the hydrology, sediment, and associated pollutant transport through VFS[5].	Applies finite element solution, Green-Ampt infiltration method, and contaminant transport component to provide water and sediment balance, sediment graph and deposition pattern within the filter, and filter efficiency. It could not accurately predict the amount and size of sediment in the outflow, especially when sediment is highly distributed (Akram et al., 2015).	(Munoz-Carpena and Parsons, 2004, Munoz-Carpena et al., 1999, Han et al., 2005, Dosskey et al., 2008, White and Arnold, 2009)
TRAVA[6]	Field performance of grass filters (strip and swale) in TSS removal	A mathematical model uses a series of empirical equations and able to simulate the outflow particle size distribution. TRAVA's performance is limited to experimental conditions (Akram et al., 2015).	(Deletic, 1999, Deletic, 2000, Deletic and Fletcher, 2006)
SIMPTM[7]	Simulate the runoff volume and Pollutant loading/concentration and pollutant buildup and washoff during each storm event	Explicitly simulates the physical processes and can simulate the pollution Reduction benefits for different cleaning operations. SIMPTM model includes a rainfall analyzer called RAINEV to evaluate the characteristics of a historical rainfall record.	(Sutherland et al., 2006)
k-C* [8]	Assessing BMPs performance by storage-release models for pollutant removal		(Wong et al., 2006, Rousseau et al., 2004, Lin et al., 2005, Pack et al., 2005, Park and Roesner, 2012)
Mathematical model	Prediction of highway runoff pollutographs during storm events	Time and cost-effective model.	(Massoudieh et al., 2008)
BMPDSS [9]	Supporting analysis and decision-making processes for planning and design of BMPs		(Cheng et al., 2009)
STUMP [10]	Simulation of micropollutants transport to the surrounding environment	Flexible and dynamic fate model given the inherent properties of substance's, to partition between the particle-bound phase and the dissolved phase (Vezzaro et al., 2012).	(Vezzaro et al., 2012)
Monte-Carlo simulation	Assessing the effect of BMP design on pollutant removal efficiency and uncertainty analysis		(Abrishamchi et al., 2010, Park and Roesner, 2012)
SEWSYS	Simulation of runoff quality based on sources of pollution		(Lindblom et al., 2011)
STORM [11]	Quantitative and qualitative simulation of runoff, bypass flow, and flow through BMPs, given watershed land use.	STORM considers land use (urban), hydrology (surface runoff, subsurface runoff, snowmelt), water quality (sediments, nutrients), and time frame (continuous simulation) (Tsihrintzis and Hamid, 1997).	(Pack et al., 2004, Viavattene et al., 2010, Park and Roesner, 2012)
SWMM [12]	Simulation of runoff quantity and quality, modeling the contaminant build-up and wash-off behavior, has a different variation (e.g., PCSWMM[13] to assess the effectiveness of BMPs for retaining the first inch of highways runoff and functionality in plan and design)	2D hydrodynamic model, which has pollutant predictive method (empirical, buildup and washoff, soil loss), pollution transport (completely mixed reactor), and mathematically describes the contaminant's build-up and wash-off (Zoppou, 2001). SWMM applies diverse methods in estimation of runoff (Green Ampt, Horton, CN, Manning) and water quality constituents (continuously stirred tank reactor or CSTR, power function, saturation function, rating curve, EMC, first-order decay) (Ahiablame et al., 2013). Considers land use (urban), hydrology (surface runoff, subsurface runoff, snowmelt), water quality (sediments, nutrients), and time frame (single event load, continuous simulation) (Tsihrintzis and Hamid, 1997). Limited in pond hydraulics and pond nutrient treatment (Troitsky et al., 2019).	(A.A. Bloorchian et al., 2016, Wicke et al., 2012, Baek et al., 2015, Flanagan et al., 2016, Moore et al., 2017, Osouli et al., 2017, Sañudo-Fontaneda et al., 2018, Lin et al., 2018)
SUSTAIN [14]	A decision-support system for both watershed and BMP by evaluating the optimal location, type, cost, planning, and design of BMPs.	It enables the analysis of multiple alternatives for water quality management considering different objectives such as location, scale, and cost (Lee et al., 2012). Have single event time frame (Gao et al., 2015), which uses a wide range of stormwater quantity (Green Ampt, Holtan-Lopez, CN, Manning) and quality (CSTR, power function, saturation function, rating curve, emc, storage routing, first-order decay)simulation algorithms. SUSTAIN currently covers a variety of BMPs, including bioretention, cistern, constructed wetland, dry/wet pond, grassed swale, green roof, infiltration basin/trench, porous pavement, rain barrel, sand filter, and VFS (Ahiablame et al., 2013)	(Lee et al., 2012, Gao et al., 2015)

(*continued on next page*)

Table 4 (*continued*)

Model	Application in highway runoff	Features	Reference
L-THIA-LID [15]	Evaluates the benefits of BMPs; measure the impact of land use on hydrology and water quality.	Evaluates runoff volume using the Curve Number method (Miller et al., 1986) and estimates pollutant loads by runoff volume and EMC of specific land use. It has both a single event and a continuous time frame.	(Liu et al., 2016, Ahiablame et al., 2013, Lindström and Håkanson, 2001, Shirmohammadi et al., 2006, Engel et al., 2007, Park et al., 2010, Granato, 2014, Granato and Jones, 2014, Y. Liu et al., 2015, Y. Liu et al., 2015, Beck et al., 2017, Granato and Jones, 2019, Weaver et al., 2019)
SELDOM [16]	Provides risk-based information for decision-makers about streams and lakes that receive runoff from highways.	Uses Monte Carlo methods to generate a mass balance model for a receiving stream (Granato and Jones, 2019). Also, it applies the trapezoidal distribution and the rank correlation with the highway-runoff variables to model volume reduction, hydrograph extension, and water-quality treatment (Granato, 2014).	(Granato and Jones, 2019, Weaver et al., 2019)
WASP [17]	3D hydrodynamic and water quality model.	Flexible to be coupled with other 3D models include uncertainty analysis tools, water quality sub-model that has sediment oxygen demand and nutrient fluxes. Limited in mixing/complex hydraulics zones and settling /floating particles.	(Troitsky et al., 2019)
GUEST [18]	Simulates the water and sediment transport for grass buffer strips	Considers the deposition and erosion of sediment in single-runoff events	(Akram et al., 2015)
TELR [19]	Quantify runoff reduction	Lower input data and user expertise. Responsive to management actions, such as the installation of structural BMPs	(Beck et al., 2017)
GSSHA [20]	A physical model to model the fate and transport of sediment and constituent in streams and channels	1-D infiltration and streamflow, 2-D overland flow and groundwater, and considers the interaction of streams, shallow soils, groundwater, and overland flow. Useful for shallow soils and overland flow.	(Moore et al., 2017)
FullSWOF-ZG [21]	Evaluate the road-bioretention stripes' performance	Simulation of the incompressible Navier–Stokes flow occurring in the water body. This model can consider spatialized rainfall, infiltration, and friction determination as well as a new 2D-1D drainage inlet submodule. Modeling impervious and pervious surfaces simultaneously in one domain.	(Li et al., 2021)

[1] CREAMS (chemicals runoff and erosion from agricultural management systems),
[2] WEPP (water erosion prediction project),
[3] RPM (riparian particulate model),
[4] VFSMOD (vegetative filter strips modeling system),
[5] VFS (vegetative filter strips),
[6] TRAVA (a deterministic model based on the Aberdeen Equation),
[7] SIMPTM (the SIMplified Particulate Transport Model),
[8] k-C* (a first-order kinetic model, where k is the first-order decay rate and C*is the equilibrium concentration),
[9] BMPDSS (best management practice decision support system),
[10] STUMP (the stormwater treatment unit model for micropollutants),
[11] STORM (the storage treatment overflow and runoff model),
[12] SWMM (the US EPA's stormwater management model),
[13] PCSWMM (the personal computer stormwater management model),
[14] SUSTAIN (the system for urban stormwater treatment and analysis integration),
[15] L-THIA-LID (the long-term hydrologic impact assessment-low impact development),
[16] SELDM (the stochastic empirical loading and dilution model),
[17] WASP (water quality analysis simulation program),
[18] GUEST (Griffith University soil erosion and deposition-vegetative buffer strips 2),
[19] TELR (the stormwater tool to estimate load reductions),
[20] GSSHA (gridded surface/subsurface hydrologic analysis).

Simulation accuracy is more likely dependent on the skill of the modeler, parameterization, and model formulation than model type (Moore et al., 2017). Model selection for a project is generally driven by the problem that needs to be solved, and the project goal (Engel et al., 2007). The complexity of a model has consequences on the reliability of the results produced by the model. Reliability places confidence limits on the outputs of the model due to the uncertainties and should be an integral part of the decision-making process. Furthermore, risk analysis that considers the probability of system failure (depends on the climate, hydrology, and/or management strategies) is another useful approach for the decision-making process (Abu-Zreig et al., 2001) in highway runoff management (Zoppou, 2001). Given the model uncertainty, it is notable that the uncertainty sources can be divided into model parameters, conceptual model (model structure), and observation data (measurement) uncertainties. In addition, the uncertainty stemmed from boundary conditions is sometimes referred to as scenario uncertainty (Lindblom et al., 2011). This is particularly important to the stormwater runoff quality, where the dynamics exceed those of most other environmental systems (Lindblom et al., 2011). Uncertainty analysis attempts to quantify the effect of uncertain parameters of the model on the models' response. Uncertainty analysis can be performed by analytic, approximation, and numerical methods. The derived-distribution method (DDM) is the most classical approach in analytical uncertainty analysis (Park et al., 2010). The numerical methods include sensitivity analysis (Baek et al., 2015, Vezzaro et al., 2012, Lindblom et al., 2011), the first-order second-moment (FOSM) method (Park and Roesner, 2012, Shirmohammadi et al., 2006, Park et al., 2010), Monte Carlo simulation (MCS) (Park and Roesner, 2012, Shirmohammadi et al., 2006, Daebel and Gujer, 2005), and Mellin transform. Other approaches such as Latin hypercube sampling (LHS), which is a modified stratified sampling of MCS, (Shirmohammadi et al., 2006, Park et al., 2010), and the generalized likelihood uncertainty estimation (GLUE) technique

Table 5
United States legislation about highway drainage, water quality and environmental protection (Malamataris, 2014).

Legislation	Year	Aims and scope
Federal-Aid Highway Act (Public Law 81–769)	1950	Hold public hearings for projects bypassing cities or towns.
National Environmental Policy Act (NEPA)	1970	Declaring and promoting the appropriate national policies, goals, and measures for environmental protection.
Federal Water Pollution Control Act of (Clean Water Act)	2011	Principal federal law in the United States regulating subjects about water pollution and ensuring that surface waters would meet the standards for water consumption. The discharge regulation has been applied to all communities with a population of 10,000 or more (US-EPA 2011).
The Federal-Aid Highway Act of 1973 (Public Law 93–87)	1973	Highway safety improvement and the funding provision for urban and rural primary and secondary roads.
The Safe Drinking Water Act of 1974 (SDWA)	1974	Standards for protecting the water sources: lakes, rivers, reservoirs etc. and drinking water quality in order to protect public health.
Surface Transportation Assistance Act of 1982 (Public Law 97–424)	1982	Extensive policy act to deal with problems about the surface transportation infrastructure.
The intermodal Surface Transportation Efficiency Act of 1991 (Public Law 102–240)	1991	Regulation in the post-interstate highway system era.
Moving Ahead for Progress in the 21st Century Act of (Public Law 112–141)	2012	Funding bill to govern federal surface transportation spending (Delaware Department of Transportation 2008)

Table 6
EU legislation about highway drainage, water quality, and environmental protection.

Aims and scope	Legislation
Possibility of pollution of water resources by highway effluent	(Directive2000/60/EC 2020)
Investigation of surface and groundwater status of highway effluent receiving environment	(Directive2011/92/EU 2011) (Directive2013/39/EU 2013) (Directive2010/75/EU 2010)
Effluent discharge standards to drinking water sources or areas with groundwater wellhead protection program	(Directive2000/60/EC 2020)
Effluent discharge legislations to water sources of economically significant aquatic species	(Directive2000/60/EC 2020)
Effluent discharge legislations to the sensitive area defined by the UWWD criteria	(Directive91/271/EEC 1991)
Effluent discharge legislations to a water body within an area defined as Natura 2000 habitat or ecosystem area	(Directive92/43/EEC 1992)

(Vezzaro et al., 2012) have also been utilized to assess uncertainty in BMP performance.

5. Legislations

According to the authors' knowledge, there are no specific directives or regulations in the EU in the field of drainage and highway stormwater management. Existing frameworks are mostly based on the type of water consumption and different characteristics of receiving water bodies. Tables 5 and 6 provide a set of legislations and guidelines for highway effluent management in the United States and the EU based on their discharge points. In general, the main legislation instruments in the EU to restrict the discharge of highway runoff into water resources include the EU WFD assessment guidelines (Directive2000/60/EC 2020), EU Groundwater Directive (European Union 2006), EU Habitats Directive (Directive92/43/EEC 1992), surface and groundwater (drinking water) protection zones, Natura 2000 areas (areas designated for the protection of habitats or species), and non-legislative initiatives on the management of receiving water bodies influenced by traffic-related activities. The mentioned set of legislations can be used with each other to evaluate highway runoff risks based on legal environmental/water constraints (Martins et al., 2020).

- The possibility of highway effluent contamination can be assessed by WFD (Directive2000/60/EC 2020), Groundwater (European Union 2006), EIA (Directive2011/92/EU 2011), Priority substances (Directive2013/39/EU 2013), and IPPC (Directive2010/75/EU 2010) legislative frameworks.
- If the effluent acceptor environment is drinking water or in the area with the program of groundwater wellhead protection zone, the effluent risk assessment can be evaluated using WFD (Art. 7 Drinking water) framework (Directive2000/60/EC 2020).
- If the effluent discharge site has economically significant aquatic species, the instructions of WFD guideline (Art. 6 Protected areas) (Directive2000/60/EC 2020) can be used to assess highway effluent risk.
- If the water body receiving the highway effluent is a protected area, the Natura 2000 guidelines can be used to assess the risk.

Management practices for handling highway runoff vary between the various European national road administrations (NRAs), as already documented. We concluded that the NRAs have different planning, construction, and operation system for runoff treatment facilities, see also Andersson et al. (Andersson et al., 2018). The Water Framework Directive (WFD) (Directive2000/60/EC 2020) in Europe and related directives set Environmental Quality Standards (EQS) for water bodies and demand measures to improve the water quality if the standards are not met. But there is also a wide variety of national guidelines, recommendations, and requirements that regulate road runoff management. In Sweden and Norway, policy documents are qualitative and focus mainly on water quality, retention capacity, aesthetics, and ecology. Germany, Austria, and Switzerland focus on particle transport and TSS as the major pollution.

In Norway, there are four main guidelines for road runoff handling, indicated in Table 7.

In some countries, ADT is considered as a first parameter in determining the status of runoff and management action plans. Table 8 presents the classification of runoff quality based on ADT in Germany, Norway, and Austria. In Germany and Austria, roads with a traffic load of more than 15,000 (vehicles/day) need to be treated, while in Norway, roads with a traffic load of more than 30,000 (vehicles/day) need to be treated. In Germany, in addition to ADT, the expected annual load of TSS smaller than 63 μm (AFS_{63}) is also used to classify highway effluents. For example, the AFS_{63} loads above 530 kg/ha per year indicate high pollutant loads that require treatment (DWA-A102-2/BWK-A3-2 2020).

There are also different legislations for road runoff outside of settlements, road construction in sensitive areas, and maintenance of stormwater treatment facilities (Andersson et al., 2018). In Sweden, the Swedish Environmental Law and WFD regulate stormwater management. Despite the nine documents outlining recommendations and requirements for handling road runoff in Sweden, there is no prescribed

Table 7
Norwegian guidelines for road run-off management.

Name & Number	Reference
N200 (Handbook N200 for building roads)	(Y. NPRA 2014)
R760 (Handbook R760 Control of road-building projects)	(Y. NPRA 2014)
Nr. 597 (Water reservoirs vulnerability to road runoff during building and operational phase)	(Y. NPRA 2016)
Nr. 212 (State of the stormwater facilities in Norway)	(NPRA 2013)
Nr. 650 (Inventories of facilities in the Southern region)	(Y. NPRA 2016)

Table 8
Guidelines of Germany, Norway, and Austria to the classification of runoff quality based on ADT.

Pollutant load	ADT (vehicles/day)			Action
	Germany	Norway	Austria	
Low	<2000	<3000		Released to surface or groundwater without treatment (Infiltration in the road shoulder)
Moderate	2000–15,000	3000–30,000		Treatment is generally required prior to discharge
Highly polluted	>15,000	>300,000	>15,000	Highway runoff is considered highly polluted, and treatment is required before release

decision-making process to determine when a treatment facility is required. The current Swedish Transport Administration (STA) document to determine the need for stormwater treatment is STA (Andersson et al., 2018). STA also operates a spatial database of the Swedish roads and railways network to identify runoff risks close to existing infrastructure and to plan maintenance and construction work of existing BMPs. In Austria, the OEWAV regulation, Regelblatt 25, stipulates the guidelines and technical instructions for planners (Binner, 2002). The minimum requirements for purification are mechanical treatment (sedimentation) and filtration. In Switzerland, permitting procedures follow the national road law. Permitting procedures include the rebuilding of national roads (construction), structural modification of an existing national road (expansion), and maintenance practices. Based on Andersson et al. (Andersson et al., 2018), the current Norwegian and German guidelines and regulations regarding the handling of stormwater sediments are synchronized and up to date. Sweden's guidelines are, however, outdated, and present challenges that may lead to technical issues.

6. Knowledge gaps and potential research directions

According to the EU WFD, all countries should achieve 'good status' for their water bodies by 2015 or finally by 2027. But in 2015, 47 % of the EU's surface waters did not achieve the standards (Meland, 2015). Although not documented, runoff from roads probably contributes significantly to this gap. Studies on highway runoff characteristics and suited treatment technologies should, therefore, be encouraged. Stormwater management is a complex matter and comparing the results of various studies necessitates collecting and analysis of proper, consistent, and scientifically valid data for each specific case and considering their site-specific parameters (e.g., geographic and climatic issues). Notably, some significant topics, including monitoring network and measurement technology, frequency of data collection, sampling method, and data analysis should be considered in highway runoff management. Also, the particle size distribution and the associated pollutants will have a strong influence on runoff toxicity, BMP design, and removal efficiency. We propose here potential research directions for future studies.

1. There is a notable lack of documentation on the operation and the need for maintenance of BMPs. If run without such documentation and control, poor performance or breakdown may cause undesired environmental effects in downstream water bodies. For instance, many of the existing wet ponds in Norway are in poor condition with accordingly limited performance, partly because of low construction quality and partly due to insufficient operation and maintenance. The development of models that can be run to identify shortcomings should be initiated.
2. Due to the variety of regulating factors and their complicated interactions, there is a need for models that handle the most important variables for the resulting road runoff chemistry during different scenarios. Models may be used to calculate the uncertainties and effects of a set of treatment technologies.
3. Different decision scenarios can be defined based on economic or technical constraints. Advanced and high-tech alternatives do not necessarily result in large and adequate improvements if the use of simple techniques meets the standards set. Hence, the selection of the best alternative depends on adequate information on the road runoff itself, the efficiency of treatment systems based on site-specific parameters, and water regulations. Economic analysis (e.g., life cycle cost and cost-benefit analysis) can provide a powerful tool to assess different alternatives.
4. Limited knowledge exists on the buildup/washout of pollutants and mobilization of inorganic and organic compounds by stormwater in the present and future climate. This probably results in a non-optimal design of BMPs and how they should be adapted for future conditions. This issue is of great importance in the climate change framework.
5. Future research should aim to optimize BMPs in terms of smaller and more cost-effective BMPs with low-maintenance and high removal efficiency. Developing multi-objective optimization models that consider the objectives of different involved stakeholders can facilitate the selection of BMPs.
6. A comprehensive study is required to develop a guideline for the choice of treatment based on site-specific conditions, expected pollutant load, and environmental impact. The guideline should give advice on when treatment is necessary.
7. The performance of existing BMPs under climate change scenarios and for the different forms of pollutants (particle-bound or dissolved) should be investigated. Another knowledge gap is related to changing pollutant behavior on impervious surfaces over dry and wet periods, particularly under the first flush effect.
8. More relevant parameters than ADT should be developed. Systematic monitoring with a recommended sampling strategy at sites with different ADT could, however, reveal that the relation between ADT and contaminant runoff is adequate for decision-making.
9. Risk analysis and uncertainty analysis are not adequately addressed in modeling. There is a challenge for modelers to include these issues in the development of user-friendly decision support tools.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Paper B

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Spatiotemporal assessment of surface water vulnerability to road construction

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Abstract

Highway construction may pose different pollutants, including suspended solids, metals, and hydrocarbons such as oil and polycyclic aromatic hydrocarbons (PAH's) to water resources and decrease water quality. The principal contribution of this study is developing a practical approach for assessing the spatiotemporal vulnerability of surface water to road construction by using water quality data from the environmental monitoring during construction of a new 22-km-long highway in southern Norway (2017–2019). First, the data were used to assign the relative weights of parameters, and the water quality index (WQI) was computed for all monitoring stations. Then, by defining six time periods, the temporal variation of WQI in various stations was determined, and by classification of WQI in different levels (i.e., excellent water, good water, poor water, very poor water, and unsuitable for drinking), the temporal changes were analyzed. To assess the spatial variation in surface water quality during road construction, the averages of WQI in all monitoring stations of each catchment area were computed, and for each section of the road, the vulnerability map was plotted in all time periods. Besides, evaluating the impact of road construction activities on surface water quality is another innovation of this study. By extracting the activity type in each section of the road over the construction time, the average WQI for each activity was computed for all time periods. The results showed that construction activities such as blasting, area cleaning, and water management have the highest impact on surface water. The results deliver a feasible knowledge to decision-makers for establishing best management practices to control the effects of road construction on surface water bodies.

Keywords Road construction · Water quality index · Spatiotemporal variation of water quality · Surface water vulnerability to road construction

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1 Introduction

The construction of highways and related structures (e.g., bridges and tunnels) plays a significant role in social and economic development. Road construction projects as one of the main urban construction projects (Enshassi et al., 2015) can highly contribute to pollution in the living environment (Li et al., 2010, Shen et al., 2005). Construction and operation of roads may pose severe challenges to the various components of the environment, especially surface and groundwater resources (Balaguera et al., 2018, Enshassi et al., 2015). For example, a set of activities such as the construction of tunnels, bridges, and culverts, blasting, runoff treatment, mineral leakage during concrete and asphalt preparation, and accidental spills of chemicals may cause contamination of surrounding surface water. Surface water pollution, in turn may cause eutrophication. Based on (Moretti et al., 2018), construction of an embankment and a trench road cross section (both sections are 1-m long and 4-m high) can cause 1.08, and 2.61 kg ($PO4\ ^{3-}$) eq, respectively. Depending on the size and type of construction activities, various pollutants such as bitumen chemicals, antifreeze chemicals, dyes, solvents, compounds from explosives, oil and petroleum products, minerals, human wastewater, and heavy metals may be produced and transported to surface waters (Licbinský et al., 2012). The large amounts of pollutants with different physical, chemical, and biological properties can cause a serious threat to aquatic ecosystems (Qaderi et al., 2018, Qaderi and Babanezhad, 2017).

According to the literature, most previous studies have focused on the impact assessment of the highways in the operation phase (Banerjee et al., 2018 Licbinský et al., 2012). However, in the construction phase, due to a variety of construction activities and related pollutants, as well as prolonged construction periods in some projects, irreversible damages to water resources can be created. For instance, Restrepo et al., 2019 examined the water quality in a river system during and after road construction. The physicochemical analysis showed an increase in some qualitative parameters such as oils and greases, and biochemical oxygen demand (BOD), and a decrease in dissolved oxygen (DO). More importantly, the results of the mitotic index test showed that the river water was toxic after the construction phase (Restrepo et al., 2019). Despite the few published research works on the construction phase (Chen et al., 2009 Houser and Pruess, 2009 Restrepo et al., 2019), the knowledge gap on the spatiotemporal assessment of the road construction effects on the surface water quality is quite apparent.

Water quality monitoring programs often provide big time series data, including many water quality variables, which is challenging in analyzing and understanding for decision-makers (Mooselu et al., 2020). Water quality index (WQI) is a useful managerial tool for interpretation of qualitative data (Munna et al., 2013), classification of water quality (Boyacioglu, 2010 Nikoo and Mahjouri, 2013), and water management (Khan et al., 2005). WQI is applicable for investigating the effects of construction projects on the quality of water resources (Mgbenu and Egbueri, 2019 Mooselu et al., 2020 Sikder et al., 2015). During road construction, WQI can determine the impact of natural factors and anthropogenic activities on water resources (Mgbenu and Egbueri, 2019). This index has been used to evaluate the quality of surface water, groundwater, and sediments under the influence of various industrial pollutants (Abrahão et al., 2007), drilling and mining (Madzin et al., 2017), and in-operation highways (Banerjee et al., 2018).

The novelty of this study lies in the spatiotemporal assessment of the surface water vulnerability in the road construction project using a feasible WQI index. Besides, evaluating the impact of each construction activity on the quality of surface water resources is another contribution of the paper. Accordingly, 28 parameters, including heavy metals, physical properties, anions, cations, and biological parameters from 48 water quality monitoring stations during the construction of a new 22-km-long highway in southern Norway, were selected to assess the WQI. The spatial vulnerability of surface water resources was specified at various stations by calculating the WQI. For temporal vulnerability assessment, six time periods between 2017 and 2019 were defined, and variations of WQI for different sections of the road were computed. Also, since the highway construction projects consist of various activities, the WQIs for different activities were calculated. The results of this study will make a significant contribution to the selection of Best Management Practices (BMPs) in various construction projects.

2 Methods

A four-step approach was developed for the spatiotemporal assessment of water resources vulnerability during road construction, which is shown in Fig. 1.

According to this framework, the water quality index was calculated for all stations (step 2). Then, the spatiotemporal vulnerability of water resources given various catchments (step 3) and different construction activities (step 4) was computed. These steps are clarified in more detail in the following next sub-sections.

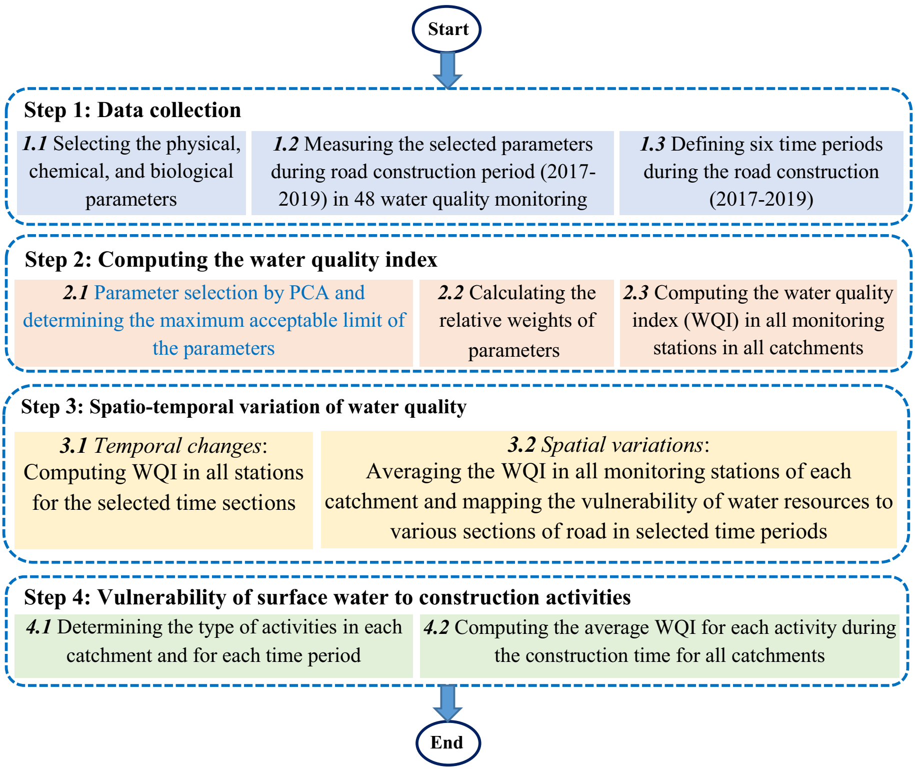

Fig. 1 Proposed method for spatiotemporal assessment of water resources vulnerability

2.1 Data collection

The first step was gathering qualitative information along the construction site, which is the new 22-km-long highway (E18) from Arendal to Tvedestrand in southern Norway (Fig. 2). The total drainage area of the highway (7180 hectares) includes seven

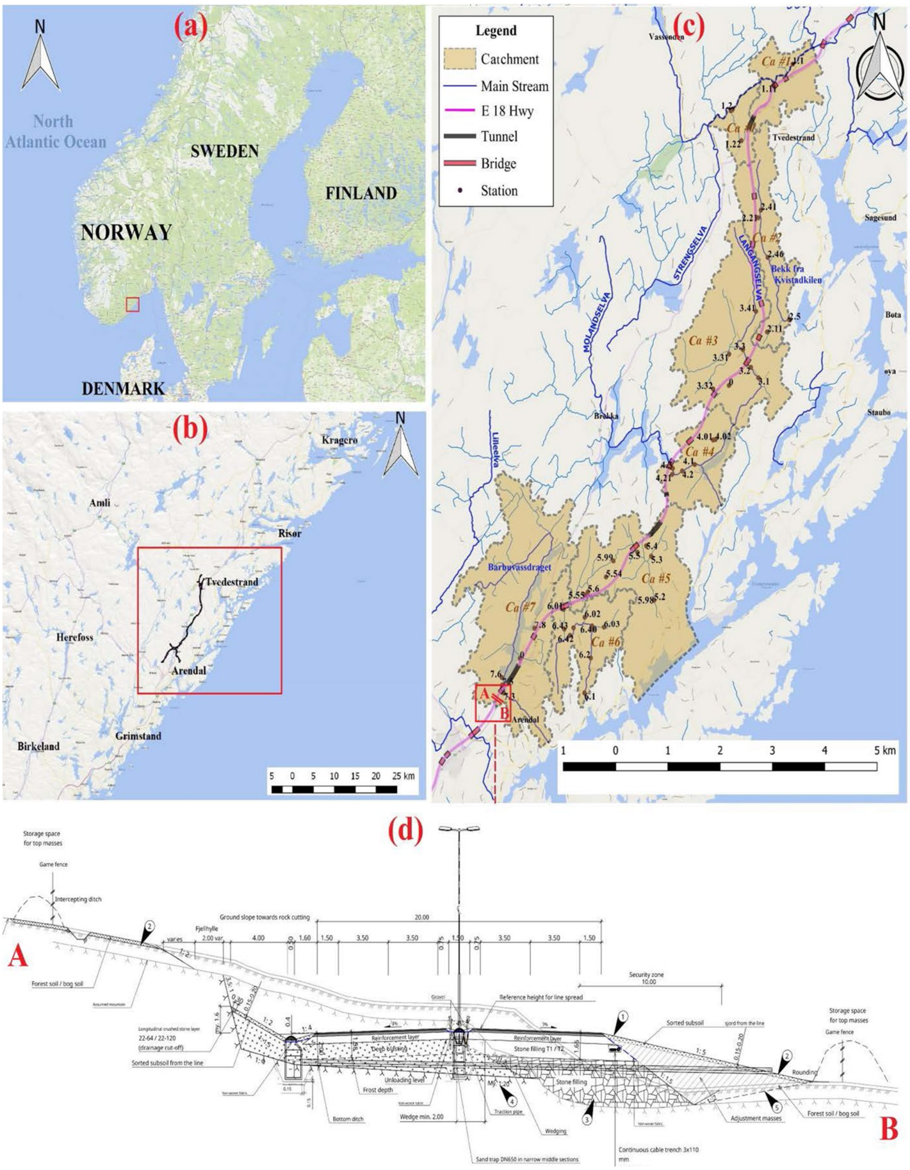

Fig. 2 (**a**-**c**) Location of construction project and receiving water resources, (**d**) a cross-sectional profile of E18 highway

catchment areas, namely Storelva (# 1), Vennevann (# 2), Langangselva (# 3), Sagene (# 4), Mørfjær (# 5), Songebekken (# 6), and Longum/ Barbu (# 7).

Figure 2 shows the main and side streams in different catchments and the intersections with the road. The main streams, such as Langangselva, Bekk fra Kvistadkilen, Molandselva, and Barbuvassdraget, were directly influenced by construction activities. The construction project consisted of various sections with different sizes and types of activities. A total of nine bridges and four tunnels were constructed, with runoff into the streams, which may have posed negative impacts to the quality of surface waters. The design manual Handbook N200 Vegbygging (Statens, 2014) was used in the construction of E18 highway. Figure 2-d shows the sectional profile of the road, including the material and thickness of each layer. As indicated, the subbase and frost protection layer consist of unbound aggregates, and the base layer is often constructed from hot mix asphalt. The thickness of layers depends on subgrade conditions and the traffic load. Regarding the topography of the catchments, and the direction of the main and side streams in catchments, several monitoring stations (see Fig. 2-c) were established on the main- and side streams of each catchment area to monitor the spatiotemporal changes in physical and chemical parameters of surface water during the road construction. In Fig. 2-c, the first digit in the number of each station indicates the catchment number. The location of stations is not dependent on the hydrological aspects in the catchment. Hence, the water flow is not the subject of the proposed methodology. The monitoring was carried out in different periods of the project according to the construction activities and environmental requirements established by the Environmental Department of the Governor of Agder County, Norway. In this study, six time periods of one month each, divided by intervals of 4 months, were considered during the construction phase from 2017 to 2019. The time periods were selected based on different activities and start operations in different parts of the road project. The first period (4/2017) indicates the basic conditions of the water resources, during which the main activities were limited to preparation and mobilization. Construction activities started from the second period (10/2017), and since then, with the progress of construction activities in different sections of the project sampling has continued in a four-month sequence.

The selected monitoring parameters were divided into four categories, including physical properties (total suspended solids (TSS), turbidity, color, and pH), sum parameters (chemical oxygen demand (COD), alkalinity, electrical conductivity (EC)), nutrients (total-N, total-P, NO_3-N), minerals and ions (SO_4^{2-}, Mg^{2+}, Ca^{2+}, Na^+, Cl^-, K^+), and metals and heavy metals (Fe, As, Ba, Pb, Cd, Cu, Co, Mn, Hg, Cr, Ni, and Zn). The average values and standard deviations for the six time periods are given in Table 1 and represent data from all stations.

2.2 Water quality index

The proposed WQI in this research takes advantage of the relative weighting method (Kangabam et al., 2017) based on previous studies to achieve a feasible balance among water quality parameters. The WQI was calculated to determine the qualitative status of surface water in each time period. Regarding the parameter selection for calculation of the WQI, the principal component analysis (PCA) was performed on the present dataset to reduce the dimensionality of the dataset while retaining as much as possible the variability present in the dataset (Uddin et al., 2021). The results of the PCA indicated that the first ten components have an eigenvalue > 1 and explain almost 90% of the variance. Then, to decide the importance of each parameter in resulted PCs, the contribution of different

Table 1 Average and standard deviation of measured parameters during road construction

Parameters	Unit	April 2017		October 2017		February 2018		June 2018		October 2018		February 2019	
		Avg	Stdev	Avg	Stdev	Avg	Stdev	Avg	Stdev	Avg	Stdev	Avg	Stdev
TSS	mg / L	8.2	11.0	12.2	29.0	3.8	3.2	5.5	8.5	2.7	1.4	6.1	14.5
Turbidity	(FNU)	7.6	11.8	7.6	11.1	4.1	4.5	4.2	12.6	1.4	1.2	5.4	11.5
Color	mg Pt/ L	66.1	25.0	77.7	25.8	41.4	19.3	32.2	18.3	35.4	14.4	41.2	22.2
pH	–	6.6	0.3	6.8	0.3	6.8	0.4	7.1	0.3	7.2	0.3	6.9	0.3
COD	mg / L	32.5	19.7	24.1	13.8	31.5	3.6	32.3	6.5	30.7	2.5	30.1	0.8
Alkalinity	mmol / L	0.2	0.1	0.3	0.3	0.4	0.3	0.5	0.3	0.5	0.3	0.3	0.3
EC	mS/ m	7.2	3.5	14.3	23.3	18.2	13.3	26.3	25.6	32.8	35.4	22.1	16.0
Total-N	µg / L	1169.3	959.4	7405.2	29,015.3	4462.8	6341.6	6058.8	8869.1	9367.0	20,182.4	3709.0	4089.1
Total-P	µg / L	21.9	21.0	21.0	19.6	11.8	11.6	15.4	16.0	7.3	4.4	12.7	14.4
NO_3	mg / L	0.7	0.6	6.0	23.3	3.8	5.7	5.7	8.8	9.0	19.1	3.5	4.2
SO_4	mg / L	4.5	3.6	11.3	17.8	11.2	13.5	24.5	37.3	44.0	53.3	28.2	29.9
Mg	mg / L	1.5	0.8	2.7	3.1	3.4	2.5	5.0	5.7	6.9	8.0	4.1	3.1
Ca	mg / L	4.5	2.4	12.8	29.1	13.7	12.7	22.5	25.4	28.4	35.2	17.0	16.0
Na	mg / L	7.1	4.5	10.0	8.0	13.7	9.8	18.1	21.6	23.7	29.4	17.9	16.5
Cl	mg / L	10.5	6.6	10.8	4.5	23.3	19.0	38.3	52.7	36.9	37.7	28.9	23.9
K	mg / L	1.5	0.9	2.5	2.9	2.1	1.4	2.9	2.3	3.5	3.5	2.5	1.8
Fe	µg / L	902.9	1090.1	829.8	858.9	711.8	1414.4	390.0	554.5	230.7	148.1	428.3	583.6
As	µg / L	0.4	0.3	0.4	0.2	0.3	0.1	0.3	0.2	0.3	0.1	0.4	0.3
Ba	µg / L	9.3	6.7	14.1	17.3	13.1	7.2	19.7	19.1	22.1	18.5	14.9	9.0
Pb	µg / L	0.8	1.0	0.6	0.5	0.4	0.3	0.3	0.5	0.2	0.0	0.4	0.3
Cd	µg / L	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.1	0.1	0.1	0.1	0.1
Cu	µg / L	2.3	3.5	2.5	1.8	1.7	0.9	1.7	1.4	1.3	0.9	1.7	0.9
Co	µg / L	0.8	0.9	1.0	2.1	1.4	3.8	0.6	0.8	0.5	0.7	0.6	0.5
Mn	µg / L	85.1	170.6	89.9	131.9	167.8	279.4	102.9	131.1	102.5	270.1	86.7	82.1
Hg	µg / L	0.004	0.002	0.003	0.000	0.005	0.000	0.005	0.000	0.005	0.000	0.005	0.000

Table 1 (continued)

Parameters	Unit	April 2017		October 2017		February 2018		June 2018		October 2018		February 2019	
		Avg	Stdev	Avg	Stdev	Avg	Stdev	Avg	Stdev	Avg	Stdev	Avg	Stdev
Cr	μg / L	0.8	1.2	0.6	0.7	0.6	0.2	0.9	1.1	0.5	0.0	0.6	0.4
Ni	μg / L	1.1	0.7	2.1	4.3	2.6	7.5	1.5	1.8	1.4	1.7	1.6	1.5
Zn	μg / L	7.2	5.3	7.3	6.7	10.3	16.3	4.2	3.6	5.6	6.0	8.7	3.4

parameters in making the PCs was computed, and considering the fact that the selected parameters for WQI must have the same time series, the parameters with a lot of incomplete or missing data during the monitoring periods were excluded. Finally, 28 parameters with the highest importance and a complete time series in the monitoring periods were selected for WQI calculation (see Table 1).

After that, the quantity rating scale (Q_i) for each parameter (except pH) is calculated by Eq. 1, and for pH, the Q_i is computed using Eq. 2 (Meher et al., 2015).

$$Q_i = \frac{C_i}{S_i} \tag{1}$$

$$Q_i = \frac{C_i - 7}{S_i - 7} \tag{2}$$

where, C_i is the measured value for each parameter from all monitoring stations, and S_i is the maximum acceptable limit of each parameter according to the regulations. For all parameters, the value of S_i was determined based on the guidelines for freshwater quality released by WHO (2018) (Cotruvo, 2017 Environment and Parks, 2014), or the water quality regulations set by the discharge permit for the construction phase of E18 Arendal–Tvedestrand, established by the Environmental Department of the Governor of Agder County, Norway. Table 2 presents the values of S_i for all 28 selected parameters, applied in this study.

Notably, the proposed method is independent of standard type, and other regulations such as EU water guidelines 2020 can be applied for the maximum acceptable limits upon case. In the second step, the relative weights of the parameters were determined. In this regard, the assigned weights to water quality parameters, as used in previously published research, were considered. The normalized weights in previous studies for all 28 selected water quality parameters are given in Table 3, in which the normal weights of 1 and 4 indicate the lowest and the highest scores in determining the water vulnerability index. Then,

Table 2 Surface water quality guidelines for the protection of surface freshwater (WHO 2011, 2018)

Parameter	Unit	Limit Value WHO	Parameter	Unit	Limit Value WHO
SO_4	mg / L	250	K	mg / L	12
Mg	mg / L	50	COD	mg / L	25
Ca	mg / L	75	Cl	mg / L	250
Fe	µg / L	500	Cu	µg / L	2000
pH	–	<7.5	Co	µg / L	100
TSS	mg / L	2	EC	mS/ m	100
Turbidity	(FNU)	10	Cr	µg / L	50
Total-N	µg / L	750	Hg	µg / L	0.005
Alkalinity	mmol / L	0.4	Mn	µg / L	100
As	µg / L	5	Na	mg / L	200
Ba	µg / L	1000	Ni	µg / L	20
Pb	µg / L	10	NO_3	mg / L	50
Color	mg Pt/ L	25	Zn	µg / L	77
Cd	µg / L	0.53	Total-P	µg / L	25

Table 3 Normalized weights of water quality parameters in the literature and the calculated relative weights

NO	Parameters	(Boyacioglu 2007)	(Kannel et al. 2007)	(Abrahão et al. 2007)	(Karakaya and Evrendilek 2010)	(Ramakrishnaiah et al. 2009b)	(Rubio-Arias et al. 2012)	(Ravikumar et al. 2013)	(Bodrud-Doza et al. 2016)	(Periyasamy and Rajan 2009)	(Meher et al. 2015)	(Ravikumar et al. 2013)	(Tripathee et al. 2016)	(Şener et al. 2017)	(Batabyal and Chakraborty 2015)	(Batabyal and Chakraborty 2015)	(Mgbenu and Egbueri 2019)	(Saucedo-Terán et al. 2017)	(Ugochukwu et al. 2019)	(ARKOÇ 2016)	(Abu Khatita et al. 2017)	Average Weights	**Weights(%) (by Eq. 3)**
1	SO_4^{2-}	–	2.0	2.0	2.0	3.2	2.0	2.4	4.0	3.0	3.2	–	–	3.2	3.2	3.2	–	–	2.4	2.4	–	2.7	**3.6**
2	Mg^{2+}	–	1.0	1.0	1.0	1.6	–	1.6	2.0	1.0	1.6	1.6	–	1.6	1.6	1.6	1.6	2.0	–	1.6	–	1.5	**2.0**
3	Ca^{2+}	–	1.0	1.0	1.0	1.6	–	1.6	2.0	3.0	1.6	1.6	–	1.6	1.6	1.6	2.4	–	–	1.6	–	1.7	**2.2**
4	Fe	–	–	–	–	3.2	–	1.6	4.0	–			–		3.2	3.2	3.2	–	2.4	–	2.4	2.9	**3.8**
5	pH	1.0	1.0	1.0	1.0	3.2	4.0	2.4	4.0	1.0	3.2	2.4	–	3.2	3.2	3.2	3.2	–	3.2	–	1.7	2.5	**3.3**
6	SS	–	4.0	–	4.0	–	–	–	–	–	–	–	–	–	–	–	–	3.0	–	–	–	3.7	**4.8**
7	Turbidity	–	–	4.0	2.0	–	3.0	–	–	–	–	–	–	–	–	–	–	–	–	–	–	3.0	**4.0**
8	Total-N	–	3.0	3.0	3.0	–	2.0	–	–	–	–	–	–	–	–	–	–	–	–	–	–	2.8	**3.6**
9	Alkalinity	–	–	–	–	2.4	–	1.6	–	–	1.6	1.6	–	2.4	2.4	2.4	2.4	–	–	1.6	–	2.0	**2.7**
10	As	4.0	–	–	–	–	–	–	4.0	–	–	–	–	–	–	–		4.0	–	4.0	–	4.0	**5.3**
11	Ba	–	–	–	–	–	–	–	–	–	–	–	1.6		–	–	3.2		–	–	–	2.4	**3.2**
12	Pb	–	–	–	–	–	–	–	4.0	–	–	–	4.0	4.0	–	–	4.0	4.0	4.0	–	4.0	4.0	**5.3**
13	Color	–	–	2.0	–	–	4.0	–	–	–	–	–	–	–	–	–	0.8	3.0	–	–		2.5	**3.2**
14	Cd	3.0	–	–	–	–	–	–	–	–	–	–	4.0	–	–	–		4.0	4.0	–	2.4	3.8	**5.0**
15	K^+	–	–	–	–	–	–	1.6	2.0	2.0	-	1.6	–	–	–	–	1.6	–	–	0.8		1.8	**2.3**
16	COD	–	3.0	3.0	3.0	–	–	–	–	–	–	–	–	3.2	–	–		–	–		–	3.1	**4.0**
17	Cl^-	–	1.0	1.0	1.0	2.4	2.0	2.4	3.0	4.0	2.4	2.4	–	2.4	2.4	2.4	1.6	–	2.4	2.4	–	2.2	**2.9**
18	Cu	–	–	–	–	–	–	–	–	–	–	–	1.6	–	–	–	–	2.0	1.6	–	1.6	1.7	**2.3**
19	Co	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	3.0	–	–	–	3.0	**4.0**
20	EC	–	1.0	4.0	2.0	-	4.0	2.4	–	2.0	4.0	2.4	–	–	–	–	2.4	3.0	4.0	–	–	2.8	**3.7**
21	Cr	–	–	–	–	–	–	–	–	–	–	–	4.0	4.0	–	–	4.0	4.0	–	–	–	4.0	**5.3**
22	Hg	3.0	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	3.0	**4.0**
23	Mn	–	–	–	–	3.2	–	–	4.0	–	–	1.6	3.2	4.0	3.2	3.2	3.2	2.0	–	2.4	2.4	3.0	**3.9**
24	Na^+	–	–	1.0	–	–	–	2.4	4.0	4.0	0.8	2.4		1.6	–	–	2.4		–	2.4	–	2.3	**3.1**

Table 3 (continued)

NO	Parameters	(Boyacioglu 2007)	(Kannel et al. 2007)	(Abrahão et al. 2007)	(Karakaya and Evrendilek 2010)	(Ramakrishnaiah et al. 2009b)	(Rubio-Arias et al. 2012)	(Ravikumar et al. 2013)	(Bodrud-Doza et al. 2016)	(Periyasamy and Rajan 2009)	(Meher et al. 2015)	(Ravikumar et al. 2013)	(Tripathee et al. 2016)	(Şener et al. 2017)	(Batabyal and Chakraborty 2015)	(Batabyal and Chakraborty 2015)	(Mgbenu and Egbueri 2019)	(Saucedo-Terán et al. 2017)	(Ugochukwu et al. 2019)	(ARKOÇ 2016)	(Abu Khatita et al. 2017)	Average Weights	**Weights**(%) **(by Eq. 3)**
25	Ni	–	–	–	–	–	–	–	–	–	–		3.2	–	–	–	4.0	4.0	–	–	–	3.7	**4.9**
26	NO_3	3.0	2.0	2.0	2.0	4.0	-	4.0	-	-	-	4.0		4.0	4.0	4.0	4.0		4.0	4.0	1.8	3.3	**4.4**
27	Zn	–	–	–	–	–	–	–	3.0	–	–	–	0.8	–	1.0	0.8	1.6	1.0	–	–	1.6	1.4	**1.9**
28	Total-P	2.0	1.0	1.0	1.0	-	1.0	–	–	–	–	–	–	–	–	–	–	–	–	–	–	1.2	**1.6**
Sum																					**75.8**	**100**	

for each parameter, the average of assigned weights ($\overline{w}_i$) was calculated, and the relative weight (%) of each parameter was achieved by Eq. 3. The values of relative weights are presented in the last column of Table 3.

$$w_i = \frac{\overline{w}_i}{\sum_{i=1}^{28} \overline{w}_i} \times 100 \tag{3}$$

The relative weights of the parameters are expressed in percentage to standardize the comparison of the water quality indexes under different conditions (e.g., in various times and due to different construction activities).

Lastly, by defining the relative weight of each parameter (w_i), the WQI is achieved according to Eq. 4.

$$\mathrm{WQI} = \sum_{i=1}^{28} w_i \times Q_i \tag{4}$$

The larger the obtained WQI, the greater the violation of the standard and vulnerability of surface water due to the entry of pollutants. If the water quality index exceeds 100, it means that its quality situation is deteriorating. Similarly, waters with WQI less than 100 have better quality (Uddin et al., 2021).

2.3 Spatiotemporal variation of water quality

The type and volume of construction activities vary in different parts of the project, and consequently makes spatiotemporal changes in the quality of receiving surface water. By measuring 28 physical and chemical parameters in 48 monitoring stations and defining a water quality index, the effect of road construction on the qualitative status of surface water was evaluated. Using the calculated WQI for different monitoring stations during the construction period, the quality of surface water bodies was classified (Yadav et al., 2018) for the six selected time periods.

In addition, one of the most significant issues in assessing the vulnerability of the water bodies during road construction was evaluating the effects of activities in each section of the road, considering the location of catchments and monitoring stations. The resulted runoff from the road construction activities in each catchment entered the surface water streams. Therefore, for comparing the vulnerability of water resources to different sections of the road, the average of WQI in monitoring stations of each catchment area was calculated.

The effects of the most important activities in road construction were determined. The activities included cut and fill (earthwork), area cleaning (preparing the existing surface for construction activities), swamp/wetland replacement, establishing pilot roads, excavation, drilling, blasting, tunnel construction, water management (for rainfall, surface runoff, and wastewater), paving, asphalting, bridge construction, casting for the bridge, culvert construction, and construction of water treatment plants for runoff water. The vulnerability of surface water bodies in the construction project largely depends on the type and size of activities for each section of the project. Therefore, the variety of activities performed in each part of the project during the selected time periods was extracted. Then,

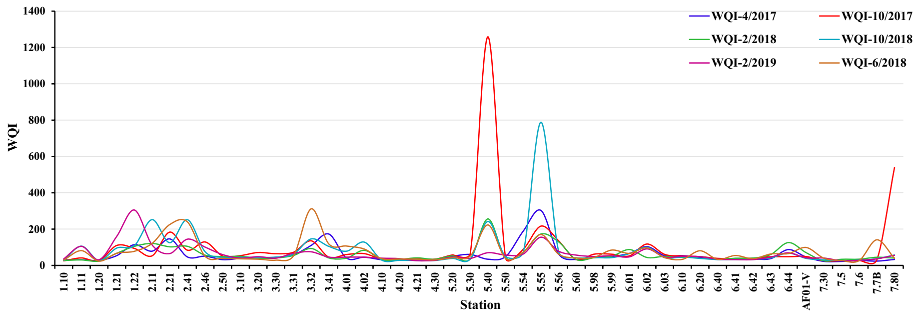

Fig. 3 Variation of WQI at different monitoring stations during the six time periods

Table 4 Statistical features of calculated WQIs from all the monitoring stations in the six time periods of road construction

Feature	WQI over construction time (2017–2019)					
	4/2017	10/2017	2/2018	6/2018	10/2018	2/2019
Average	60.0	99.3	61.8	75.6	83.8	63.4
Maximum	302.8	1259.2	256.2	311.5	788.5	304.7
Minimum	21.8	25.1	24.0	23.2	26.6	26.0
Stdev. *	50.8	186.6	42.8	62.2	116.7	47.2

* Standard deviation

the vulnerability of surface water bodies to various activities was calculated considering the average value of WQI for each operation in all catchments and during all selected time sections.

3 Results and discussion

3.1 Water quality index in different stations

In determining the weights for WQI, the parameters of Pb, As, and Cr all received the highest values with the relative weight of 5.28, and the parameters of Total-P, Zn, and Mg with the relative weights of 1.58, 1.85 and 1.97, respectively, adopted the lowest relative importance compared to other parameters (see Table 3). By employing the results of the measurements from the different monitoring stations, the WQI was calculated in the six time periods. The variation of the WQI in different time periods is shown in Fig. 3. The stations located in catchments # 4 and # 6 have a lower WQI variation than that of other catchments during the construction. In contrast, the changes in catchment # 5 are more severe than that in others. This may be due to the construction of a 1.1-km-long tunnel in two lines in this catchment.

The maximum value of WQI of 1259 was recorded in October 2017 at station # 5.40. The road construction in this station included tunneling, and during this time period, blasting was carried out for tunneling in the area. As a result, the parameters of total-N, TSS, and Mn increased to 200,000 (μg/L), 86 (mg/L), and 600 (μg/L), respectively. The minimum value of WQI (21.8) was recorded in the period of 04/2017 at station # 7.5, which

Table 5 Classification of water quality according to WQIs in the different monitoring periods

WQI variation range	Water quality mode	Percentage of monitoring stations in each category					
		4/2017	10/2017	2/2018	6/2018	10/2018	2/2019
<50	Excellent water	62.5	43.8	60.4	47.9	58.3	56.3
50-100	Good water	22.9	37.5	22.9	33.3	20.8	29.2
100-200	Poor water	12.5	12.5	14.6	10.4	12.5	12.4
200-300	Very poor water	0.0	2.1	2.1	6.3	6.3	0.0
>300	Unsuitable for drinking	2.1	4.1	0.0	2.1	2.1	2.1

indicates the basic quality of water resources. The highest average values of 347.28 and 300.98 were registered at stations # 5.4 and # 5.55, respectively. The index indicates that these stations were most affected by the construction work if all six time periods are considered. The statistical features (e.g., the average, maximum, minimum, and standard deviations) of calculated WQIs from the monitoring stations are given in Table 4.

Among the six monitoring periods, the first period (4/2017), which indicates the quality of surface waters at the beginning of the project with the minimum construction activity, has the minimum average value (60.0). This number suggests that before the start of the project, the quality of the surface water bodies with an index of less than 100 were in good condition. During the first monitoring period, the violation of the limit occurred in the parameters of SS, turbidity, total-N, and some metals (e.g., Fe and Mn). During the monitoring period of 10/2017, the highest average water quality index of 99.3 was recorded, which indicated that this time period produced the highest average pollution load compared to the other time periods. By analyzing the parameters involved in calculating the WQI, it was concluded that this pollution load resulted from elevation in EC, COD, total-N, SS, Hg, and Mn. The highest standard deviation (186.6) was registered in the second time period (10/2017), which shows that the range of variation in WQI in this period was higher than in other monitoring periods.

3.2 Spatiotemporal variation of WQI

Based on the values of WQI in different monitoring stations, the classification of surface water quality in different time periods (Mohanty, 2005; Ramakrishnaiah et al., 2009a, Yadav et al., 2018) is given in Table 5. The stations with WQI less than 50 have the best water quality, and the surface water bodies seem unaffected by the road construction. For example, by comparing the values of WQI in all stations in the first monitoring period (4/2017), 62.5% of the samples from the monitoring stations resulted in WQIs less than 50. However, as the project progressed over time, the percentage of stations with WQI less than 50 decreased in all the monitoring periods thereafter (2 to 6).

The highest percentage of samples (4.1) with WQI > 300 is related to the second monitoring period (10/2017). As the project progressed to the fifth monitoring period (10/2018), the amount of these samples with WQIs in the range of > 100 increased to 20.9% (12.5 + 6.3 + 2.1). In the fifth monitoring period, the impact of road construction on surface water was higher than that in other time periods. In contrast, the results from the first monitoring period (4/2017) revealed that 85.4% of the surface water bodies were in excellent and good modes.

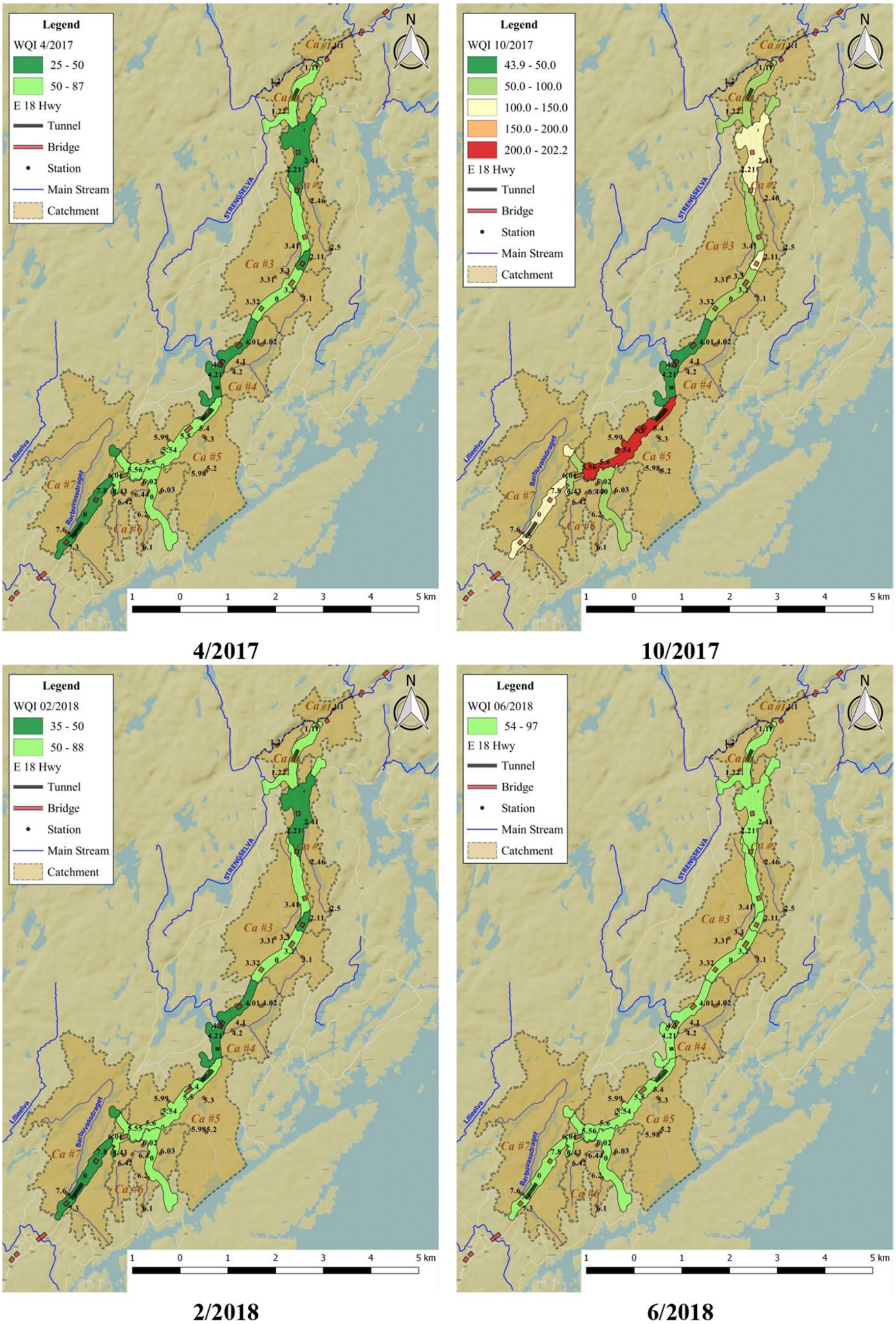

Fig. 4 Spatiotemporal variation of WQI in different sections of the road during construction time

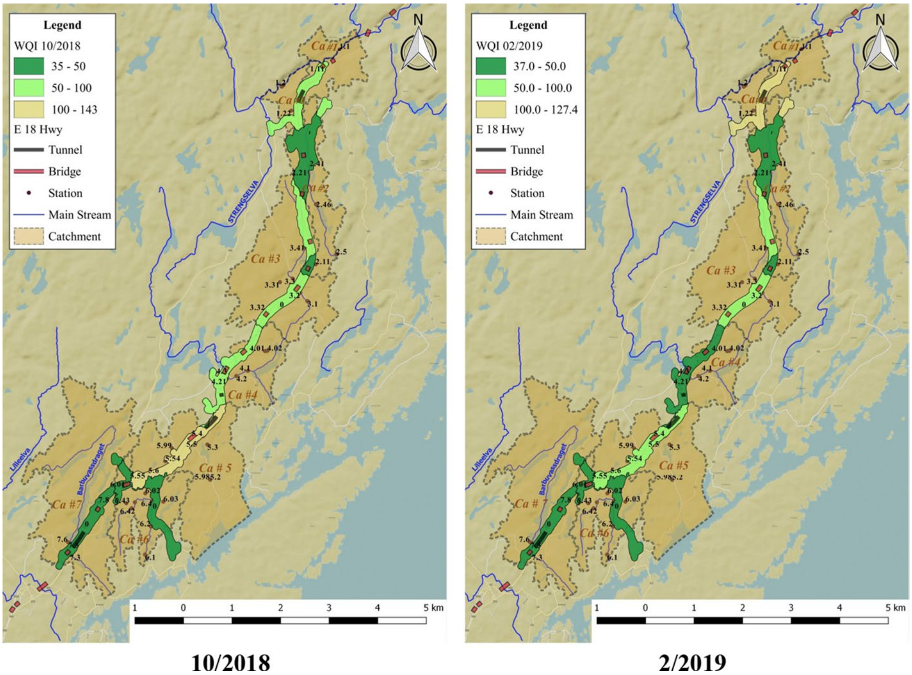

Fig. 4 (continued)

Then, utilizing the average of WQI values in monitoring stations of each catchment and considering six time periods for monitoring, the vulnerability of the surface water bodies in different sections of the road (the spatiotemporal changes of the WQI in different sections of the road) was computed (Fig. 4).

Figure 4 shows that in the first time period (4/2017), when the road construction activities have not been started completely, the vulnerability of surface water due to construction in all sections of the road is low (WQI < 100 in most parts of the project). Also, during the third time period (2/2018), the project activities only imposed small impact on the water quality in the catchment areas. But in general, from the second period (10/2017) onward, as the construction activities progressed in different sections of the road, the amount of discharged runoff also increased. Among the six time periods, the impact of road construction on surface water bodies in time period # 2 (10/2017) was higher than that in the other time periods. In this time period, for the catchment area # 5, the WQI was higher than 200. As shown in Fig. 4, in the catchment area # 5, a large part of road construction activities were related to bridge and tunnel construction, including polluting activities such as drilling and blasting, and the average WQI in this catchment area increased significantly. For example, in station # 5.40, the area cleaning and blasting in time period # 2 (10/2017) resulted in WQI of 1259.2, which alone played a significant role in increasing the average of WQI in this catchment. Figure 4 also shows that catchment area # 5 in time period 10/2018 received the highest impact from road construction activities. This was mainly explained by blasting in stations # 5.4 and # 5.55, which increased WQI at these stations to 241.8 and 788.4, respectively. Accordingly, the catchment area # 1 in the last time period (2/2019) had the highest WQI, which can be attributed to blasting and water management in station # 1.22. These activities were likely to increase the WQI in station # 1.22 to 304.7.

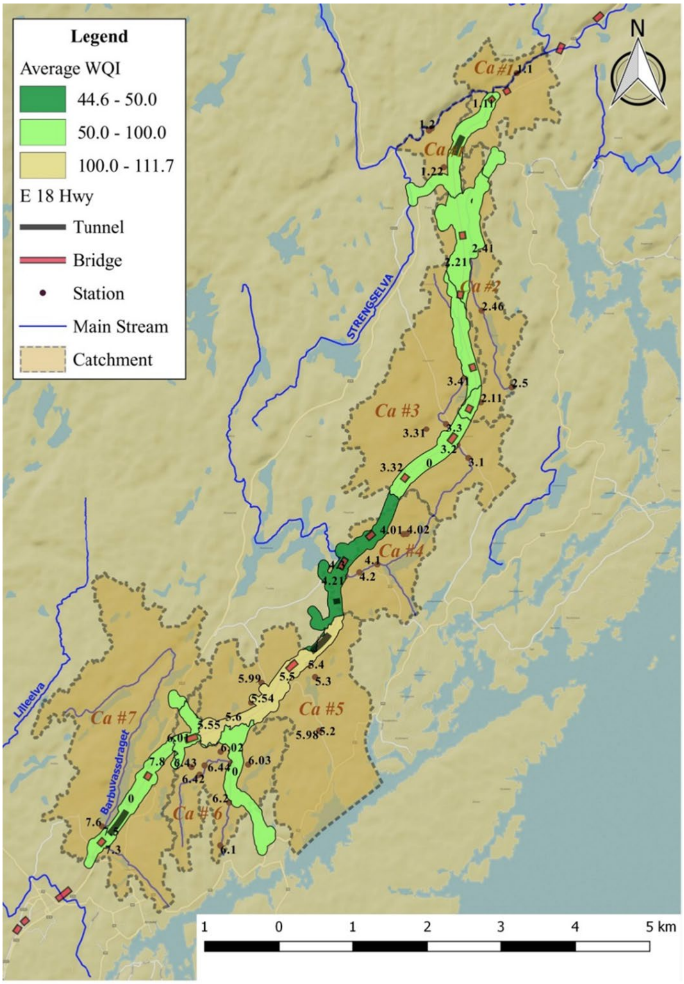

Fig. 5 Overall impact of construction to surface water bodies in various parts of the road

The spatiotemporal variation of WQI in different parts of the road is primarily related to the type and size of operations. The overall impact of the road construction project on surface water bodies in the catchments was obtained by averaging the values of WQI in the six time periods (Fig. 5). Based on Fig. 5, the least impacts of the road construction was observed in the catchment area # 4. In contrast, the highest value of WQI during the whole period of road construction was found in catchment area # 5, where the construction activities related to bridges and tunnels were higher than in other catchments. There were ten monitoring stations in catchment area # 5. Based on the topography of this catchment, the maximum effect of tunnel construction was related to station # 5.4, in which the WQIs were 34, 1259, 256, 223, 242, and 70 from the first to the sixth monitoring periods, respectively. Catchment areas # 1, # 2, # 3, # 6 and #7 were only moderately affected by the road construction, compared to other catchments of the project.

3.3 The effect of various construction activities on the vulnerability of surface water resources

The most important construction activities performed in different catchments and during the selected time periods were extracted based on the reports of the Nye Veier AS. In Table 6, 15 activities related to road construction are listed. The spatial and temporal distribution of these activities varies at different stations and during the construction period. The first sampling period represents the basic conditions of the water resources, since in some stations, no particular activity was carried out; however, at some other stations, activities related to site preparation such as cleaning and blasting were performed.

As shown in Table 4 and Fig. 4, the value of WQI was calculated for different activities performed in each time period. The most repetitive activities performed in this project was related to blasting, area cleaning, cut and fill, swamp/wetland replacement, respectively. Figure 6 indicates the calculated WQI for each activity and reflects the vulnerability of the surface water under any type of activity. The numbers suggest that construction of treatment plants for runoff water, paving, and bridge-building has a minor impact on the receiving water bodies. In contrast, activities such as blasting, area cleaning, water management, and drilling led to the most qualitative deterioration of surface water resources, with WQI > 100. Other activities such as swamp and wetland replacement, tunnel excavation, culvert construction, bridge construction and casting also resulted in significant negative effects on water resources. Notably, as more than 2 km of tunneling was performed in this project, activities such as drilling and blasting have been very repetitive, which resulted in elevated values of some parameters in the receiving streams, including total-N, turbidity, and SS. For example, in the second monitoring period (10/2017), the blasting activities in a construction section with drainage to monitoring station # 5.40 resulted in WQI of 1259. Analyzing this value showed that approximately 77% of the pollution load measured at this station (967 out of the 1259) came from total-N, which increased to more than 200,000 µg/L. The high N-content in dynamite used for blasting is a reasonable explanation to the elevated N-concentration in the receiving water body. Also, the parameters of SS and Mn contributed to the WQI of 1259 by 16% and 1%, respectively. The share of other parameters was 6%. In addition, drilling activity increased the concentration of EC, SS and turbidity and consequently raised the WQI in areas with this type of activity.

It is assumed that the surface washout by heavy precipitation may in general increase the transport of several compounds, including total ions (EC), SS, and turbidity during construction activities. Such a washout effect was indicated during asphalting, which is one of the final activities during road construction. The precipitation diagram in the time periods of 2/2019 and 10/2018 at the closest Meteorological station to the project (i.e., Arendal Meteorological station) is shown in Fig. 7. For example, close to stations # 3.31 on February 05, 2019, asphalting was performed. As shown in Fig. 7b, a, precipitation of approximately 25 mm was registered for this date. Our data indicate that the rainfall increased the transport of pollutants from the asphalting activity, which resulted in elevated values in parameters such as turbidity (5.7 FNU) and SS (7 mg/L) in the receiving waters.

In contrast, there is no precipitation for station # 4.20 on October 09, 2018, and the values of turbidity (0.58 FNU) and SS (2 mg/L) in the receiving waters are less than those in station # 3.31. The influence of precipitation may have introduced some uncertainty when assessing the impact of different construction activities on surface water quality. However, most of the activities were distributed over the total project period, including both wet and dry periods, thereby equalizing some of the precipitation impact.

Table 6 Construction activities in different catchments (E18 Arendal–Tvedestrand)

	Discharge area	Stations	Activities					
			4/2017	10/2017	2/2018	6/2018	10/2018	2/2019
1	*Storelva-vassdraget*	*1.11*	1, 2	3	5	7	2	5
		1.21, 1.22		4	2,4	4	2	2,11,12
2	*Vennevann-vassdraget*	*2.41*	5, 2	13	1, 2, 14	2,12	1, 2	2, 3, 14
		2.46	2, 5	3	15	12	7,12	7,12
		2.11		2, 5	2	No activity, 10	14	7, 11, 10
		2.50	2, 5	1, 13	11	1, 12	7, 12	11, 12
3	*Langangselva-vassdraget*	*3.41*	no activity	2, 5, 13	2	No activity, 1	1	7
		3.32, 3.31	2, 5	2, 13	1	7, 13	10	7, 12
		3.20, 3.10	5	2, 5	2, 6	1, 2, 14	7	1, 7, 12, 10
4	*Sagene-vassdraget*	*4.10*	5	2, 5	2	2	12	1, 12
		4.20, 4.21	2, 5	2, 5	2	7	No activity	8
		4.30	5	2, 15	2	7	10	10
5	*Mørfjær-vassdraget*	*5.30*	1, 5	1, 2, 4, 5	8	2	9, 8	8
		5.40	2, 5	2, 5	2	2, 7	2, 14	1, 3, 8
		5.50		15	15	12	2, 5	6, 12, 15
		5.99	2, 5	2, 5	2	1, 2	5	1, 11, 8
		5.54		2, 5	7	2	2, 7	No activity
		5.55, 5.56		2, 5	2, 5	1, 2, 13	2	8
6	*Songebekken-vassdraget*	*6.10, 6.20*	Little to no activity	Little to no activity	13	1, 3, 5	1, 2, 12	1, 2, 12
		6.01, 6.41, 6.42, 6.43	2, 5	2, 5	15	1	8	1, 2, 8
		6.44		2, 5, 13	3, 13	2, 3, 14	8	8
		6.02	Little to no activity	Little to no activity	1	13	2	2, 13
		AF01		6	13	2, 10	12	12

Table 6 (continued)

	Discharge area	Stations	Activities					
			4/2017	10/2017	2/2018	6/2018	10/2018	2/2019
7	*Longum/ Barbuvassdraget*	*7.30*	Little to no activity	Little to no activity	13, 15	1, 14	12	No activity
		7.6, 7.5	4, 5	No activity	2	1, 2	5, 8	4, 8
		7.7		2	1	2, 9	no activity	9
		7.4	1	2, 5, 9	1, 2, 12, 13	1, 2, 8	8	No activity

1 = Cut and fill, 2 = blasting, 3 = excavation, 4 = tunnel construction and equipment, 5 = area cleaning, 6 = construction of treatment plant, 7 = asphalting, 8 = paving, 9 = culvert, 10 = establishing new pilot road, 11 = water management 12 = casting for bridge, 13 = swamp/wetland replacement, 14 = drilling, 15 = bridge construction

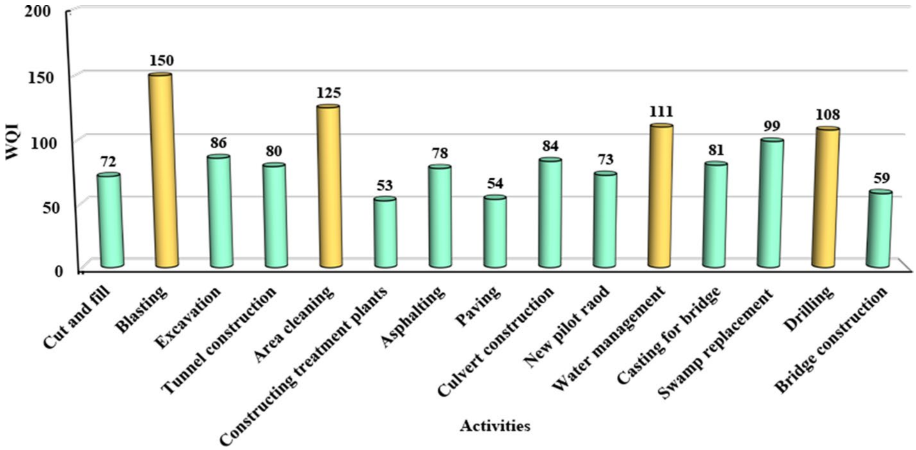

Fig. 6 Vulnerability of water resources to different construction activities of the project (brown and green colors indicate good and poor water quality according to Table 5)

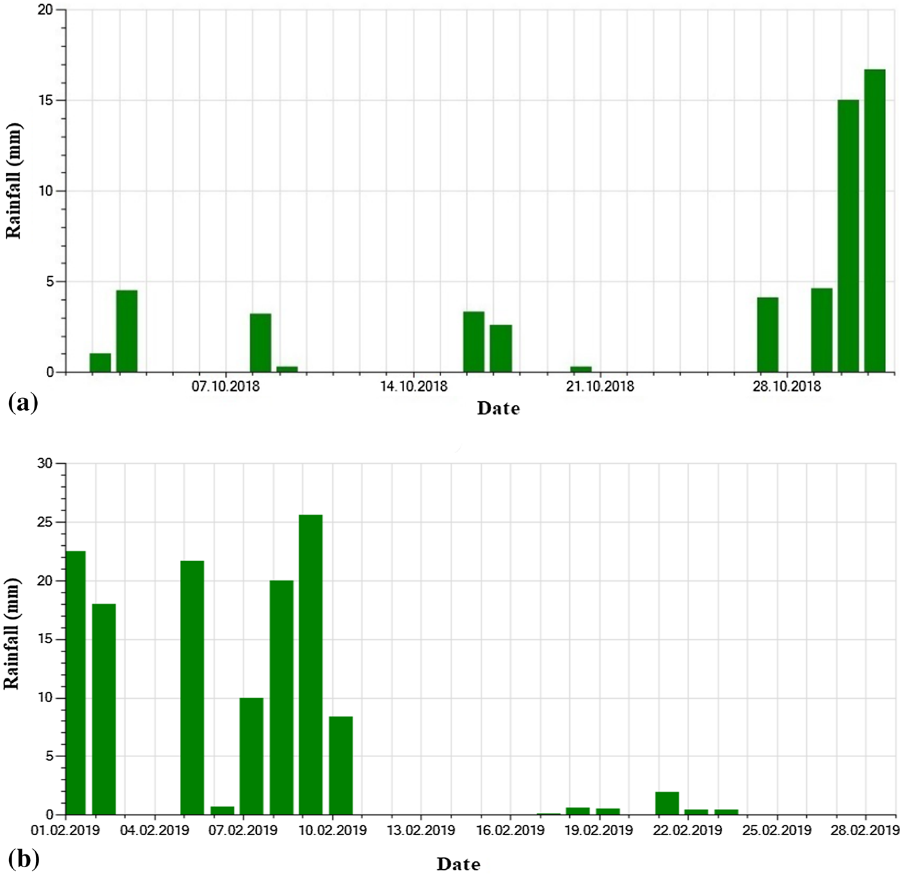

Fig. 7 Precipitation in Arendal Meteorological station in time period 10/2018 and 2/2019

4 Summary and conclusion

The results presented here provide a feasible knowledge for decision-makers regarding the effects of various construction activities on the quality of surface water and facilitate the selection of the Best Management Practices (BMPs) for road construction projects. The proposed approach was applied to a road construction site with 48 monitoring stations in seven catchment areas, which received runoff from the construction of the 22-km-long E18 highway in southern Norway.

First, using the water quality data and the relative weights of the different parameters, the WQI was calculated for all monitoring stations. Then, the temporal variation of WQI in various stations was determined over six time periods during the road construction (2017–2019) and analyzed by classification of WQI. The spatial variation of surface water quality was investigated by making averages of WQIs for all monitoring stations of each catchment area and then mapping the vulnerability of water resources to different sections of the road in the different time periods.

To evaluate the impact of each construction activity on the surface water quality, the type of activities in each section of the road was mapped, and the averages of WQIs for each activity in all catchments and for selected time periods were calculated. The results indicated that activities such as construction of treatment plants for runoff water, paving, and bridge-building have a minor impact on the receiving water bodies. In contrast, blasting, area cleaning, water management, and drilling have the highest deteriorating impact on surface water during road construction. The proposed methodology contributes to filling the lack of information in assessing the impact of road construction activities on the spatiotemporal variation of surrounding surface water quality. The provided knowledge by this research is applicable for decision-makers to achieve the optimum solution in managing the pollution of road construction and selecting the best management practice considering the type of construction activities and vulnerability of receiving surface water. The results can also help to achieve a more environmentally friendly design for road construction projects.

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Paper C

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Research papers

Assessing optimal water quality monitoring network in road construction using integrated information-theoretic techniques

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ABSTRACT

The environmental impacts of road construction on the aquatic environment necessitate the monitoring of receiving water quality. The main contribution of the paper is developing a feasible methodology for spatial optimization of the water quality monitoring network (WQMN) in surface water during road construction using the field data. First, using the Canadian Council of Ministers of the Environment (CCME) method, the water quality index (WQI) was computed in each potential monitoring station during construction. Then, the integrated form of the information-theoretic techniques consists of the transinformation entropy (TE), and the value of information (VOI) were calculated for the potential stations. To achieve the optimal WQMNs, the Non-dominated Sorting Genetic Algorithm II and III (NSGA-II, and III) based multi-objective optimization models were developed considering three objective functions, including i) minimizing the number of stations, ii) maximizing the VOI in the selected network, and iii) minimizing redundant information for the selected nodes. Finally, three multi-criteria decision-making models, including Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Preference Ranking Organisation Method for Enrichment Evaluations (PROMETHEE), and Analytical Hierarchy Process (AHP) were utilized for choosing the best alternative among Pareto optimal solutions considering various weighing scenarios assigned to criteria. The applicability of the presented methodology was assessed in a 22 km long road construction site in southern Norway. The results deliver significant knowledge for decision-makers on establishing a robust WQMN in surface water during road construction projects.

1. Introduction

Road construction makes physical, chemical, and biological impacts on receiving aquatic environments. The spatiotemporal impacts of road construction may cause acute alterations (Vikan and Meland, 2013). Hence, it is vital to assess the receiving water quality during road construction. Water quality monitoring networks (WQMN) are designed for quantitative data on the spatiotemporal variation of water quality. The provided information is applied by decision-makers for reliable assessment of water quality and supporting adopted policies for protecting the water resources (Alfonso and Price, 2012; Behmel et al., 2016). The importance of surface water in delivering water demands with adequate quality and the significant economic burden of the monitoring systems necessitates an optimum design of WQMN. Optimization of WQMN balances the fiscal burden of monitoring networks while a sufficient source of qualitative information is provided (Alizadeh et al., 2018; Alilou et al., 2019). This optimization will allow decision-makers to check deviations from set water quality standards in national and international water regulations (Pourshahabi et al., 2018a; Maymandi et al., 2018). The design of a robust WQMN is still a debatable topic, in which the selection of optimal locations for stations is crucial (Alilou et al., 2019).

Several studies focused on the difficulties in determining the sampling objectives, water quality parameters to be monitored, location of stations (Alilou et al., 2018, 2019), and variations in sampling frequency (Karamouz et al., 2009; Zeng et al., 2016; Khorshidi et al., 2018). The optimization process is a key step towards a comprehensive monitoring program in which every element of the existing WQMN is

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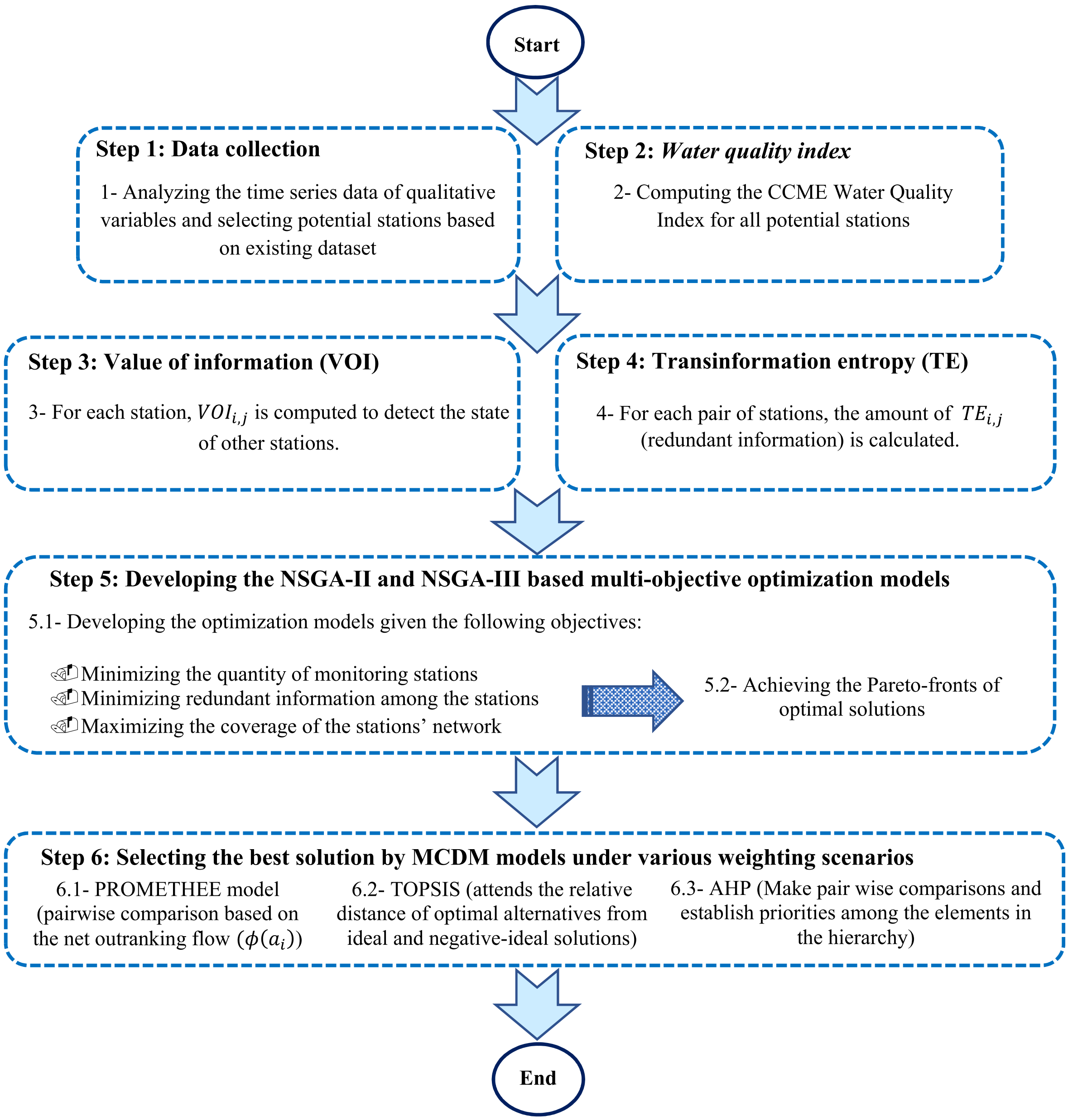


Fig. 1. The proposed methodology for optimization of the WQMN in surface water.

evaluated, and the monitoring objectives are met (Behmel et al., 2016; Pourshahabi et al., 2018b). Utilizing an optimized monitoring system has been extensively considered in water resources management owing to their better performance compared to opinion- and rule-based methods (Khorshidi et al., 2018). A review of previous studies indicates the lack of knowledge on the optimization of the WQMN in surface water during road construction. Hence, in this paper, two information-theoretic techniques, including Value of Information (VOI) and Transinformation Entropy (TE), were integrally (Pourshahabi et al., 2018a; Khorshidi et al., 2020) used for the optimal design of WQMN in a road construction project.

Information obtained from stations in receiving streams may provide diverse signals with different values to the decision-maker. Therefore, an information theory-based method (the concept of VOI) was applied to design an optimized WQMN with the highest value for qualitative information from the stations (maximum VOI), which could provide a reasonable view of the whole system. On the other hand, monitoring networks with the same number of stations (but separate locations) and comparable VOI, may bring in a different level of information redundancy. Thus, the TE method was employed for minimizing the mutual (redundant) information in the selected monitoring network. As an example, the spatial distance of monitoring stations can affect the TE level in any pair of potential stations. Therefore, minimizing the TE value would, in this case, result in a monitoring network with a more spatial distribution of monitoring sites and, subsequently, a better understanding of water quality variations (Khorshidi et al., 2018). Very few works have been published using the combination of VOI and TE. In these, optimum sensor placement (Khorshidi et al., 2018) and optimum WQMN in reservoirs (Pourshahabi et al., 2018a,b; Maymandi et al., 2018) were explored. However, the lack of an integrated method, capable of taking the advantages of both methods in surface water quality is quite apparent. Also, one of the most significant challenges related to the application of information theory in surface water quality monitoring is related to the type of applied data for computing prior and posterior probabilities. Therefore, in this study, using the sampling data from the field, a hybrid form of information-theoretic techniques was proposed for the optimum design of a WQMN in surface water, and a road construction project.

The Non-dominated Sorting Genetic Algorithm II and III (NSGA-II and NSGA-III) were then developed according to three objectives, including 1) minimizing the number of monitoring stations; 2) minimizing redundant information among monitoring stations; and 3) maximizing VOI in the selected WQMN. Finally, three different multi-criteria decision-making (MCDM) models, including Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Preference Ranking Organisation Method for Enrichment Evaluations (PROMETHEE), and Analytical Hierarchy Process (AHP) were used to achieve the best alternative on the Pareto-optimal solutions. The paper contributes to filling the knowledge gap in the following cases, which have not been adequately attended in previous assessments:

1) Computing the prior and posterior probabilities in the information theory based on water quality data from the field sampling and experimental analyses
2) Application of the Canadian Council of Ministers of the Environment (CCME) Water Quality Index (WQI) in surface water for optimization of WQMN during the road construction project
3) Utilizing NSGA-III for optimization of the WQMN in surface water and road project
4) Proposing a feasible framework consists of a water quality index, an integrated form of information theory techniques, efficient optimization, and decision-making models for monitoring network in surface water.

The feasibility of the proposed framework was assessed over a 22 km length of a new highway in southern Norway.

2. Material and methods

For optimization of the WQMN, a six-step approach (outlined in Fig. 1) is developed by coding in Matlab *ver. R2016b*.

The first step is to select potential stations based on existing datasets. Notably, the dataset consists of a) pre-construction monitoring and b) monitoring during the construction phase. However, the methodology is developed based on the latter part, including 42 measurements for each station. For all stations, the water quality index (step 2), the value of information (step 3), and the transinformation entropy (step 4) are calculated. Thereafter, the NSGA-II and III based optimization models were developed (step 5), and finally, the best solution was chosen using the MCDM models (step 6). In the next sub-sections, the applied methods are explained in more detail.

2.1. Data collection

The study area was the construction site of the new 22 km long highway (E18) from Arendal to Tvedestrand in the southern part of Norway (Fig. 2 includes a map of the area). The construction area consisted of seven catchments (the first digit in the number of stations shows the number of discharge area, see Fig. 2). There are different main streams and side streams that are connected. The construction activities (e.g., excavation, drilling, and blasting, transport, tunnel, and bridge construction) and the resulted runoff is the main source of pollution in surface water during road construction. Several monitoring stations were irregularly established on receiving main streams and side streams to assess spatiotemporal variation of surface water quality due to construction activities (Fig. 2). The location of stations is not dependent on the hydrological aspects in the catchment. Hence, the water flow in these streams and the amount of road construction runoff are not the subjects of the proposed methodology and consequently are not simulated. Samples for analysis were collected regularly throughout the pre-construction (2015–2016) and construction phase (2017–2019). The parameters included general water quality parameters (pH, alkalinity, conductivity, Fe, Mn, Na, Cl, Ca, Mg, K, Al and $SO_4 2^-$), trace elements (As, Ba, Cd, Co, Cr, Cu, Ni, Mo, Pb, Hg, and Zn), nutrients (NH_4-N, NO_3-N, total-N, total-P), organic matter parameters (color, chemical oxygen demand, total organic carbon), particulate matter parameters (suspended solids and turbidity) and organic micro-pollutants (polycyclic aromatic hydrocarbons; the PAH_{16}EPA-group).

Of the time series from all established stations, the stations with relatively complete time series over the total sampling period were selected, which are shown by green circles in Fig. 2 (hereafter called potential monitoring stations). Reference stations, which were not affected by road construction activities, were not included as potential monitoring stations. The red circles in Fig. 2 show both reference stations and the stations with relatively incomplete time series.

2.2. Water quality index (WQI)

Monitoring programs provide detailed qualitative data, including many water quality variables, and it is challenging to evaluate the experienced water quality for sensitive aquatic organisms (Nikoo et al., 2011). The Canadian Council of Ministers of the Environment (CCME) Water Quality Index (WQI), see Khan et al. (2005) and Nikoo et al. (2011), is a useful management tool for producing a meaningful interpretation of qualitative data, i.e. for evaluation of water quality (Terrado et al., 2010; Nikoo et al., 2011; Munna et al., 2013), classification of water quality (Boyacioglu, 2010; Nikoo and Mahjouri, 2013), and water management (Khan et al., 2005). Since optimization of WQMN given a specific water quality variable may not be necessarily reliable in terms of other qualitative variables, the CCME-WQI was utilized to get a more comprehensive view of the water quality in receiving streams.

The CCME index operates according to different end-use objectives and is thereby flexible in selecting suitable parameters (Nikoo et al., 2011). The index allows site-specific reference objectives and standards to be integrated into the rankings process (Khan et al., 2005). Therefore, this index can be developed based on different national water quality criteria and limits (Nikoo et al., 2011). The CCME-WQI incorporates three variance values (scope, frequency, and amplitude) to achieve the overall water quality state in the form of a unitless number between 0 and 100. There are five categories based on the values of CCME-WQI, including poor ($\leq$44), marginal (45–64), fair (65–79), good (80–94), and excellent (95–100). The application of the CCME-WQI necessitates water quality guidelines or water quality objectives (Mahagamage and Manage, 2014). Hence, in this study, the water quality regulations set by the discharge permit for the construction phase of E18 Arendal-Tvedestrand, released by the Environment Department of Agder County, Norway, was applied for every single station (see Table A1). In this permit, regarding the location of stations, each one has specific limits for water quality parameters. More information related to CCME-WQI is presented in Appendix 1.

The CCME-WQI was applied to determine the water quality at the potential monitoring stations based on five categories (excellent, good, fair, marginal, poor), as prior and posterior probabilities and define the “Value Matrix” that shows the cost (value or damage) of decision-makers' act given the various states in each station.

2.3. Value of information (VOI)

The VOI technique was developed by Grayson (1960) to evaluate the importance of obtained new information in the decision-making process. Over the past few decades, the VOI technique has been widely used for time-series analysis in water-related topics, including optimal monitoring network in reservoirs (Maymandi et al., 2018), design of groundwater quality monitoring networks (Hosseini and Kerachian, 2017a,b), designing contamination warning system (Roberts et al., 2009; Khorshidi et al., 2018), and impact assessment and flood monitoring (Verkade and Werner, 2011; Alfonso and Price, 2012; Alfonso et al., 2016).

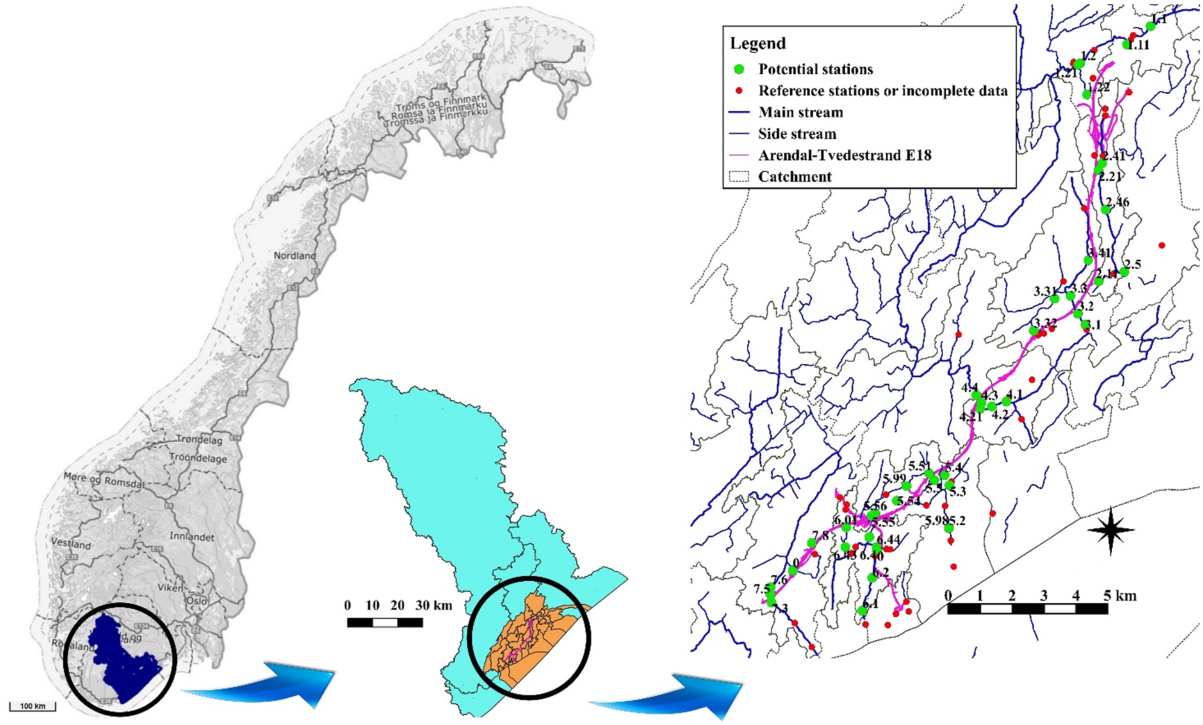


Fig. 2. The E18 highway (Arendal-Tvedestrand) and the established monitoring stations.

Each monitoring station might have different states (e.g., excellent, good, fair, marginal, and poor) and can contribute with relevant water quality information (message) to other stations. Each message (of water quality from each station) affects the decision about the state of the system, and if it is true or false, the message can be of value or damage, respectively. Therefore, by measuring at a potential monitoring station, prior probabilities could be corrected (using Baye's theorem). The VOI theory evaluates the importance of new information and updates the earlier probability, p(s), about the state of a system (Alfonso and Price, 2012; Pourshahabi et al., 2018a). In Bayes' theorem, the posterior (updated) probability considering the new information is represented as Eq. (1) (Khorshidi et al., 2018):

$$\mathrm{P(s|m)} = \frac{\mathrm{P(m|s).\ P(s)}}{\mathrm{P(m)}} \tag{1}$$

where,

p(s) Earlier probability for being in state "s",
p(m) Probability for receiving message "m", (given new data),
p(m|s) Conditional probability of receiving the message "m" when the system is in state "s",
p(s|m) The posterior (updated) probability for state of system following the delivery of message "m" (given new data).

When new information appears, if the message "m" from station "i" is sent for the decision-maker to sense the state "s" in station "j", the VOI of the station "i" for this process is calculated by Eq. (2) (Alfonso and Price, 2012):

$$VOI_{(i,j)} = \sum_m p(m)\left[\max_a\left(\sum_s C(a, s)p(s|m)\right) - \max_a\left(\sum_s C(a, s)p(s)\right)\right] \tag{2}$$

where, $C(a, s)$ shows the value (cost) of the action"a" chosen among available alternatives to coupe up with the state "s" in the monitoring station "j". The action "a" is valued by its distance to the state "s". The closer it is to "s", the more valuable the action "a"is (Pourshahabi et al., 2018a). The $C(a, s)$ is defined through the "Value Matrix", in which arrays are the differences between the mid values of five categories in CCME-WQI (see section 2.2), and show the cost (value or damage) of each action regarding the various states in potential stations. The arrays of "Value Matrix" have an active role in computing the $VOI_{i,j}$. Hence, the matrix should be determined based on a valid standard, which in this study is CCMW-WQI. The applied "Value Matrix" is presented in Table 1.

Because all arrays in Table 1 show damage, they are negative values. The rows represent the activities (a) of decision-maker according to their belief about the water quality at the monitoring station, and columns indicate the various states of the monitoring station (s), that may occur. For example, if the water quality at the station$i$ is in "Good" condition (WQI value 80–94, and the mid-value of this category is 87) and the decision-maker declares it to be "Poor" (WQI value 0–44 and the mid-value of this category is 22), this wrong decision will lead to (87–22 = 65) 65 units of damage (cost) in the scale of CCME-WQI. Considerably, the arrays on the matrix diameter, are set to one instead of zero, to keep the probabilities multiplied by the matrix diameters and play their role in VOI calculation.

Table 1
The "Value matrix" for calculation of the $VOI_{i,j}$.

	$C(a, s)$,(the cost (damage) of action "a", when the station has the state of "s")				
	Poor	Marginal	Fair	Good	Excellent
Poor	1	–32.5	−50	−65	−75
Marginal	–32.5	1	−17.5	–32.5	−42.5
Fair	−50	−17.5	1	−15	−25
Good	−65	–32.5	−15	1	−10.5
Excellent	−75	−42.5	−25	−10.5	1

Raws: Decision-maker's actions and *Columns*: stations' states.

2.4. Transinformation entropy (TE)

The core idea behind the theory of entropy is the evaluation of the information content for a series of data (Shannon 1948). In this method, TE quantifies the mutual (redundant) information between two variables (or dataset) (Pourshahabi et al., 2018b). The entropy method can also predict the probabilities of possible water quality levels at upstream stations based on observed variation in quality levels of a downstream location (Karamouz et al., 2009). Different functional forms of this method have also been effectively utilized for qualitative analyses, management, and network design in groundwater (Mogheir et al., 2009; Masoumi and Kerachian, 2010; Owlia et al., 2011; Mondal and Singh, 2012; Alizadeh and Mahjouri, 2017; Keum et al., 2017; Hosseini and Kerachian, 2017a,b), reservoirs (Lee et al., 2014; Nikoo et al., 2016a,b; Maymandi et al., 2018), rivers (Jha and Singh, 2008; Karamouz et al., 2009; Mahjouri and Kerachian, 2011; Memarzadeh et al., 2013; Pourshahabi et al., 2018a, b), and rainfall and streamflow monitoring networks (Krstanovic and Singh, 1992a,b; Stosic et al., 2017).

A new monitoring station provides more qualitative information and consequently reduces the uncertainty in the water quality evaluation. The additional value of each new station may vary, however. TE can show the redundant information in a WQMN, which is mainly because of spatiotemporal correlation among the qualitative variables. Therefore, TE is efficiently applicable to the optimization of WQMN design (Karamouz et al., 2009). In the proposed framework, the concept of TE is employed to achieve the amount of mutual information between stations and help to identify essential and unnecessary stations. In most of the WQMNs, many qualitative variables are measured, which their time series have non-normal (asymmetrical) probability distribution function and necessitates applying the discrete form of entropy theory for evaluating the efficiency of the monitoring system. (Memarzadeh et al., 2013; Alizadeh et al., 2018). There are different basic ways to measure information according to entropy, including marginal, joint, conditional, and transinformation entropies. (Karamouz et al., 2009). Given a discrete random variable x, the marginal entropy is defined by $H(x)$ as Eq. (3):

$$H(x) = \sum_{i=1}^{N} p(x_i) log p(x_i) \tag{3}$$

where N characterizes the number of events such as x_i with the probability of $p(x_i)(i = 1, ..., N)$. The joint (total) entropy for two independent random variables (e.g., x and y) is the probability of accruing both of them simultaneously and expressed as the sum of their marginal entropies.

$$H(x, y) = H(x) + H(y) \tag{4}$$

Conditional entropy of x given y is the uncertainty remaining in x when y is known, and vice versa:

$$H(x|y) = H(x, y) - H(y) \tag{5}$$

Transinformation entropy calculates the mutual (redundant) information between each pair of stations (e.g., x and y) and is calculated by the following equation (Pourshahabi et al., 2018a, 2018b; Khorshidi et al., 2020):

$$TE(x, y) = -\sum_{i=1}^{n} \sum_{j=1}^{n} p(x_i y_j) ln \left[\frac{p(x_i y_j)}{p(x_i) p(y_j)} \right] \tag{6}$$

where,

n The number of stations
$p(x_i)$ The occurrence probability of x_i,
$p(y_j)$ The occurrence probability of y_j,
$p(x_i y_j)$ The joint probability for x_i and y_j.

In this study, the amount of transformed information was determined for each pair of potential monitoring stations.

2.5. Optimization models

The NSGA-II (Deb et al., 2002) algorithm utilizes non-dominant sorting, and crowded comparison approaches in a single-objective form of the genetic algorithm to evaluate variety between non-dominated options. On the other hand, the Non-Dominating Sorting Genetic Algorithm III (NSGA-III) is a multi-objective algorithm with the basic structure similar to the NSGA-II, which maintains diversity based on reference points (Deb and Jain, 2014). NSGA-III does not require additional parameters compare to NSGA-II and eliminates the weaknesses of NSGA-II considering the lack of uniform diversity and absence of lateral diversity preserving operator among the current best non dominated solutions (Deb and Jain, 2014; Jain and Deb, 2014).

The NSGA-II and III based optimization models were developed according to the three following objectives: *i*) minimizing the number of potential monitoring stations (U_1), *ii*) maximizing the VOI in the selected network (U_2), and *iii*) minimizing redundant information among the selected stations (U_3). Hence, VOI and TE were determined for all pairs of potential stations in a WQMN and resulted in two square matrices, in which the arrays in i^{th} row and j^{th} column define $VOI_{i,j}$ and $TE_{i,j}$, respectively. Accordingly, the optimization models were formulated as in Eqs. (7–10) to achieve an optimal WQMN.

$$Minimize\ U_1 = \sum_{i=1}^{M_P} \rho_i \tag{7}$$

$$Maximize\ U_2 = \sum_{\forall j} \max_{i} (\rho_i \times VOI_{i,j}) \tag{8}$$

$$Minimize\ U_3 = \sum_{i=1}^{M_P} \sum_{\forall j \neq i} \left(\frac{TE_{(i,j)} - TE_{min(i)}}{TE_{max(i)} - TE_{min(i)}} \right) \tag{9}$$

$$\sum_{i=1}^{M_P} \rho_i = M_{opt} \tag{10}$$

where:

U_i The values for the utility functions of the objectives,
M_{opt} The optimized number of monitoring stations,
M_P The number of potential monitoring stations,
ρ_i Binary variable (0 if potential station i is not selected as a monitoring station, otherwise 1),
$VOI_{i,j}$ Value of information in i^{th} station for detecting the state of j^{th} monitoring station,
$TE_{i,j}$ The transinformation entropy between station i and station j.
$TE_{\min(i,j)}$ The minimum transinformation entropy between station i and other stations
$TE_{\max(i,j)}$ The maximum transinformation entropy between station i and other stations

The characteristics of the best structure for the NSGA-II and III algorithms, including population size and the number of generations, were achieved over a sensitivity analysis. The optimization models deliver the Pareto front (trade-off curve) between objectives (Alizadeh et al., 2017; Ghorbani Mooselu et al., 2020), which consists of the right answers for the optimization problem. So, the MCDMs (next paragraph) are required for the decision-maker to get the best solution.

2.6. Multi-criteria decision-making models

In this study, three MCDM models, including TOPSIS (Hwang and Yoon, 1981), PROMETHEE (Mareschal et al., 1984), and AHP (Saaty 1988) were utilized to reach the best WQMN among the alternatives on the trade-off curve. Besides, to evaluate the effects of weighing scenarios on results, different weighting scenarios were assigned to objectives by experts.

TOPSIS model attends the alternatives' distance from ideal and negative-ideal solutions, which both are achieved by normalizing the alternatives in the decision matrix and then weighing them based on the assigned weights to decision criteria. The best solution in this method has the lowest distance from the ideal solution (Mooselu et al., 2019). Also, PROMETHEE, as a flexible and straightforward decision-making model, is extensively applied in water resources management (Kuang et al., 2015; Pourshahabi et al., 2018a; Sapkota et al., 2018; Mooselu et al., 2019). PROMETHEE focuses on pairwise comparison in the ranking process. In this study, complete ranking (PROMETHEE-II) was employed, which ranks a set of alternatives $A = \{a_1, a_2, ..., a_n\}$ given a set of criteria Z= $\{z_1, z_2, ..., z_m\}$ in four steps (Zhang et al., 2009). First, the weighting of the criteria by expert's opinions that show their relative importance compared to one another. Then, preference function is adopted that conveys the priority of each pair of alternatives (e.g., a_i, a_j) in comparison to each other based on a single criterion such as z_i. In this study, the "V-shape with indifference preference function" was utilized, which provides a sensible pairwise comparison between alternatives. In the third step, for any pair in the set of alternatives (A) the global preference index, $\pi(a_i, a_j)$, is defined and indicates the preference of $a_i$over a_j. The higher value for$\pi(o_i, o_j)$, the more preference of a_i compared to a_j. In the final step named outranking flows, for ranking the a_i among other alternatives in the set of alternatives (A), the positive outranking flow or $\varphi^+(a_i)$ (the values of preference of a_i) and negative outranking flow or $\varphi^-(a_i)$ (not preferring of a_i over the other alternatives) have to be computed. The alternative with the highest value of the net outranking flow ($\varphi(a_i) = \varphi^+(a_i)$-$\varphi^-(a_i)$) is selected as the best solution. More applications and information about PROMETHEE are provided by (Pourshahabi et al., 2018a; Mooselu et al., 2019).

AHP is a suitable method for multi-objective analyses in discrete mode, which can enter qualitative and quantitative factors (criteria) in the decision model. It derives priorities among criteria and alternatives and simplifies preference ratings among decision criteria using pairwise comparisons (Saaty, 1988). The basic procedure in AHP consists of three steps, including 1) Developing the scores for each decision alternative for each criterion 2) Determining the weights of criteria and 3) Calculating the weighted average rating for each decision alternative. The details of AHP is presented in (Saaty, 1988).

3. Results and discussion

The CCME-WQI was computed for all potential monitoring stations and for all time steps during the construction period (2017–2019). The states of the potential monitoring stations in two different random time steps are presented in Fig. 3.

This figure clearly shows that a single station could have different states in various time steps, depending on different reasons such as weather situation (e.g., sampling conducted after a rain episode or after a longer dry period), and the type of activity being performed at the station. Hence, these issues will affect the water quality, and consequently, the prior probabilities resulting from CCME-WQI. Given the five categories in CCME-WQI (poor, marginal, fair, good, excellent), the value matrix was calculated, which is highly influential on the final results of the VOI method. Accordingly, VOI and TE were computed for all pairs of the potential monitoring stations, and the results were two square matrices (44 × 44) of $VOI_{i,j}$ and $TE_{i,j}$.

Fig. 4a provides a graphical interpretation for $VOI_{i,j}$, in which the normalized values of VOI in station 4.4 ($VOI_{4.4,j}$) for detecting the state of all other potential monitoring stations is mapped. Besides, Fig. 4b demonstrates the redundancy of information given station 4.4 against all other potential monitoring stations ($TE_{4.4,j}$). Fig. 4 clearly shows the concept of spatial distribution for TE and VOI given each monitoring station (here, station 4.4).

$TE_{i,j}$ is measured between an origin station (i) and a goal station (j) and shows that how much information from station j is achievable by the station i. The closer the values of normalized $TE_{i,j}$ to 1, the more accessible the information of the station j through station i. By moving away from station 4.4, the VOI obtained from this station to determine the quality status of other stations will be reduced. The spatial distribution of TE in station 4.4 shows that for other stations in the same catchment area (e.g., 4.1, 4.2, 4.21, and 4.3), the amount of mutual information is more than other stations.

After that, running the optimization models for three objectives led to the trade-off curves composed of 27 and 18 optimal solutions for NSGA-II and NSGA-III, which are the best match for the selected objectives (Fig. 5).

NSGA-II uses crowding distance to keep uniform coverage of Pareto solutions, while NSGA-III takes advantage of the reference point mechanism as its selection operator to look at the solution space and preserve diversity (Deb and Jain, 2014). Comparing the results of the optimization models, the NSGA-II based optimization model provides optimal solutions with higher VOI and broader range for the number of stations in the WQMN. In contrast, NSGA-III based optimization model delivers more solutions with a minimum value of redundant information. From a decision-making perspective, it seems that NSGA-II is more applicable since it can offer more optimized alternatives to decision-makers. The values of normalized transinformation entropy in some of the optimal solutions (both NSGA-II and III) were zero. It is mainly because the third objective function of the optimization model is defined to minimize the summation of the normalized TE values between the selected stations in the optimized network (Eq. (9)). Consequently, by selecting the minimum values for$TE_{i,j}$, the final value of this objective function would be zero. Therefore, the optimal solutions (selected set of stations) meet the objective of the problem (minimizing the redundancy between stations). However, the outlier point in the Pareto-front of NSGA-II model shows the optimal solutions that have a different value of $TE_{i,j}$. Both optimization models showed acceptable performance by providing the solutions that meet the selected criteria. The optimum alternative on the Pareto-front space was obtained by three different MCDM models, including TOPSIS, PROMETHEE, and AHP, for different weighing scenarios, which are assigned to criteria based on experts' opinions. In fact, the weighting scenarios show the priority of objectives in order to achieve optimum WQMN. Table 2 shows various weighing scenarios and corresponding solutions selected by TOPSIS and PROMETHEE models. Due to TE values in optimal solutions, which in the majority of the optimal solution is zero and shows the high performance of the model in minimizing the transinformation entropy, in most of the listed weighing scenarios, the assigned weight to this objective was adopted less than other two objectives.

As can be seen, for the results of the NSGA-II, if the objective function 1 (number of monitoring stations) receives more importance (e.g., weighing scenarios of 7, 8, and 9), TOPSIS selects solution #14 with 33 monitoring stations, while PROMETHEE and AHP pick three different solutions. When the first and third objective functions have the same importance (e.g., weighing scenarios of 3, 4, 6, and 10), PROMETHEE and AHP certainly chose the solution #18 with 28 monitoring stations, and TOPSIS has two different choices (solutions #14 and #4). If the experts prioritize the VOI as the most significant objective (e.g., weighing scenarios of 1, 2, and 5), all MCDM models deliver different solutions, depending on the assigned weights. Finally, solution #14, and #18 were recognized as the preferable solutions by MCDM models, respectively. For the Pareto optimal solutions of the NSGA-III based optimization model, the performance of MCDMs was different from that for the NSGA-II based model. In most of the weighing scenarios, TOPSIS selected solution #1 with 30 stations in the network, while PROMETHEE, as well as AHP, picked the solution #9 with 29 stations. The objective values in the selected solutions are presented in Table 3.

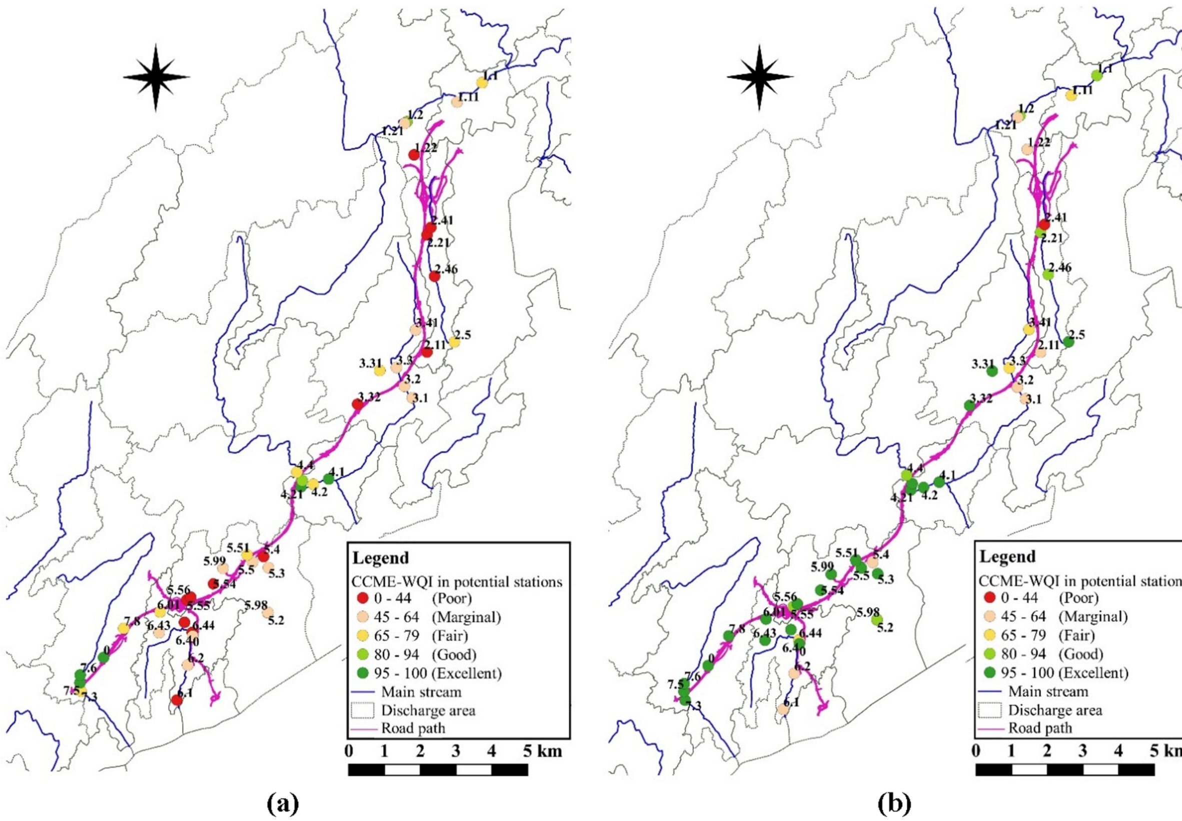


Fig. 3. The CCME-WQI values in all potential monitoring stations for a) Oct.2017, and b) Nov.2018.

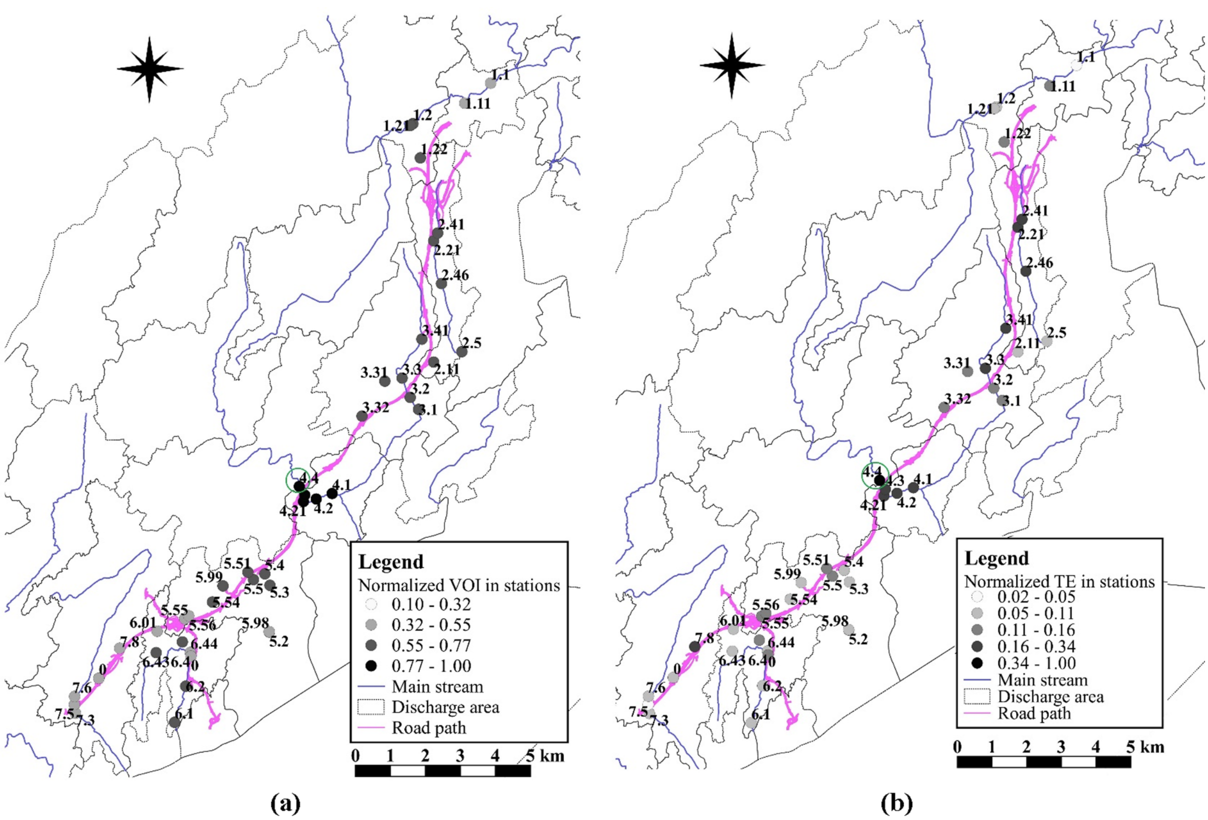
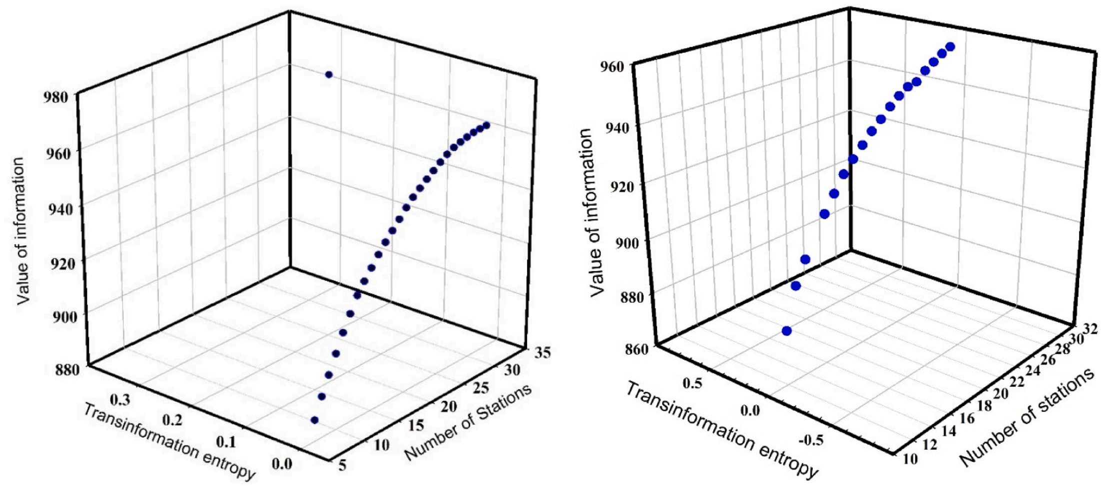


Fig. 4. The spatial distribution of normalized a) VOI, and b) TE values given station 4.4.



Pareto optimal solutions of NSGA-II model

Pareto optimal solutions of NSGA-III model

Fig. 5. The Pareto optimal solutions resulted from the optimization models.

Table 2
Different weighing scenarios and selected solution by MCDM models.

Weighing scenario	The weights of objectives*			Selected solution on the Pareto of NSGA-II			Selected solution on the Pareto of NSGA-III		
	W_1^{**}	W_2	W_3	TOPSIS	PROMETHEE	AHP	TOPSIS	PROMETHEE	AHP
1	0.40	0.10	0.50	4	11	14	1	9	9
2	0.30	0.10	0.60	2	10	4	1	3	3
3	0.45	0.10	0.45	4	18	18	1	6	12
4	0.35	0.30	0.35	14	18	18	15	9	15
5	0.30	0.20	0.50	14	7	4	1	9	9
6	0.40	0.20	0.40	4	18	18	1	9	9
7	0.50	0.10	0.40	14	18	18	1	9	9
8	0.60	0.10	0.30	14	6	7	1	5	8
9	0.50	0.20	0.30	14	8	4	1	9	3
10	0.30	0.40	0.30	14	18	18	15	9	9

* Objectives: 1) the number of stations, 2) the VOI, and 3) normalized TE. W_i^{**} is the assigned weight to the i^{th} objective.

Table 3
The objective values of the selected alternative by MCDM models.

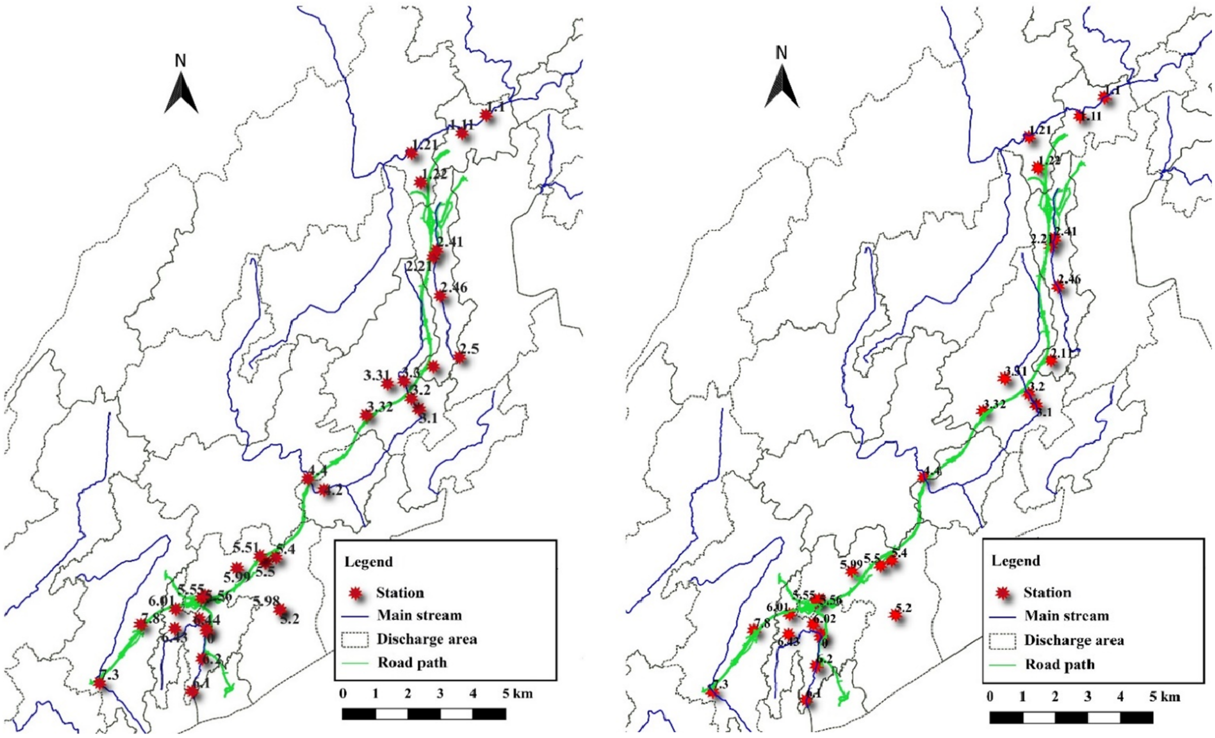
Optimization model	Solution number	The value of objectives		
		No. of stations	Value of information (Eq. (8))	Normalized transinformation entropy (Eq. (9))
NSGA-II	14	33	963.80	0.29
	18	28	962.70	0.00
NSGA-III	1	30	955.56	0.00
	9	29	954.08	0.00

The selected solutions provided the optimum WQMN during road construction, with the optimum number of stations and minimum redundant information among stations, while maximizing the value of information for the monitoring stations in WQMN. This network facilitates the situation for decision-makers to update their judgment about the quality of water in the road construction area. As an example, the selected WQMNs from the solutions of the NSGA-II model (solutions #14 and #18) are presented in Fig. 6.

It is vivid that both WQMNs have a reasonable spatial distribution over the seven catchment areas, which provides a reliable evaluation of the impact of road construction activities on receiving streams. However, the reference stations were not considered in selected stations, and only affected potential stations were attended. In order to analyze the selected solutions based on provided VOI and TE, the union of the VOI_i curves in the selected WQMNs, and TE among the selected stations in both optimum solutions (#14 and #18), are presented in Fig. 7a, b and Fig. 7c, d, respectively.

The best state of the monitoring system regarding the value of information is achieved by having all the potential stations in the final WQMN. Maximizing the value of VOI guarantees that the selected WQMN (with fewer stations) is approached to having the monitoring station in all potential points. However, the locations of the selected stations could have different distributions. Therefore, minimizing the TE secures that the selected stations have the best spatial distribution over the catchment areas.

As shown, both solutions have almost the same status in satisfying the objectives (VOI_i and TE). Consequently, the same situation given VOI_i and TE provides a suitable condition for the decision-maker to confidently select the best solution based on the number of stations. Hence, solution # 18, with 28 stations distributed in all seven catchment areas, is the final WQMN. With the same logic for the selected WQMNs from the NSGA-III, solution # 9, with 29 well-distributed stations, is the ultimate solution. The optimized WQMNs are the cost-effective solutions (with fewer monitoring stations) in comparison with the current monitoring program while provides reliable information on the water quality along the construction site.



(a) (b)

Fig. 6. The selected monitoring networks from NSGA-II model a) solution #14, b) #18, (the first digit of the station labels shows the catchment area).

4. Summary and conclusion

This study proposed an applicable methodology for spatial multi-objective optimization of WQMN during a road construction project. Included are the CCME-WQI, the information-theoretic approaches (VOI and TE), NSGA-II and III, and MCDM models. The approach was applied to a monitoring program consisting of 44 potential monitoring stations in seven catchment areas, which received runoff from the construction of a 22 km long E18 highway in southern Norway. CCME-WQI was determined considering qualitative parameters in the time series dataset over the construction period. There were three main objectives, including *i*) minimizing the number of monitoring stations, *ii*) maximizing the value of information among stations, and *iii*) minimizing TE (redundant information) in the selected WQMN. Accordingly, the NSGA-II and NSGA-III based optimization models were utilized to achieve the Pareto-front of optimal solutions. Then, given different weighting scenarios (selected by experts' opinion) for objective functions, the best solution was found using the TOPSIS, PROMETHEE, and AHP multi-criteria decision-making methods. The application of the proposed methodology for optimizing WQMN during road construction provides feasible knowledge regarding the surface water quality and contributes to filling the information gap in utilizing CCME-WQI, a hybrid VOI-TE method, and NSGA-III, for optimization of the WQMN during the road construction project.

The resulting extent of measurements has minimum redundancy and maximum value for the decision-making process. Having optimized the spatial part of WQMN (the distribution of monitoring stations), a temporal optimization and selection of an optimal sampling frequency could be the next steps. Besides, the Bayesian Maximum Entropy (BME) method (Hosseini and Kerachian, 2017a,b) can be applied to get a reliable spatiotemporal fit of WQI. Also, the uncertainty in determining the WQI could be analyzed by interval number programming (Nikoo et al., 2013; Nikoo et al., 2016a,b). CCME WQI needs the same time series for all qualitative parameters in each assessment, which in practice leads to a decrease in the number of parameters examined. Hence, the results of this study (using the CCME index) could be compared with other water quality indices such as the EU Water Framework Directive (WFD) or leachate pollution index (LPI).

CRediT authorship contribution statement

Mehrdad Ghorbani Mooselu: Methodology, Software, Investigation, Writing - original draft, Writing - review & editing, Visualization, Resources. **Helge Liltved:** Project administration, Conceptualization, Investigation, Writing - review & editing, Resources, Supervision. **Mohammad Reza Nikoo:** Project administration, Conceptualization, Software, Investigation, Writing - review & editing, Visualization, Resources, Supervision. **Atle Hindar:** Supervision, Writing - review & editing. **Sondre Meland:** Supervision, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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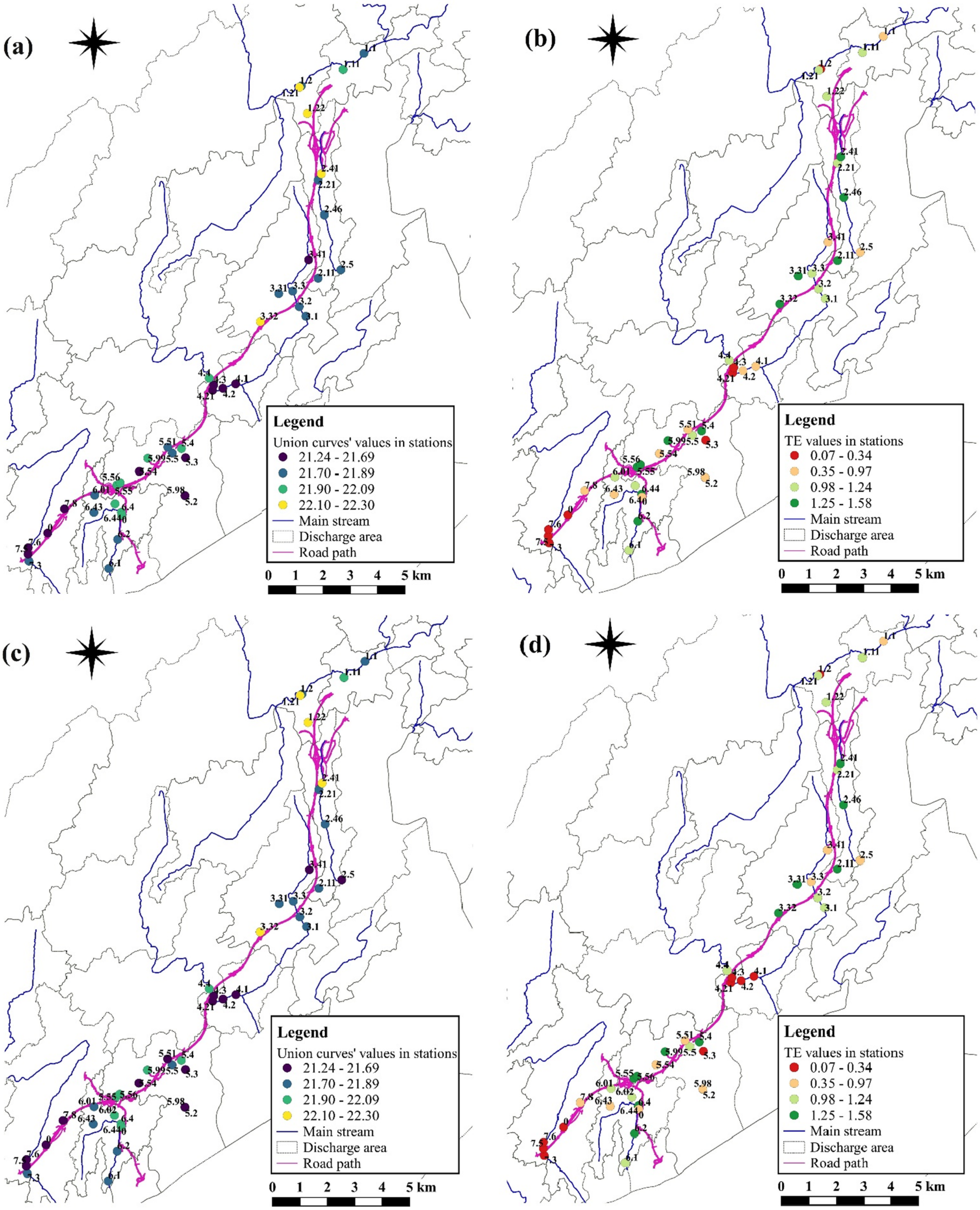

Fig. 7. The union of the VOI_i curves for solution number 14 (a) and 18 (c), and TE for solution number 14 (b) and 18 (d).

Appendix 1. . CCME-WQI

CCME-WQI was developed to facilitate the process of transmitting the qualitative data into qualitative information and then knowledge (Khan 2005). This index combines three measures of variance (scope; frequency; amplitude) to indicate the overall water quality as follow:

– Scope (F_1): the number of variables that violate the standards

$$F_1 = \left(\frac{Numberoffailedvariables}{Totalnumberofvariables}\right) \times 100 \tag{1A}$$

Table A1
The water quality objectives in different stations.

Catchment	Station ID	Water quality objectives				Catchment	Station ID	Water quality objectives			
		Fe (µg/l)	pH	SS (mg/l)	Turbidity (FNU)			Fe (µg/l)	pH	SS (mg/l)	Turbidity (FNU)
1	**1.10**	500	7.5	100	2	**5**	**5.30**	500	7.5	100	4
	1.11	900	8	100	8		**5.40**	500	7.5	100	4
	1.20	500	7.5	100	2		**5.50**	500	7.5	100	4
	1.21	900	8	100	8		**5.51**	900	8	100	4
	1.22	900	8	100	8		**5.54**	900	8	100	4
2	**2.11**	500	7.5	100	4		**5.55**	900	8	100	4
	2.21	500	7.5	100	4		**5.56**	900	8	100	4
	2.41	900	8	100	2		**5.98**	500	7.5	100	6
	2.46	500	7.5	100	5		**5.99**	500	7.5	100	6
	2.50	500	7.5	100	5	**6**	**6.01**	900	8	100	8
3	**3.10**	500	7.5	100	5		**6.02**	900	8	100	8
	3.20	500	7.5	100	4		**6.10**	500	7.5	100	4
	3.30	500	7.5	100	5		**6.20**	500	7.5	100	4
	3.31	900	8	100	4		**6.40**	500	7.5	100	4
	3.32	500	8	100	4		**6.43**	900	7.5	100	4
	3.41	900	8	100	4		**6.44**	900	7.5	100	1
4	**4.10**	500	7.5	100	2		**AF01-V**	900	8	100	8
	4.20	500	7.5	100	2	**7**	**7.30**	500	7.5	100	4
	4.21	500	7.5	100	2		**7.50**	500	8	100	4
	4.30	500	7.5	100	2		**7.60**	500	8	100	4
	4.40	500	7.5	100	1		**7.7B**	500	7.5	100	4
5	**5.20**	500	7.5	100	4		**7.80**	500	8	100	4

CCME-WQI was calculated for 42 measurements in each station. The result was a matrix of 42 × 44, which applied for computing the value of information and the transinformation entropy.

– Frequency (F_2): the number of times that violation happens

$$F_2 = \left(\frac{Numberoffailedtests}{Totalnumberoftests}\right) \times 100 \tag{2A}$$

– Amplitude (F_3): the magnitude of the violation. In order to compute F_3 , first, the excursion, which is the number of times by which an individual concentration is greater than (or less than), the water quality objective must be determined as follow:

when i^{th} test value must not exceed the respective guideline (objective):

$$Excursion_i = \left(\frac{failedtestvalue_i}{guideline_i}\right) - 1 \tag{3A}$$

when i^{th} test value must not fall below the respective guideline (objective):

$$Excursion_i = \left(\frac{guideline_i}{failedtestvalue_i}\right) - 1 \tag{4A}$$

Then, the Normalized Sum of Excursions (NSE) is calculated by Eq. (5A).

$$NSE = \frac{\sum_{i=1}^{n} excursion_i}{Totalnumberoftests} \tag{5A}$$

After that, by scaling the NSE to the range of 0–100 (Eq. (6A)), the amplitude (F_3) is calculated:

$$F_3 = \left(\frac{NSE}{0.01NSE + 0.01}\right) \times 100 \tag{6A}$$

Finally, the CCME-WQI is achieved by utilizing Eq. (7A):

$$CCME_{WQI} = 100 - \left(\frac{\sqrt{F_1^2 + F_2^2 + F_3^2}}{1.732}\right) \tag{7A}$$

The computed values of CCME-WQI are then transformed into rankings through the index categorization schema, which makes five categories of poor (0–44), marginal (45–64), fair (65–79), good (80–94), and excellent (95–100).

In this study, considering the length of the time series for the measured parameters, four parameters including Fe (iron), Turbidity, Suspended Solids (SS), and pH, which had a complete time series during the construction period were selected for the rest of analysis. The water quality regulations set by the discharge permit for the construction phase of E18 Arendal-Tvedestrand, released by the Environment Department of Agder County, Norway, was applied for every single station (see Table A1).

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Paper D

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Network design for surface water quality monitoring in a road construction project using Gamma Test theory

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ABSTRACT

Road construction has a negative environmental impact on the surrounding aquatic environment, requiring the continuous monitoring of surface water quality. Here, optimization of the water quality monitoring network (WQMN) is an essential step in supporting the sustainable development of road construction projects. This study introduces Gamma Test theory (GTT) as a practical method for optimizing the WQMN of surface waters during road construction. The water quality index (WQI) was computed in 48 monitoring stations for six monitoring periods from 2017 to 2019; data was acquired from a primary monitoring network over a new highway in southern Norway. Based on the results, it is possible to reduce the number of stations by 23% in comparison with the original empirical network. The proposed method could be useful to design the monitoring networks of projects with limited construction time and budget, as well as projects lacking enough data.

1. Introduction

One of the most important challenges of road construction projects is waste discharge due to various construction works, which negatively affects the physical, chemical, and biological quality of receiving surface water bodies. In addition, it may pose serious health and safety risks to consumers [1]. Over the course of a road construction project, the volume and quality of the waste discharge and its impacts on surface water bodies vary spatiotemporally due to road construction works, as well as the weather conditions in the catchment and construction areas. Therefore, the right design of a water quality monitoring network (WQMN) is needed to provide useful input on spatial-temporal variations of surface water quality during construction projects. This may support decision-makers in

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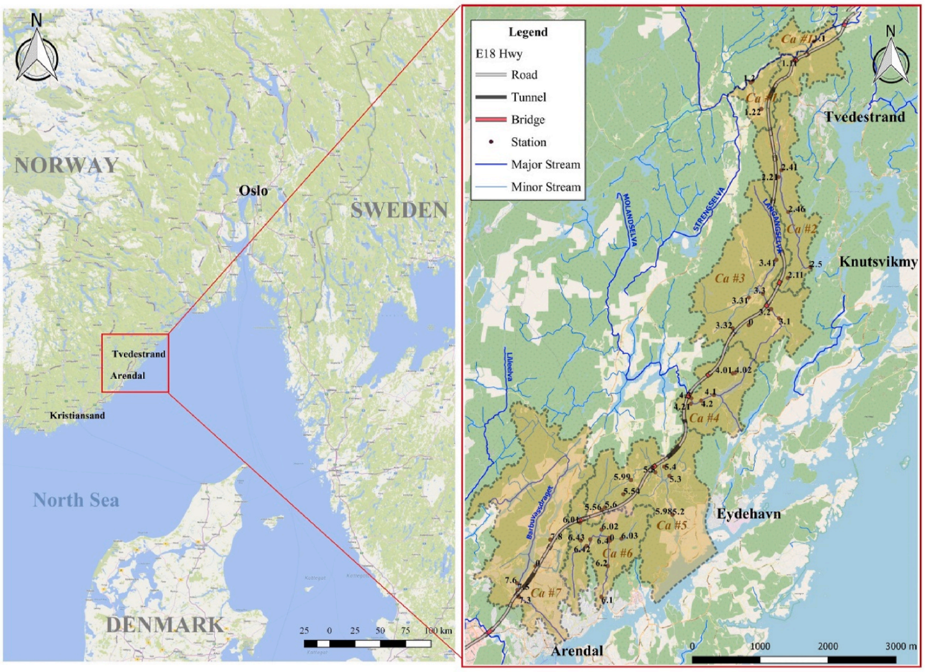

Fig. 1. Construction site of the Arendal-Tvedestrand highway with monitoring stations (Note: the first digit in the number of each station specifies the catchment number).

terms of managing the health risks of stakeholders, self-purification capacity of the environment, and implementation of remedial policies [2–5]; unfortunately, the optimal design of WQMN is a complicated process. Firstly, the uneven distribution of monitoring stations, or their insufficient number, provides a limited understanding of the surface water system of the study area [6]. On the other hand, if the number of monitoring stations is too large, additional information may be obtained, making the monitoring network costly and inefficient [6]. In road construction projects, sometimes after a long monitoring period and spending a lot of time and money, it becomes clear that the number of monitoring stations is large and consequently a lot of money has been wasted. In addition to this, the number of stations is insufficient, and the collected information gives a rudimentary understanding of the environmental impact of the construction works. Therefore, finding a method to determine the optimal number and location of stations after the first monitoring period gives valuable assistance to local authorities in managing the costs and environment.

The primary point for optimization of WQMN is designing a network with the maximum possible number of monitoring stations by empirical [7], statistical [4], and ranking methods [8]. For empirical methods, the WQMN is designed based on technical knowledge, the location of main streams and tributaries, and the distribution of pollution sources [9], while for statistical methods, different design scenarios are considered by assessing the ratio of explained data through the selected WQMN to the spatiotemporal variations of the water quality in the monitored catchment [10]. Finally, for ranking methods, the zoning layer of effective parameters in surface water quality is developed, and by weighing each layer and combining them, a monitoring priority map is then drawn [3]. After the initial design of the monitoring stations, the surface water quality is monitored for several periods and the monitoring network is then optimized using several methods, such as fuzzy clustering [8,11,12], genetic algorithms [13–16], multi-objective discrete particle swarm optimization [17], the value of information [18–20], entropy [20–23], optimal partition analysis [24], and strategic decision analysis [25]. However, there is evidence that most of the proposed methods are incapable to determine the optimal number of monitoring stations, and consequently, this number is often selected empirically or based on available data and related design limitations (e.g., project budget and the value of provided data) [15,25]. Furthermore, few studies have determined the optimal number of monitoring stations, in which the optimization process has been conducted using data of whole monitoring periods after the completion of the project [20]. In this condition, the results are less feasible to be applied since the authorities realize that the monitoring network presents issues once the project has been completed, and there is no way back to improve the monitoring network and data collection.

To solve these problems and determine the optimal number and location of monitoring stations after the first monitoring period, this paper presents the idea to apply Gamma Test theory (GTT), which is a nonlinear modeling tool that can be used to determine the minimum set of data needed to create a smooth model lacking in any knowledge of the equations that describes the phenomenon [26–28]. GTT was first introduced by Ref. [29] and it was examined and used in more detail years later by Ref. [30]. This study evaluates the ability of GTT to determine the optimal number and location of surface water monitoring stations in a construction project. For this purpose, the proposed method was applied to optimize a WQMN after the first monitoring period in the construction project of the Arendal-Tvedestrand highway in Norway. The construction of this highway took about three years, from 2017 to 2019.

Over this time, 28 physical, chemical, and biological parameters were monitored every four months at 48 stations in the catchment area of this highway. Then, the water quality index (WQI) was computed for each station and monitoring period. Subsequently, GTT was applied to determine the optimal surface water monitoring network using the data of the first monitoring period. Finally, the proposed optimal monitoring network was systematically verified using the data from the second to the sixth monitoring period. The paper also contributes to addressing the knowledge gap in finding an optimal monitoring network for short- and mid-term projects in the shortest possible time via GTT.

2. Methods

The proposed methodology consists of two main steps: (i) determining the WQI in all stations based on the existing network, generating the required data for the second step; and (ii) optimizing the number and location of monitoring stations in different periods based on GTT.

2.1. Data collection

In the first step, qualitative information of surface water along the road construction site was collected. Fig. 1 illustrates the location of the construction site, which is a new 22-km long section of the Arendal-Tvedestrand highway in Norway. The drainage area of the highway (ca. 7180 ha) consists of seven catchment areas, including Storelva (#1), Vennevann (#2), Langangselva (#3), Sagene (#4), Mørfjær (#5), Songebekken (#6), and Longum/Barbu (#7). Fig. 1 also indicates the main and side streams of different catchments and their connections with the road. Various road construction works, including area cleaning, blasting, drilling, water management, asphalting, culvert work, and bridge construction, were carried out during the three years of construction between 2017 and 2019. Considering the requirements of the Department of Environment, County Governor of Aust-Agder (Norway) and based on the type of activities in different parts of the road, the surface water quality was monitored over different periods of the project. Accordingly, six time periods of one month each, at four-month intervals, were considered during the construction phase from 2017 to 2019. The first period (i.e., 4/2017) included preparation and mobilization steps. Most of the construction works were initiated from the second period (i.e., 10/2017); and by then, as the project progressed, one-month periods of monitoring continued, which were separated by four-month periods (i.e., 2/2018, 6/2018, 10/2018, 2/2019).

Different qualitative parameters, including physical properties (total suspended solids (TSS), turbidity, color, and pH), sum parameters (chemical oxygen demand, COD), alkalinity, and electrical conductivity, EC)), nutrients (total-N, total-P, and NO_3–N), minerals and ions (SO_4^{2-}, Mg^{2+}, Ca^{2+}, Na^+, Cl^-, and K^+), and heavy metals (Fe, As, Ba, Pb, Cd, Cu, Co, Mn, Hg, Cr, Ni, and Zn) were monitored at 48 stations in the catchment area of the highway. The monitoring stations in the primary WQMN (see Fig. 1) were established based on the catchment topography, the direction of main and side streams, and experts' experiences for evaluating the spatiotemporal variation in surface water quality during road construction.

2.2. Water quality index

The WQI is a management tool that makes a reasonable interpretation to assess water quality based on qualitative data [20]. In this study, the relative weighting method was applied to calculate the WQI in each station and monitoring period. Herein, the quantity rating scale (Q_i) was calculated according to Eq. (1) for all parameters, except for pH which was determined by Eq. (2) [31,32], as follows:

$$Q_i = \left(\frac{C_i}{S_i}\right) \tag{1}$$

$$Q_{i_{pH}} = \left[\frac{C_i - 7}{S_i - 7}\right] \tag{2}$$

where C_i represents the measured value for each parameter, and S_i corresponds to the maximum acceptable limit of each parameter. The value of S_i for all 28 parameters applied in this study (Table 1) was determined based on the WHO guidelines for drinking water (2017) [50,51], together with the regulations of water quality for the construction phase of the Arendal-Tvedestrand highway established by Department of Environment, County Governor of Aust-Agder (Norway).

Then, a normalized weight ranged from 1 to 4 for the lowest and highest negative impacts on water quality is assigned to each parameter based on experts' opinions. In this study, the normalized weight of each parameter was collected from various studies, and the average of the collected values ($\overline{w}_i$) was assigned as the normalized weight for each parameter (see Table 1). Afterward, the relative weight of each parameter (w_i), as reported in the last column of Table 1, was calculated according to Eq. (3):

$$w_i = \frac{\overline{\overline{w}}_i}{\sum_{i=1}^{28} \overline{w}_i} \times 100 \tag{3}$$

As observed in Table 1, specific parameters, such as As, Pb, and Cr with the relative weight of 5.3%, followed by Cu and Ni (5 and 4.9%, respectively), present the highest importance, while Total-P, Zn, and Mg^{2+} (1.2, 1.4, and 1.5%, respectively) have minor importance in water quality. Importantly, it is extremely needed to consider the negative effects of heavy metals with greater impact

Table 1
The maximum acceptable limits, normalized weights of parameters based on literature, and calculated relative weights.

NO.	Parameters	Unit	Standard Limit Value	Assigned weights in different studies								
				[33]	[34]	[35]	[36]	[37]	[38]	[39]	[40]	[41]
1	SO_4^{2-}	mg / L	250	–	2.0	2.0	2.0	3.2	2.0	2.4	4.0	3.0
2	Mg^{2+}	mg / L	50	–	1.0	1.0	1.0	1.6	–	1.6	2.0	1.0
3	Ca^{2+}	mg / L	75	–	1.0	1.0	1.0	1.6	–	1.6	2.0	3.0
4	Fe	μg / L	500	–	–	–	–	3.2	–	1.6	4.0	–
5	pH	–	<7.5	1.0	1.0	1.0	1.0	3.2	4.0	2.4	4.0	1.0
6	SS	mg / L	2	–	4.0	–	4.0	–	–	–	–	–
7	Turbidity	(FNU)	10	–	–	4.0	2.0	–	3.0	–	–	–
8	Total-N	μg / L	750	–	3.0	3.0	3.0	–	2.0	–	–	–
9	Alkalinity	mmol / L	0.4	–	–	–	–	2.4	–	1.6	–	–
10	As	μg / L	5	4.0	–	–	–	–	–	–	4.0	–
11	Ba	μg / L	1000	–	–	–	–	–	–	–	–	–
12	Pb	μg / L	10	–	–	–	–	–	–	–	4.0	–
13	Color	mg Pt/ L	25	–	–	2.0	–	–	4.0	–	–	–
14	Cd	μg / L	0.53	3.0	–	–	–	–	–	–	–	–
15	K^+	mg / L	12	–	–	–	–	–	–	1.6	2.0	2.0
16	COD	mg / L	25	–	3.0	3.0	3.0	–	–	–	–	–
17	Cl^-	mg / L	250	–	1.0	1.0	1.0	2.4	2.0	2.4	3.0	4.0
18	Cu	μg / L	7	–	–	–	–	–	–	–	–	–
19	Co	μg / L	100	–	–	–	–	–	–	–	–	–
20	EC	mS/ m	100	–	1.0	4.0	2.0	–	4.0	2.4	–	2.0
21	Cr	μg / L	50	–	–	–	–	–	–	–	–	–
22	Hg	μg / L	0.005	3.0	–	–	–	–	–	–	–	–
23	Mn	μg / L	100	–	–	–	–	3.2	–	–	4.0	–
24	Na^+	mg / L	200	–	–	1.0	–	–	–	2.4	4.0	4.0
25	Ni	μg / L	20	–	–	–	–	–	–	–	–	–
26	Nitrate	mg / L	50	3.0	2.0	2.0	2.0	4.0	–	4.0	–	–
27	Zn	μg / L	77	–	–	–	–	–	–	–	3.0	–
28	Total-P	μg / L	25	2.0	1.0	1.0	1.0	–	1.0	–	–	–
Sum												

NO.	Parameters	Assigned weights in different studies												Weights (%) (by Eq. (3))
		[31]	[39]	[42]	[43]	[44]	[44]	[45]	[46]	[47]	[48]	[49]	Average Weights	
1	SO_4^{2-}	3.2	–	–	3.2	3.2	3.2	–	–	2.4	2.4	–	2.7	**3.6**
2	Mg^{2+}	1.6	1.6	–	1.6	1.6	1.6	1.6	2.0	–	1.6	–	1.5	**2.0**
3	Ca^{2+}	1.6	1.6	–	1.6	1.6	1.6	2.4	–	–	1.6	–	1.7	**2.2**
4	Fe			–		3.2	3.2	3.2	–	2.4	–	2.4	2.9	**3.8**
5	pH	3.2	2.4	–	3.2	3.2	3.2	3.2	–	3.2	–	1.7	2.5	**3.3**
6	SS	–	–	–	–	–	–	–	3.0	–	–	–	3.7	**4.8**
7	Turbidity	–	–	–	–	–	–	–	–	–	–	–	3.0	**4.0**
8	Total-N	–	–	–	–	–	–	–	–	–	–	–	2.8	**3.6**
9	Alkalinity	1.6	1.6	–	2.4	2.4	2.4	2.4	–	–	1.6	–	2.0	**2.7**
10	As	–	–	–		–	–		4.0	–	4.0	–	4.0	**5.3**
11	Ba	–	–	1.6		–	–	3.2		–	–	–	2.4	**3.2**
12	Pb	–	–	4.0	4.0	–	–	4.0	4.0	4.0	–	4.0	4.0	**5.3**
13	Color	–	–	–	–	–	–	0.8	3.0	–	–		2.5	**3.2**
14	Cd	–	–	4.0	–	–	–		4.0	4.0	–	2.4	3.8	**5.0**
15	K^+	–	1.6	–	–	–	–	1.6	–	–	0.8		1.8	**2.3**
16	COD	–		–	3.2	–	–		–	–		–	3.1	**4.0**
17	Cl^-	2.4	2.4	–	2.4	2.4	2.4	1.6	–	2.4	2.4	–	2.2	**2.9**
18	Cu	–		1.6	–	–	–	–	2.0	1.6	–	1.6	1.7	**2.3**
19	Co	–		–	–	–	–	–	3.0	–	–	–	3.0	**4.0**
20	EC	4.0	2.4	–	–	–	–	2.4	3.0	4.0	–	–	2.8	**3.7**
21	Cr	–	–	4.0	4.0	–	–	4.0	4.0	–	–	–	4.0	**5.3**
22	Hg	–	–	–	–	–	–	–		–	–	–	3.0	**4.0**
23	Mn	–	1.6	3.2	4.0	3.2	3.2	3.2	2.0	–	2.4	2.4	3.0	**3.9**
24	Na^+	0.8	2.4		1.6	–	–	2.4		–	2.4	–	2.3	**3.1**
25	Ni	–		3.2	–	–	–	4.0	4.0	–	–	–	3.7	**4.9**
26	Nitrate	–	4.0		4.0	4.0	4.0	4.0		4.0	4.0	1.8	3.3	**4.4**
27	Zn	–		0.8	–	1.0	0.8	1.6	1.0	–	–	1.6	1.4	**1.9**
28	Total-P	–	–	–	–	–	–	–	–	–	–	–	1.2	**1.6**
Sum													**75.8**	**100**

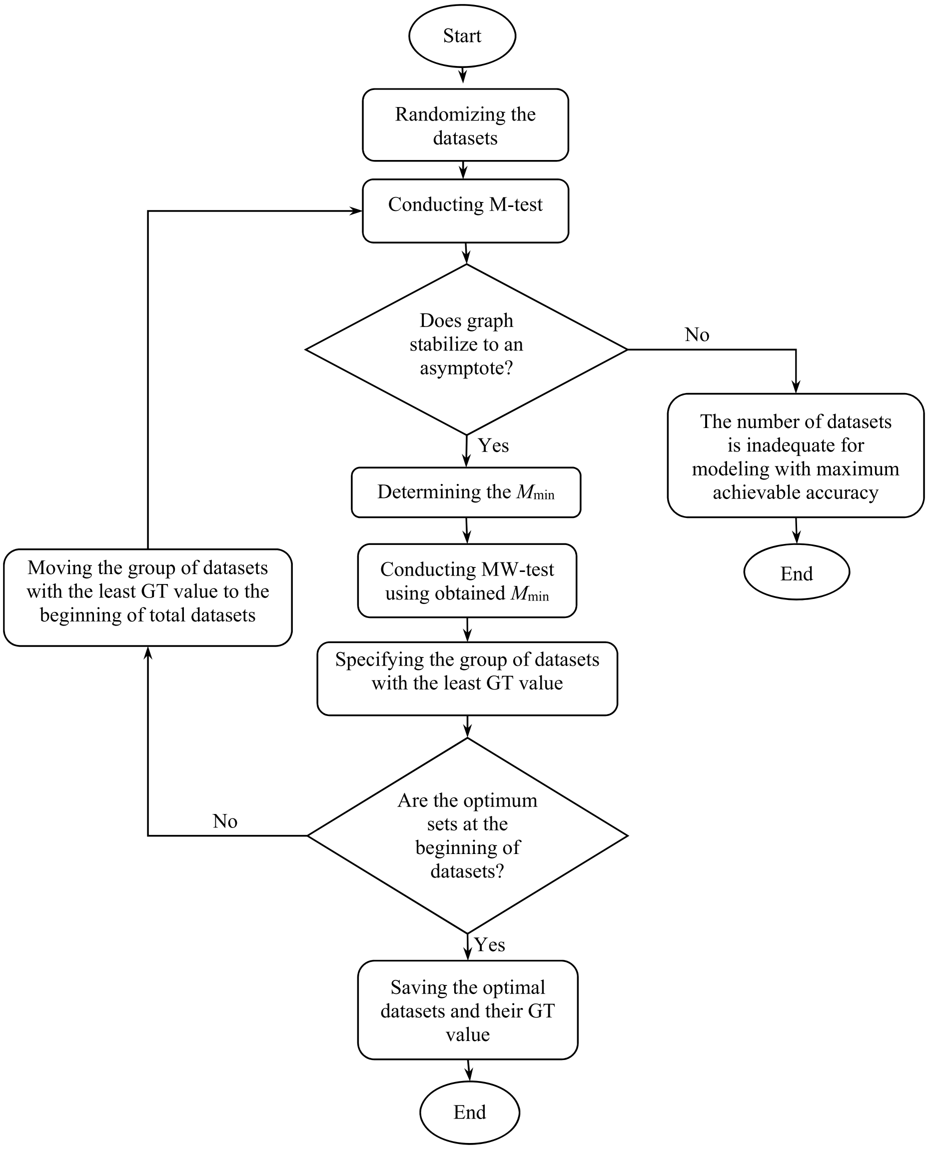

Fig. 2. Optimization algorithm towards WQMN in road construction using GTT.

than other parameters in water quality calculations.

Lastly, the WQI was calculated according to Eq. (4):

$$WQI = \sum_{i=1}^{28} w_i \times Q_i \tag{4}$$

In principle, the larger the WQI value, the lower the water quality. To determine the significance of the difference among the calculated WQI data in two different monitoring periods, the probability distribution of the WQI data in each monitoring period must be first determined using the Kolmogorov–Smirnov test (K–S test) [52,53]. If the data are normally distributed, the paired *t*-test can be used for specifying the significance of the difference among the WQI data in two periods [54]. Otherwise, data distribution must be normalized using transformation functions.

2.3. Gamma test theory

GTT is a statistical method of analysis used to specify three critical issues before developing a model; this method implies the following steps: 1) the adequacy of datasets to develop a causal model, 2) the maximum reachable accuracy of a smooth model to estimate a dependent variable, and 3) the best and minimum datasets applicable for training a model [55,56]. In this method, it is

Table 2
Evaluation statistics of all WQI values in each monitoring period.

Feature	Monitoring period					
	1st	2nd	3rd	4th	5th	6th
Maximum	302.8	1259.2	256.2	311.5	788.5	304.7
Minimum	21.8	25.1	24.0	23.2	26.6	26.0
Mean	60.0	99.3	61.8	75.6	83.8	63.4
Coefficient of variation (%)	84.6	187.9	69.2	82.2	139.2	74.4

supposed that if the two points are close together in the input space, their outputs should be close in the output space unless they contain noise. For GTT, data analysis is conducted based on the calculation of a statistic number, named gamma. Therefore, for each vector of independent variables, i.e., $X_i(1 \le i \le M)$, and scalar of the dependent variable (y_i), the nearest k^{th} neighbor for X_i (i.e., $X_{N[i,k]}$), must be determined. Then, the delta (δ) and gamma (γ) functions are calculated according to Eqs. (5) and (6), respectively:

$$\delta(k) = \frac{1}{M}\sum_{i=1}^{M}\left|X_{N[i,k]} - X_i\right|^2 (1 \le k \le p) \tag{5}$$

$$\gamma(k) = \frac{1}{2M}\sum_{i=1}^{M}\left|y_{N[i,k]} - y_i\right|^2 (1 \le k \le p) \tag{6}$$

where | | represents the Euclidean distance, M is the number of datasets, and $y_{N[i,k]}$ is the y value corresponding to $X_{N[i,k]}$, and i is the index of observations. In the previous equations, it is suggested to consider $10 \le p \le 20$ [55–57]. After that, a linear regression line ($\gamma = A\delta + GT$), which provides useful input about the datasets before developing a model, is fitted to the p points of ($\delta(k)$, $\gamma(k)$). The slope of the regression line (A) indicates the complexity of the relationship between dependent and independent variables. The higher the A value, the greater the complexity [55,58]. Furthermore, the intercept of the regression line ($\delta = 0$), which is equal to the gamma statistic (GT), shows the maximum reachable accuracy by smooth modeling tools. The higher the GT value, the weaker the modeling performance, which is mainly due to: 1) much noise in measured data, 2) a low number of datasets, and 3) the low number of independent variables in the model [59].

In theory, increasing the M in modeling leads to a rise in the degree of reliability. However, increasing the M above the minimum number does not increase the modeling accuracy [55,56]. M-test, as a GTT tool, determines the minimum required number of training datasets (M_{min}) in a given order of datasets to develop a model with maximum reachable accuracy, directly from the dataset [55,56]. For this purpose, GT is computed for an increasing number of datasets, and GT is then plotted against the number of datasets. As the number of datasets reaches the M_{min}, the graph is stabilized to an asymptote [60].

The moving window test (MW-test) is another tool in GTT, which indicates the variation of GT value for different subsets of the datasets displaying the same size [61]. In MW-test, a virtual window with the length of M_{min} is moved along the datasets with a special order, and the GT value is computed for the datasets in the window. Here, the datasets with the lowest GT value are selected as the best training set for modeling [61].

2.4. *Optimization of the surface water monitoring network using GTT*

The surface water quality monitoring network can be substantially optimized using GTT. For this, the minimum and the best-required number of monitoring stations (or datasets) is specified using M − and MW-tests. However, the results strongly depend on the order of datasets, while evaluating all possible permutations of orders is extremely complicated and time-consuming. Interestingly, a GTT-based optimization algorithm proposed by Ref. [62] (see Fig. 2) was applied to optimize the number and location of monitoring stations. The algorithm consisted of seven major steps. Initially, the total datasets are randomized to create a random order of datasets. In the second step, M_{min} is determined by the M-test tool. Then, the MW-test is conducted with the M_{min} to specify a group of datasets with the least GT value. In the fourth step, the specified group is located at the beginning of the rest of the datasets. After that, steps 2 to 4 are repeated to put the minimum number of stations (M_{min}) with the lowest value of GT at the beginning of the total datasets. This process is repeated several times by randomizing the datasets and changing the initial order of the datasets. Lastly, the group of datasets with the lowest number and GT value is selected as the optimal group. In this study, a GTT-based optimization algorithm was applied to optimize the number and location of surface water monitoring stations during the construction of the 22-km long highway in southern Norway. The latitude and longitude of stations were considered as independent variables while WQI was the dependent variable.

3. Results and discussion

3.1. *Water quality index from different stations*

As mentioned previously, the WQI was calculated based on 28 qualitative parameters of surface water at 48 monitoring stations in the catchment area of the Arendal-Tvedestrand highway for six monitoring periods. Over the highway construction project, WQI

Table 3
Water quality classification based on WQI and the number of stations in each class [63].

Water type	Value of WQI	Monitoring period					
		1st	2nd	3rd	4th	5th	6th
Excellent	<50	30	21	29	23	28	27
Good	50–100	11	18	11	16	10	14
Poor	100–200	6	6	7	5	6	6
Very poor	200–300	0	1	1	3	3	0
Polluted	300–400	1	0	0	1	0	1
Very polluted	>400	0	2	0	0	1	0

Table 4
K–S test results of the logarithmic transformed WQI data.

Transformed WQI data	Monitoring period					
	1st	2nd	3rd	4th	5th	6th
Number of data	48	48	48	48	48	48
Mean	1.69	1.79	1.72	1.78	1.76	1.73
Standard deviation	0.25	0.33	0.23	0.29	0.32	0.22
K–S Z	1.14	1.17	1.12	1.00	1.33	0.95
Asymp. Sig. (2-tailed)	0.15	0.13	0.16	0.27	0.06	0.32

Table 5
Paired *t*-test results of the different monitoring periods.

Pairs	Paired Differences			t	Degree of Freedom	Sig. (2-tailed)
	Mean	Std. Deviation	Std. Error Mean			
1st – 2nd	0.10	0.32	0.04	2.23	47	0.03
2nd – 3rd	−0.07	0.24	0.03	−2.03	47	0.04
3rd – 4th	0.06	0.20	0.02	2.09	47	0.04
4th – 5th	−0.01	0.19	0.02	−0.66	47	0.51
5th – 6th	−0.03	0.20	0.02	−1.08	47	0.28

presents spatiotemporal variations depending on the type of construction works. The maximum value of WQI (ca. 1259) was recorded on 10/2017 at station #4.5 due to the explosions for tunneling. Due to construction works in the vicinity of this station, the concentration of TN, TSS, Mn, and EC in surface water increased by 200,000 (μg/L), 86 (mg/L), 600 (μg/L), and 161 (mS/cm), respectively. Table 2 reports the maximum, minimum, mean WQI values, and coefficient of variation (CV) for all calculated WQIs in each monitoring period. The CV, which is the ratio of the standard deviation of the mean, defines the degree of variation of two or more data series. As reported in Table 2, the highest average value (ca. 99.3) and degree of variation of 187.9 were recorded in the second period (i.e., 10/2017), indicating that this period had the highest range of variation in WQI and created the highest average pollution load to receiving streams compared to the other periods.

Table 3 presents the water classification based on WQI and the WQI classification for different water samples in six monitoring periods. By comparing the data reported in Tables 2 and 3, it becomes clear that during the road construction process, the average water quality in all monitoring periods was found as good, while in the second monitoring period, the average water quality was close to the poor category. During this period, two monitoring stations had very polluted quality, which led to an increase in the average WQI throughout the second period. In addition, the number of stations with excellent water quality was 21, which was the lowest in all periods. Compared to all monitoring periods, surface water in the first monitoring period had the best quality, which means the water from 30 monitoring stations had excellent quality. In the sixth monitoring period, which was related to the activities at the end of the project, the water quality in most of the stations was mostly rated from good to excellent, indicating a decrease in road construction works.

The paired *t*-test is used to evaluate the statistical significance of the difference between two related data series. Unfortunately, this test is limited to data with a normal distribution. Therefore, in this study, the normality of the WQI data of the six monitoring periods was first checked by means of K–S test. The results indicated that the WQI data did not have a normal distribution. As a consequence, a logarithmic transformation was applied to the WQI data to convert their distribution to a normal distribution. Once again, the K–S test was conducted. For instance, Table 4 reports the results of the K–S test coming from the logarithmic transformed WQI data in the six monitoring periods. It was observed that the Sig. parameter values from the first to sixth monitoring periods were 0.15, 0.13, 0.16, 0.27, 0.06, and 0.32, respectively. Since all these values are higher than 0.05, the logarithmic transformed WQI data possess normal distribution at a significant level of 0.05. Table 4 presents the mean, standard deviation, and K–S Z parameters of the logarithmic transformed WQI data for the six monitoring periods. The statistical significance and Sig. parameter values were determined by comparing K–S Z with standard values.

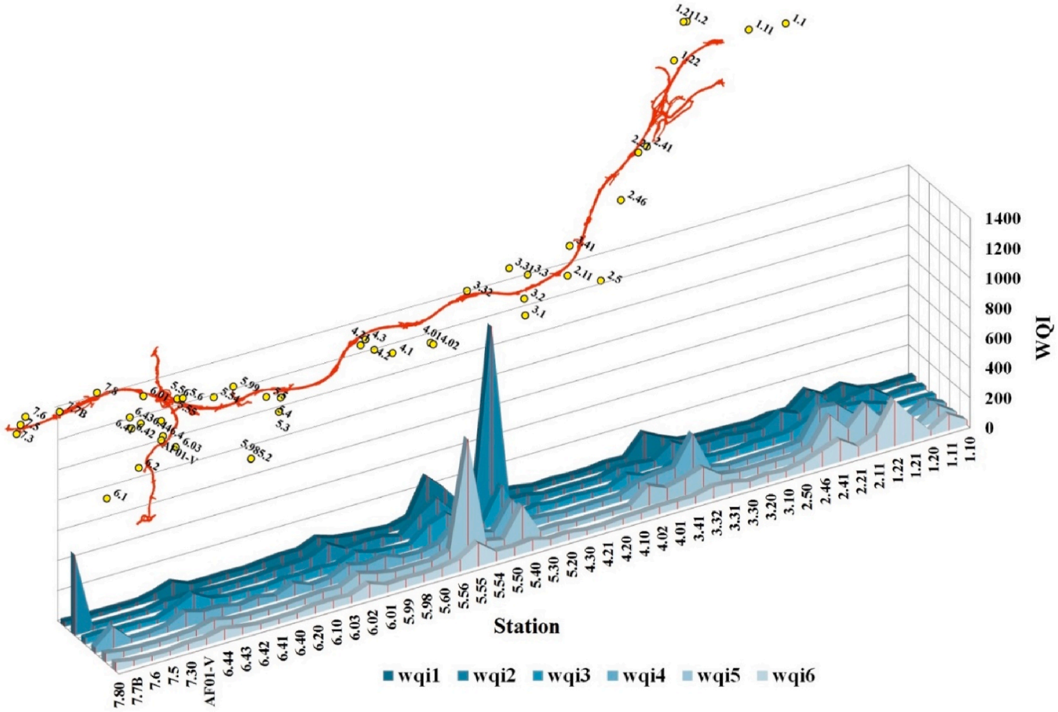

Fig. 3. Spatiotemporal variation of WQI along the road construction route.

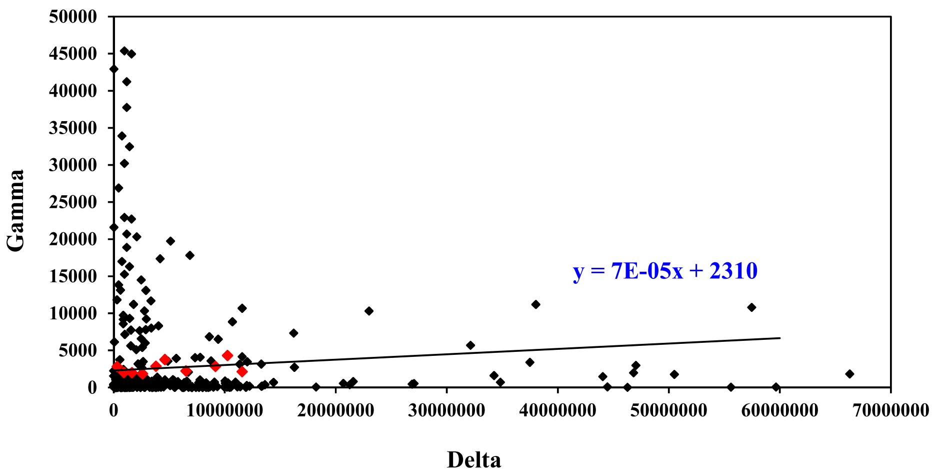

Fig. 4. GTT results for the data from the first monitoring period (4/2017).

Since the transformed WQI data in the six monitoring periods had a normal distribution, the paired *t*-test was then used to determine the statistical significance of the difference, as shown in Table 5. If the Sig. parameter value is greater than 0.05, the difference between the two data series will be insignificant. According to Table 5, there are significant differences between the first and second, second and third, and third and fourth monitoring periods, while the differences between the fourth and fifth, and fifth and sixth periods, are insignificant. From April 2017 to June 2018, there were several changes in road construction works, leading to significant differences in surface water quality. In contrast, during the fourth, fifth, and sixth monitoring periods (from June 2018 to February 2019), different construction works did not show any significant difference in surface water quality. Table 5 also presents the mean ($\bar{d}$), standard deviation (S_d), and standard error means ($S_{\bar{d}}$) of the paired differences, as well as *t* statistic ($\frac{\bar{d}}{S_{\bar{d}}}$), and degree of freedom (i.e., number of data series minus one). Sig. parameter of the paired *t*-test was determined by comparing the calculated *t* statistic with standard *t* value to 47 degrees of freedom. Fig. 3 illustrates the spatiotemporal variation of WQI during the six monitoring periods.

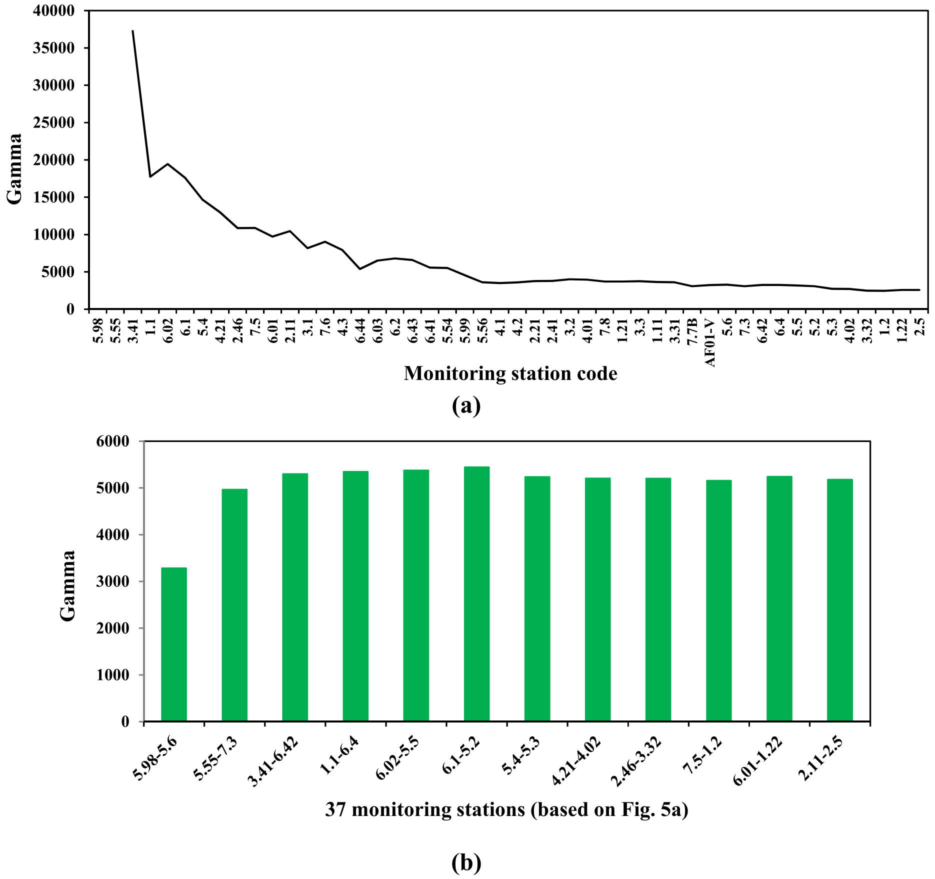

Fig. 5. a) Results of the M-test based on the data of the first monitoring period (4/2017), b) Results of the MW-test including 37 stations for the best order of stations.

3.2. Determination of the optimal WQMN using GTT

To achieve the optimal WQMN with the best spatial distribution using the minimum amount of available data, WQI data in the first monitoring period (i.e., 4/2017) was analyzed. First, 48 datasets, including latitude and longitude of stations as independent variables, and WQI as a dependent variable, were amassed. Then, GTT was conducted on the datasets. Fig. 4 shows the scatter plot and the regression line fitted to the points with coordinates of $(\delta(k), \gamma(k))$. In the scatter plot, the black dots indicate the Euclidean distance of each monitoring station from each neighboring station. The red dots represent the average Euclidean distance of the monitoring stations from the surrounding stations as the neighborhood radius increases. The gamma statistic (GT) is equal to the intercept of the regression line fitted to the red dots ($\delta = 0$). Since the regression line does not present a steep slope, creating an expected modeling function is not difficult and does not need a large number of WQI data. Importantly, the scatter plot should have no input data with small $|X_i - X_j|$ values and large values of $|y_i - y_j|$, as corresponding output (the upper left corner of the δ- γ scatter plot), since they reflect relatively high intrinsic noise of the data and thus negatively affect developing a smooth model. As shown in Fig. 4, some points are in the upper left corner of the δ- γ distribution diagram, displaying the noise in WQI data from monitoring stations.

To find the optimum number and location of monitoring stations, M − and MW-tests were performed on the datasets of the first monitoring period, and a group of datasets, which could best represent the total condition, was placed at the beginning of the total datasets using the proposed method, as shown in Fig. 2. In this way, the M-test chart tends to be asymptotic faster, and the MW-test chart rises, showing the lowest GT in the initial data. Fig. 5a displays the GT variation for the best order of data. Since the GT tends to be asymptotic, the number of monitoring stations is more than the optimum number. Based on Figure 5a and 37 stations were selected as the optimum stations to monitor the WQI and hence determine its spatial distribution. Additionally, Fig. 5b indicates the result of the MW-test for 37 monitoring stations based on Fig. 5a. As can be seen, the first 37 stations present the lowest GT, and consequently, they were selected as the optimum monitoring stations, as depicted in Fig. 6.

The selection process of the number of monitoring stations and location was performed simultaneously. For GTT, the optimal number and location of stations resulted from the data analysis of the first monitoring period, which must also provide the spatial distribution of WQI with appropriate accuracy in other monitoring periods. Hence, to validate the results, M − and MW-test were conducted on WQI data coming from the selected 37 stations in the other five periods (see Fig. 7).

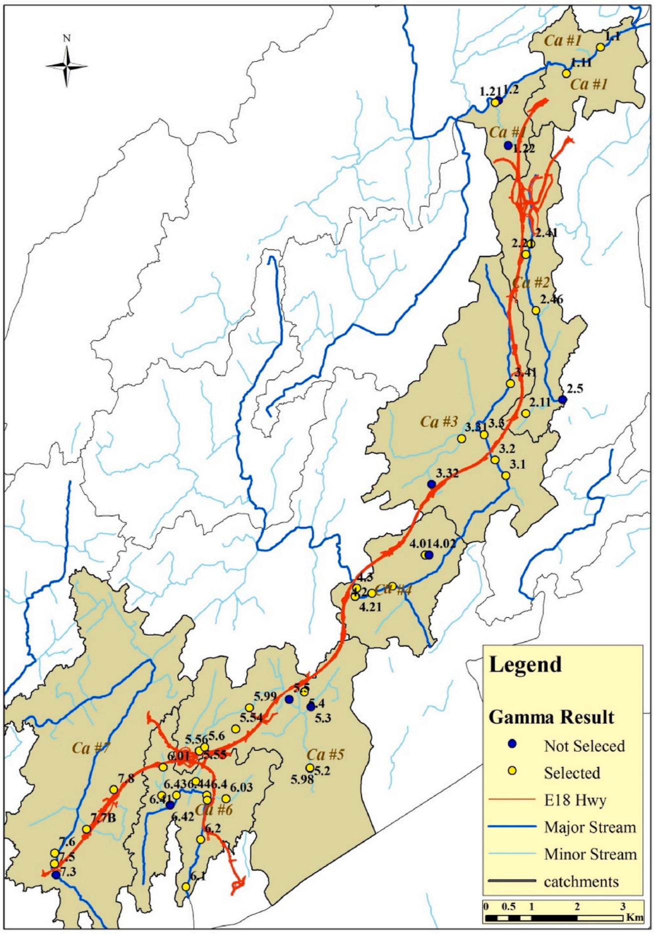

Fig. 6. The best WQMN derived from the M-test conducted on the data of the first monitoring period (4/2017).

According to Fig. 7a–e, GT tends to be asymptotic, confirming that the selected number of stations is optimum in all periods, and there is no need for more stations. By comparing GT and the asymptote location from the different periods, it can be concluded that it is possible to have a smaller number of monitoring stations for developing an optimal WQMN. However, given the M-test results in the 6th monitoring period (Fig. 7e), at least 37 stations are required to achieve an asymptote in this period. Therefore, after the first monitoring period, the initial asymptotic threshold is not necessarily the optimal number of monitoring stations in other periods.

The application of GTT has not been documented in the literature to determine the optimal monitoring network. However [20], successfully applied the transinformation entropy technique and value of information to achieve the optimum surface water quality monitoring network by using the data of multiple monitoring periods. In general, their selected network consisted of 33 stations that provided the minimum redundant information among stations while maximizing the value of information for the monitoring stations. Our best results, which were obtained using the data of the first monitoring period, revealed 37 stations for the monitoring network, covering the same stations as reported by Ref. [20]; along with four more stations, which are well distributed in all catchment areas.

4. Conclusions

The design and optimization of a surface water quality monitoring network in construction projects is a serious concern of decision-makers. This becomes even more relevant when it comes to projects with limited time and budget as well as projects with the lack of enough data for the optimal design of a monitoring network. The main goal of the current study was to evaluate the ability of GTT in determining the optimal number and location of surface water monitoring stations in a road construction project. The proposed method was successfully applied to optimize WQMN after the first monitoring period in the construction project of the Arendal-Tvedestrand highway in Norway. A primary monitoring network containing 48 stations was established based on the hydrogeological feature of the highway catchment, while the surface water quality was monitored in six periods. The water quality index (WQI), calculated based on the 28 physical, chemical, and biological parameters, was used to assess the quality of surface water. Then, the M − and MW-tests were performed on data coming from the first monitoring period to achieve the optimum number and location of monitoring stations. The results reveal that 37 monitoring stations (23% less than the number of stations in the primary WQMN) are

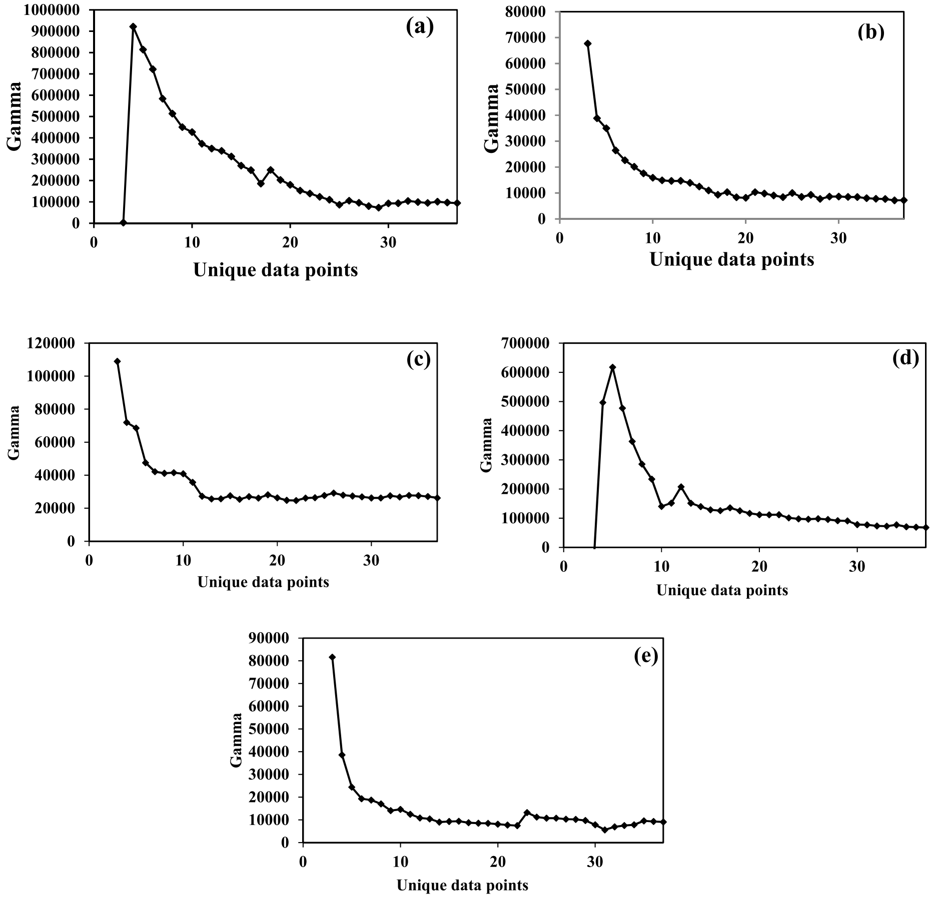

Fig. 7. Results of the M-test, graphs from a) to e) correspond to the 2nd to 6th monitoring period, respectively.

enough to assess WQI with sufficient accuracy. Additionally, they present an optimal distribution over seven discharge areas.

The proposed monitoring network was verified using the monitoring data of the next five monitoring periods. The results indicated that the optimal number and spatial arrangement of monitoring stations in a road construction project can be determined using the data of one monitoring period. In particular, some uncertainties, such as large changes in the location and type of construction works or variation of precipitation patterns in different periods, can make a difference in the results. Therefore, the proposed method is feasible to establish a WQMN in short- and mid-term construction projects, such as road construction, tunneling, and mining. Definitely, further research must be carried out to establish a basis for GTT in different environmental impact assessment (EIA) projects and design of monitoring networks in urban projects dealing with air pollution, quantitative and qualitative quality of surface water, groundwater, and soil. Finally, this study confirmed that the developed approach allows to significantly minimize the costs needed for effective environmental monitoring.

CRediT authorship contribution statement

Design of a surface water quality monitoring network in a road construction project using Gamma Test theory.

Sama Azadi: Investigation, Formal analysis, Conceptualization, Methodology, Validation, Data Curation, Writing - Review & Editing. Hamid Amiri: Investigation, Formal analysis, Conceptualization, Methodology, Validation, Data Curation. Mehrdad Ghorbani Mooselu: Data collection, Validation, Writing - Original Draft. Helge Liltved: Formal analysis, Validation, Data Curation, Writing - Review & Editing, Supervision, Project administration. Xun Sun: Writing - Review & Editing. Roberto Castro-Muñoz: Writing - Review & Editing. Grzegorz Boczkaj: Conceptualization, Methodology, Validation, Formal analysis, Data Curation, Writing - Original Draft, Writing - Review & Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Paper E

Roadside water quality monitoring and assessment by integrating remote sensing and field measurement, by Mehrdad Ghorbani Mooselu, Shahab Aldin Shojaeezadeh, Helge Liltved, Mohammad Reza Nikoo. Submitted to Remote Sensing of Environment (under review)

Evaluating turbidity and chlorophyll-a in roadside water bodies during road construction and operation by Sentinel-2A images

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Abstract

The impact of road construction and operation on roadside water bodies entails continuous monitoring and assessment of such resources. This study evaluates the applicability of Sentinel-2 Multi-Spectral Imager (MSI) satellite imagery products for water quality monitoring in roadside water bodies. In the proposed method, an optimal atmospheric correction for inland water was employed to calibrate the water leaving reflectance of Sentinel-2 images with gauge observations (115 ground-based monitoring stations). Additionally, the Otsu image segmentation method was used to identify water-only pixels, which agrees with observed water bodies. Accordingly, MSI products with a spatial scale of 10-meters and the temporal scale of 5-8 days were applied to estimate turbidity and chlorophyll-a spatiotemporally. The applicability of the presented methodology was assessed in a 22 km long road construction site in southern Norway. The proposed method, which is implemented in Google Earth Engine (GEE) showed a reliable performance for estimation of turbidity by the B3/B2 bands combination (R^2 = 0.8 and RMSE = 1.947 FNU) and chlorophyll-a by the NDCI index (R^2 = 0.79 and RMSE = 6.869 μg/l). The results were consistent with field observations on road construction and operation periods, reflecting the spatiotemporal effects of road on water quality. The generated knowledge in this study provides a better view for decision-makers on finding management strategies to protect the roadside water system.

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Keywords: Roadside water quality, road runoff, pollution, atmospheric correction, Sentinel-2, lake monitoring, remote sensing

1. Introduction

Roads are an integrated part of sustainable development and play an essential role in daily life. Environmental consequences of road development on water, soil, and biodiversity are an everlasting concern of decision-makers (Mertikas et al., 2021). Surface water resources are another key element in the sustainable development of communities. Highway construction and operation may threaten the aquatic ecosystems by imposing different pollutants. Hence, monitoring and assessment of roadside water bodies are vital to providing a holistic insight into the spatiotemporal variation of water quality (Forio and Goethals, 2020).

The physical, chemical and biological indicators of water quality are usually evaluated by field sampling and laboratory analyses. However, in-site measurements alone cannot provide sustainable data for water quality assessment and long-term water resource management plans (Ritchie et al., 2003). Ground-based sampling and measurements can generate precise and rapid information about targeted water bodies. However, when it comes to regional-scale assessment (i.e., monitoring roadside lakes on a long stretch of a road), in-situ observation methods are time-consuming and costly (Duan et al., 2013; Gholizadeh et al., 2016) and laboriously challenging for the larger number of sampling (i.e., >10,000) (Page et al., 2019). To this end, the lack of a comprehensive water quality monitoring system with proper spatial and temporal coverage across the road stretch is utterly felt. Recent advances in Remote Sensing (RS) techniques provide valuable methods and data resources to monitor environmental issues in real-time senses (Gholizadeh et al., 2016). RS techniques efficiently evaluate water quality problems on a regional scale and assess the complex interactions of environmental processes in time and space (Hassanien et al., 2020). Satellite-based sensors can measure almost all hydrological parameters (Lettenmaier et al., 2015; Zhang et al., 2016; Mccabe et al., 2017), deliver fundamental management data, and track the contaminants transport in water bodies (Sheffield et al., 2018). The monitoring and analyzing roadside water bodies are yet to be considered. Relying on the capabilities of RS technology for monitoring of the aquatic system (Vanhellemont and Ruddick, 2016; Page et al., 2019; Pahlevan et al., 2019), this study was aimed at using the Sentinel-2A information as a supplement for in-situ measurements in determining the spatiotemporal variation of turbidity and chlorophyll-a parameters in roadside lakes. Turbidity indirectly reveals the anthropogenic effects such as the variation of land use and cover, soil erosion, weather, and development of urban areas and infrastructures on water quality (Mccarthy et al., 2018; Ma et al., 2021). Thus, regular turbidity monitoring is an efficient management approach to protect water resources.

Sentinel-2A is a European optical imaging satellite launched in 2015 by the European Space Agency's Copernicus Programme. Sentinel-2 Multi-Spectral Imager (MSI) has three near-infrared (NIR) (i.e., 865 nm) bands that could be used through appropriate algorithms for detecting the chlorophyll-a concentrations (Pahlevan et al., 2019). Sentinel-2A data has been applied in previous researches for water quality monitoring, especially for turbidity (Liu et al., 2017; Sebastiá-Frasquet et al., 2019; Page et al., 2019; Niroumand-Jadidi et al., 2020; Ma et al., 2021) and chlorophyll (Vanhellemont and Ruddick, 2016; Gernez et al., 2017; Watanabe et al., 2017; Caballero et al., 2019; Vanhellemont and Ruddick, 2021). Sentinel-2 has a different spectral resolution and spectrum range than other sensors (e.g., Operational Land Imager, Thematic Mapper, and Enhanced Thematic Mapper Plus sensors), which necessitates exploring the MSI applicability in turbidity mapping (Ma et al., 2021). Nonetheless, the MSI products' capability for spatiotemporal assessment of road effects on water quality by analyzing the time-series data records over monitoring stations in lakes has not been fully explored in the literature.

This study aims to relate the water turbidity to Sentinel-2 spectral reflectance and improve spatiotemporal monitoring of roadside water bodies on a regional scale. The proposed method applies the Modified Atmospheric correction for INland waters (MAIN) (Page et al., 2019), and generates a reliable time series for turbidity and chlorophyll-a. The satellite information was precisely calibrated by in-situ monitoring data and used to map the spatiotemporal variation of the turbidity and chlorophyll-a in roadside lakes and demonstrate the effects of road activities on adjacent water resources. The results were also presented in the Google Earth Engine (GEE) environment, which is an efficient and transparent platform to access global time-series of satellite data (Moreno-Martínez et al., 2020). The paper contributes to filling the knowledge gap in the following cases:

1) More efficient and sustainable water quality monitoring during construction and operation of roads with proper regional coverage over time
2) Assessing the application of modified atmospheric correction for inland waters (MAIN) for roadside water quality monitoring
3) Trend analysis on the quality of roadside lakes considering the construction activities and site-specific climate conditions

The proposed method generates a permanent satellite-based database on roadside water bodies for future comparisons. The provided dataset is reliable, cost-effective, and systematic, which improves our understanding of the environmental impacts caused by road systems and can be confidently used by decision-makers and delivers proper knowledge for environmental planning and management. The feasibility of the proposed framework was assessed over a 22 km length of a new highway (E18 Arendal-Tvedestrand) in southern Norway.

2. Material and methods

2.1 Study area

The E18 Tvedestrand-Arendal highway in Norway is a new 22 km long four-lane road. The construction started in 2017 and opened publicly in July 2019. This road with a total catchment area of 7180 hectares include multiple catchments such as Storelva (#1), Vennevann (#2), Langangselva (#3), Sagene (#4), Mørfjær (#5), Songebekken (#6), and Longum/ Barbu (#7) as shown in Fig.1. These catchments include valuable water bodies of public interest, including drinking water sources and streams for sea trout spawning (Nye-Veier, 2021). Given these conditions, the roadside waterbodies in this area are subject to regular water quality monitoring in monthly periods by the development and operation agency (Nye Veier AS) on the request of the Norwegian Environment Agency. In this region, the average rainfall and temperature in the period of 2017-2020 were 1511 mm and 8 °C, respectively. The maximum and minimum temperature in this period was 31°C and -15 °C, respectively.

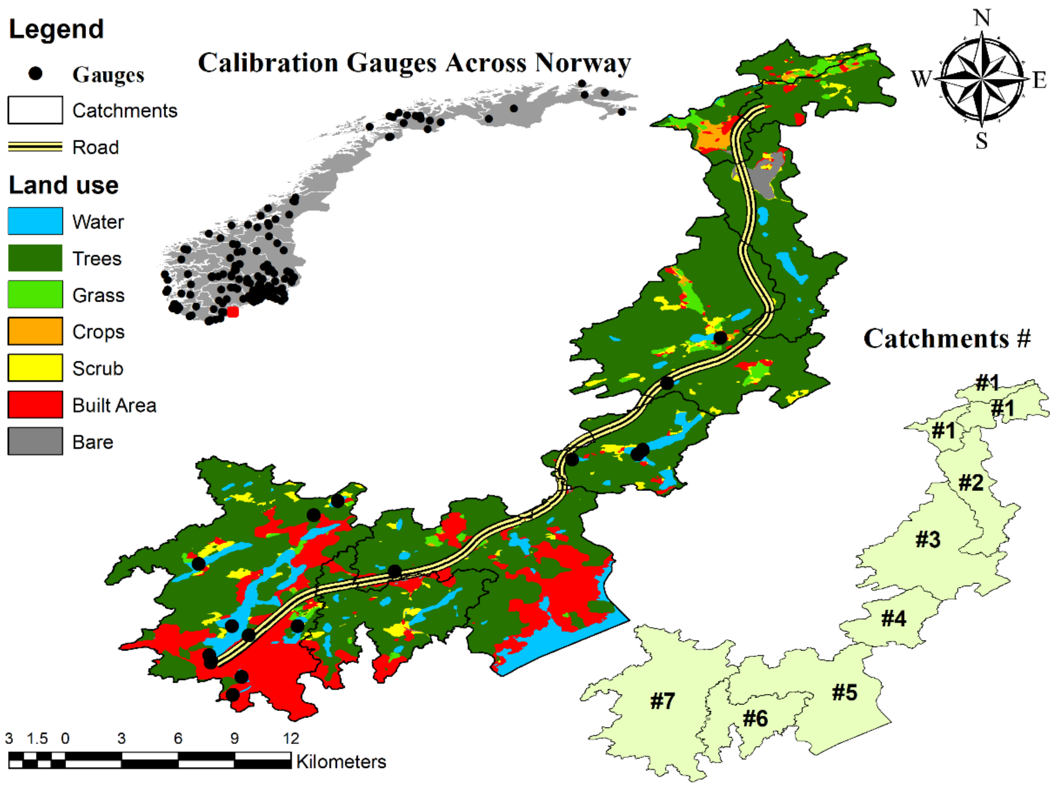

Fig. 1 The E18 Arendal-Tvedestrand highway with catchment areas, land use and gauges for water quality monitoring

2.2 Satellite data

The Sentinel 2 is a high-resolution, Multi-Spectral imaging mission. Sentinel 2A Multi-Spectral Imagery (MSI) data with high resolutions (10 to 30 meters), 13 spectral bands, and 12 bits radiometric resolution has been widely used to retrieve and map water quality characteristics in shallow waters (Potes et al., 2018; Karaoui et al., 2019; Torres-Bejarano et al., 2021). Its optical instruments sample 13 spectral bands on different resolutions and different spectrums: four visible (VIS) bands of B1 (443 nm) at 60-meter resolution, B2 (490 nm) and B3 (560 nm), and B4 (665 nm) at 10-meter resolution; five near-infrared (NIR) bands of B5 (704 nm), B6 (740 nm), B7 (783 nm) at 20-meter resolution, B8 (832 nm) at 10-meter resolution, B9 (945 nm) at 60-meter resolution; three short wave infrared (SWIR) bands of B10 (1373 nm) at 60-meter resolution, B11 (1613 nm), and B12 (2202 nm) at 20-meter resolution. Sentinel 2 provides products on Level-2A of Bottom of Atmosphere (BOA) reflectance image derived from Level-1C of Top of Atmosphere (TOA) products. The BOA images are atmospherically corrected by sen2cor (Main-Knorn et al., 2017). European Space Agency (ESA) did not produce BOA data (atmospherically corrected TOA images with sen2cor algorithm) for all TOA images as some earlier products of BOA coverages are not also global. Additionally, some previous studies addressed some limitations and errors attributed to BOA images (Martins et al., 2017; Li, 2021). Our analysis showed BOA images had fewer revisit temporal intervals (10-15 days) than TOA images (5-8 days). Hence, as previous studies suggested that the TOA images are more appropriate to map water quality parameters in surface waters (Rumora et al., 2020; Cordeiro et al., 2021), we employed TOA images and a different atmospheric correction to extract inland waters rather than using already corrected Sentinel 2A images (BOA) by sen2cor algorithm.

2.3 In-situ data

During the road construction, the spatiotemporal variation of physical and chemical parameters in surface water was analyzed using a network of monitoring stations. The monitoring network was established on the main- and side-streams of each catchment area based on catchments topography, the direction of the main and side streams, and site-specific priorities (e.g., on sea trout spawning streams) in catchments. The monitoring was performed in different time steps according to the construction activities and environmental requirements established by the Environmental Department of the Governor of Agder County, Norway (Mooselu et al., 2021). The measured water quality parameters in the catchment areas (mostly in streams) included general water quality parameters (e.g., alkalinity, pH, conductivity, Na, Cl, Fe, K, Al, Mn, Ca, Mg, and SO_4^{2-}), organic matter parameters (chemical oxygen demand, total organic carbon, color), nutrients (NO_3-N, NH_4-N, total-N and total-P), organic micropollutants (PAH_{16}-EPA-group), trace elements (As, Cd, Ba, Co, Cu, Cr, Ni, Pb, Mo, Zn, and Hg), and particulate matter (suspended solids and turbidity) (Mooselu et al., 2020). Besides, for calibration of the satellite data, the information of 115 monitoring stations (Fig 1), which are spatially located throughout Norway, were applied. This information is provided by https://vannmiljo.miljodirektoratet.no/.

2.4 Methodology

In this paper, we propose a methodology to estimate turbidity and chlorophyll-a time series and investigate the effect of road construction and operation on adjacent lakes, in which an optimal atmospheric correction for inland water was employed to calibrate the gauge observations with water leaving reflectance of Sentinel-2A images. A flowchart of this methodology is presented in Fig. 2.

2.4.1 Atmospheric correction

Numerous methods have been proposed to atmospherically correct the S2A images ranging from absolute to relative correction techniques (Richter et al., 2010; Hagolle et al., 2010; Vanhellemont and Ruddick, 2015; Sola Torralba et al., 2018). The absolute techniques remove all atmospheric influences and require a number of assumptions and additional ground and meteorological reference data, while relative corrections take one band as a baseline and transform other bands to match (Lantzanakis et al., 2017).

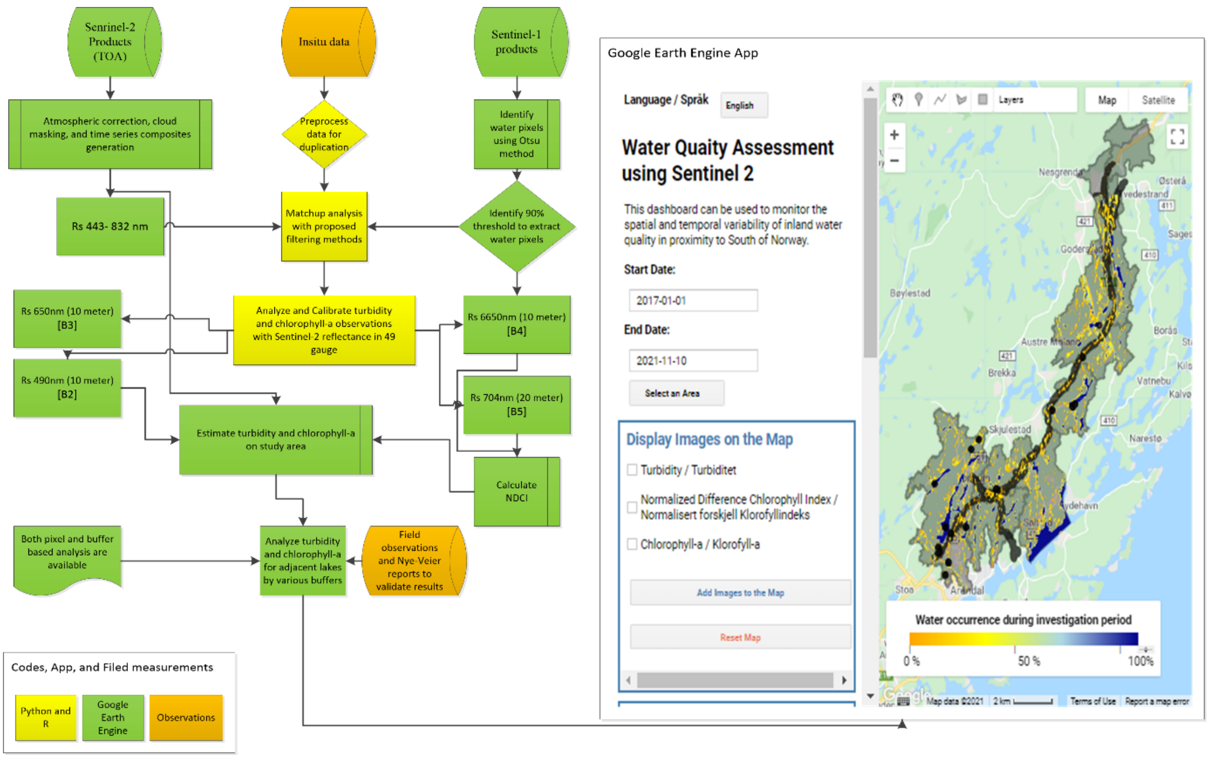

Fig. 2 Proposed methodology flowchart

We used an absolute method that clarifies inland waters named Modified Atmospheric correction for Inland waters (MAIN) (Page et al., 2019). The MAIN algorithm is based on ocean-color techniques (Vanhellemont and Ruddick, 2015) in which the desired water-leaving reflectance (ρ_w) and subsequent remote-sensing reflectance (R_{rs}) (an apparent optical property) are estimated by:

$$\rho_w\,(\lambda_i) = \rho_{rc}\,(\lambda_i) - \rho_{am}\,(\lambda_i)/\mathrm{t}\,(\lambda_i) \qquad (1)$$

$$R_{rs}\,(\lambda_i) = \rho_w/\pi \qquad (2)$$

where the diffuse transmittance of water surface to the satellite is t (λ_i), the Rayleigh corrected reflectance is indicated by ρ_{rc} and contains some other corrections, i.e., the Fresnel correction, Rayleigh scattering phase function, and ozone adjustment (Feng et al., 2018). For each spectral band of S2A, the ozone absorption coefficient was received from the Aerosol Optical Depth Value-Added Product (Koontz et al., 2013). In order to achieve the daily measured ozone concentration, the merged products of TOMS/Meteor-3, TOMS/Nimbus-7, Total Ozone Mapping Spectrometer (TOMS) Earth Probe, and the Ozone Monitoring Instrument (OMI) were applied. Moreover, the Rayleigh optical thickness was calculated on a pixel-by-pixel basis using a digital elevation model derived from the Shuttle Radar Topography Missions (SRTM, 30 m) (Farr and Kobrick, 2000). The correction of the aerosol path reflectance (ρ_a) impact in the visible and NIR spectral range may be difficult. It is mainly because the aerosols' absorbing properties vary spectrally by size, shape, chemistry, and density of aerosols (Vermote et al., 2016). It is possible to compare the responses signal of optical observation of turbid water pixels by the Rayleigh-corrected SWIR channels with the responses signal of clear water pixels (Vanhellemont and Ruddick, 2015). Eq. 3 defines the aerosol path radiance reflectance in which the k and c are constant values (Page et al., 2019):

$$\rho_a\,(\lambda_{NIR}) = ke^{(-c\,\lambda)} \quad (3)$$

The NIR signal in eutrophic lakes typically has interference with the optically active constituents (OACs). Hence, presuming minor signal in the SWIR wavelengths, two Rayleigh-corrected SWIR bands available on the MSI and OLI ($\rho_{rc}\,(\lambda_{SWIR-1,2})$) were applied for aerosol detection instead of the NIR band.

$$\rho_{rc}\,(\lambda_{SWIR-1}) = ke^{(-c\,\lambda)} = \rho_{rc}\,(\lambda_{SWIR-2}) \quad (4)$$

$$(Ln(\rho_{rc}\,(\lambda_{SWIR-2})) - Ln(\rho_{rc}\,(\lambda_{SWIR-1}))/(\lambda_{SWIR-2} - \lambda_{SWIR-1}) = -\varepsilon \quad (5)$$

The ε indicates the aerosol type (Dash et al., 2012). This method generates a raster image of the aerosol type that was extrapolated to the NIR and visible bands:

$$\rho_{am}\,(\lambda_{VIS-NIR}) = \rho_{rc}\,(\lambda_{SWIR-2}) \times (F_0' / F_0'\,(\lambda_{SWIR-2}))e^{(-\varepsilon\times(\lambda_i/\lambda_{SWIR-2}))} \quad (6)$$

In this equation ρ_{am} shows the aerosol reflectance map required to evaluate the residual aerosols contributions within each spectral band and F_0' is the instantaneous extraterrestrial solar irradiance adjusted for Earth-sun distance. Using the generated variables within the image metadata, the Rrs were derived in the Google Earth Engine (GEE) environment.

2.4.2 Identification of water pixels

We used the Otsu Method (Otsu, 1979) to identify the water pixels and segment the Sentinel-1 images using a threshold with minimum occurrences higher than 90 percent applied in Google Earth Engine (GEE). The Otsu method is an unsupervised method, which was first introduced to select a threshold and separate an object out of its background, using the gray-level histogram of the image. In this method, considering a set of all elements ($C = C_0 \cup C_1$) in which i th element belonging to the whole set with the value of x_i is sorted as $x_i < x_j$ if $i < j$ $(i, j \in C)$. Also, the density (probability) of i th element is p_i, where $\sum_{i \in C} p_i = 1$. The μ_j is the mean value (center) of disjoint subclusters of C_j, for $j = 0, 1$.

$$\mu_j = \frac{\sum_{i \in C_j} p_i \times x_i}{\sum_{i \in C_j} p_i}, \qquad for\ j = 0, 1 \tag{7}$$

and the mean value of the whole set C is $\mu = \sum_{i \in C} p_i \times x_i$. Additionally, the inner-variance of the subclusters C_j is defined as Eq. 8, and the interclass variance between the cluster C_0 and cluster C_1 is defined by Eq. 9.

$$V_j = \sum_{i \in C_j} p_i \times (x_i - \mu_j)^2, \qquad for\ j = 0, 1 \tag{8}$$

$$V_{0,1} = \sum_{j=0,1} [(\sum_{i \in C_j} p_i) \times (\mu_j - \mu)^2] \tag{9}$$

and clearly, the total variance would be $V = \sum_{i \in C} p_i \times (x_i - \mu)^2$. Otsu method minimizes the intraclass variance, which is $\sum V_j$. For each cluster, the smaller V_j (the closer distance of each point toward the cluster center) describes higher similarity shared by the elements of this cluster. Therefore, the whole set of elements is optimally separated if the similar elements could be sorted in the same cluster or the summation of inner-variance inside each cluster could be minimized. So, the objective function is mathematically defined as follows:

$$\min_{C_0, C_1} \sum_{j=0,1} V_j = \min_{C_0, C_1} \sum_{j=0,1} \sum_{j \, \epsilon \, C_j} p_i \times (x_i - \mu_j)^2 \tag{10}$$

the total-variance of the whole set (V) should be equal to the summation of each cluster's inner variance (V_j) and the interclass variance ($V_{0,1}$). Notably, V is a constant for a fixed data set. Accordingly, the objective function in Eq. 10 is equal to maximizing the $V_{0,1}$:

$$\max_{C_0, C_1} \sum_{j=0,1} [(\sum_{i \, \epsilon \, C_j} p_i) \times \left(\mu_j - \mu\right)^2] \tag{11}$$

If the Otsu method is applied to the density histogram, Θ is assumed the threshold's estimation space (or set of all possible bin's values), the i th bin in Θ with the bin value of (Θ) and density of p_θ, where $\sum_{\Theta \, \epsilon \, \Theta} p_\Theta = 1$, could be notified as $x_{i_\theta} = \Theta$ in the indexed set (C). Hence, p_{i_θ} shows density p_θ of the i th bin with value Θ from the density histogram. The final prediction of the threshold is denoted as $\hat{\theta} \, \epsilon \, \Theta$, which corresponds to the index $i_{\hat{\theta}} \, \epsilon$ C. The threshold Θ, forms two separate clusters of $C_0 = \{i : i < i_\theta , i \epsilon C\}$ and $C_1 = \{i : i \geq i_\theta , i \epsilon C\}$. In the final estimation of the threshold $\hat{\theta}$, the subcluster C_0^* and C_1^* should get the optimal value of Eq. 11. Then, $i_{\hat{\theta}} = \min_{i \, \epsilon C_1^*} i$ and $\hat{\theta} = x_{i_{\hat{\theta}}}$. At most quadratic polynomial time of the size of the Θ, this optimization problem could be solved (Otsu, 1979; Zhou et al., 2020).

2.4.3 Satellite data and in situ matchup quality control

We used the GEE platform to do atmospheric correction and matchup analysis. Accordingly, 602 atmospherically corrected images across Norway were analyzed to match up with in-situ data in 115 gauges and 2357 time-series of field observations for turbidity and chlorophyll-a parameters between 2017 and 2021 (late August, Fig. 1). To avoid the influence of clouds, the quality control band (QA60, 60 m) and a cloudy pixel percentage properties of the Sentinel-2 dataset were used in GEE, which masks clouds in pixels with cloud percentage more than 20 (%), and water-only pixels were masked using pixel identification algorithms. For pixel matchup with gauge observations and water-only pixels, the daily and monthly windows were chosen, respectively. Although Bailey and Werdell restricted matchups between satellite and observation to a 3-hour window of satellite overpass (Bailey and Werdell, 2006), other researchers suggest that for lakes with stable atmospheric conditions, matchups with less restrictive time frames (up to three days) are successful (Kloiber et al., 2002; Olmanson et al., 2011; Tebbs et al., 2013). Therefore, we used a daily windows restriction for matchups, with local overpass times between 10 a.m. and 11 a.m. ± 2 h, allowing a time difference of < 3-hour in most cases.

To achieve higher accuracy in matchups, some rare pixels with negative values were filtered as suggested by (Bailey and Werdell, 2006). Following the generation of matchups, they were filtered using Cook's distance method and values outside the one standard deviation as suggested by (Bailey and Werdell, 2006). The Cook's distance method is a commonly used statistic to estimate a data point's influence when performing a least-squares regression analysis (Mendenhall et al., 1996). The outlier influence coefficient of 0.1 was chosen to exclude the influence of extreme outliers and mixed pixels. Additionally, in some rare cases, two matchups have similar values for bands and bands combinations (up to 9 decimals comparison). Therefore, these values were filtered from matchups to ensure some observational uncertainties (i.e., extreme duplications in gauge observations) have been excluded from matchup processes. Then, to consider shoreline effects arising from mixed pixels and breaking waves at the coast for inland water, the Otsu method was applied to ensure that the waters with occurrences of >90 % are considered in matchups and further analysis. Therefore, water-only pixels with >90 % of occurrences were classified as water and <90 % as land masks. Hence, using the fast distance method on the GEE platform, observation gauges within more than one pixel distance (10 meters of Sentinel-1 data) to shorelines were excluded from matchup analysis. Finally, 18 matched up for turbidity and 49 matched up for chlorophyll-a with gauge observations across Norway were used for the calibration process.

2.4.4 Calibration

Relying on a single band or algorithm sometimes overestimates or underestimates water quality (Kuhn et al., 2019; Pahlevan et al., 2019). Thus, using either a combination of sensitive bands or different algorithms is typical for a better calibration with observed data. In this research, the correlations between multiple bands and combinations of bands (Figs. 3A and 3B) were analyzed in the calibration process. Results showed that various combinations had different correlations with turbidity and chlorophyll-a gauge observations. The B3/B2 bands combination had the best relations with turbidity observations (0.91 of Spearman correlation). Therefore, we applied the B3/B2 bands combinations to calibrate turbidity observations in 18 gauges in Norway using the following equation:

$$Turbidity = A * \ln(B3/B2) + B \quad (7)$$

Where $A = 15.31$, and $B = 3.497$ are the calibration parameters to calibrate turbidity observations. As shown in Fig. 4A, the accuracy of the regression is remarkably high ($R^2 = 0.8$ and RMSE = 1.947 FNU). The B2 band is a sensitive band to water turbidity differences, while the B3 band is known as the chlorophyll absorption band, which is useful to distinguish between turbidity deriving from vegetation or soil. Therefore, combining these two bands makes it possible to distinguish between soils and vegetation and strongly correlate with turbidity observations (i.e., 0.91). Although the maximum turbidity observations (> 17 FNU) in the calibration process was quite low, the regressed empirical equation is capable to estimate high values of turbidity (turbidity greater than 100 FNU in gauge observations).

The chlorophyll-a observations had a moderate correlation with B3/B2 bands. As suggested by (Mishra and Mishra, 2012), the Normalized Difference Chlorophyll Index (NDCI) ranges between -1 and 1 is a decent index to show the variation of chlorophyll-a in turbid waters. The NDCI was first proposed by (Mishra and Mishra, 2012) and calibrated for various regions across the United States. They suggested that the NDCI is appropriate in coastal waters and terrestrial vegetation lands. Since Norway has a long coastal line which is mostly covered by forests (sum up to 40% of total Norway's area), and open firm ground (38%) that are covered by snow or sparse vegetation in hillslopes and mountains (Bryn et al., 2018), the NDCI has a moderate correlation with chlorophyll-a observations. Hence, we used the NDCI to calibrate chlorophyll-a gauge observations using the following equations:

$$NDCI = \frac{B5 - B4}{B5 + B4} \tag{8}$$

$$Chlorophyll - a = A * NDCI^2 + B * NDCI + C \tag{9}$$

Where $A = 182.3$, $B = 142.2$, and $C = 16.93$ are the calibration parameters to calibrate chlorophyll-a with observations in 49 stations. As shown in Fig. 4B, the accuracy of the regression is high enough (R^2 = 0.79 and RMSE = 6.869 ug/l).

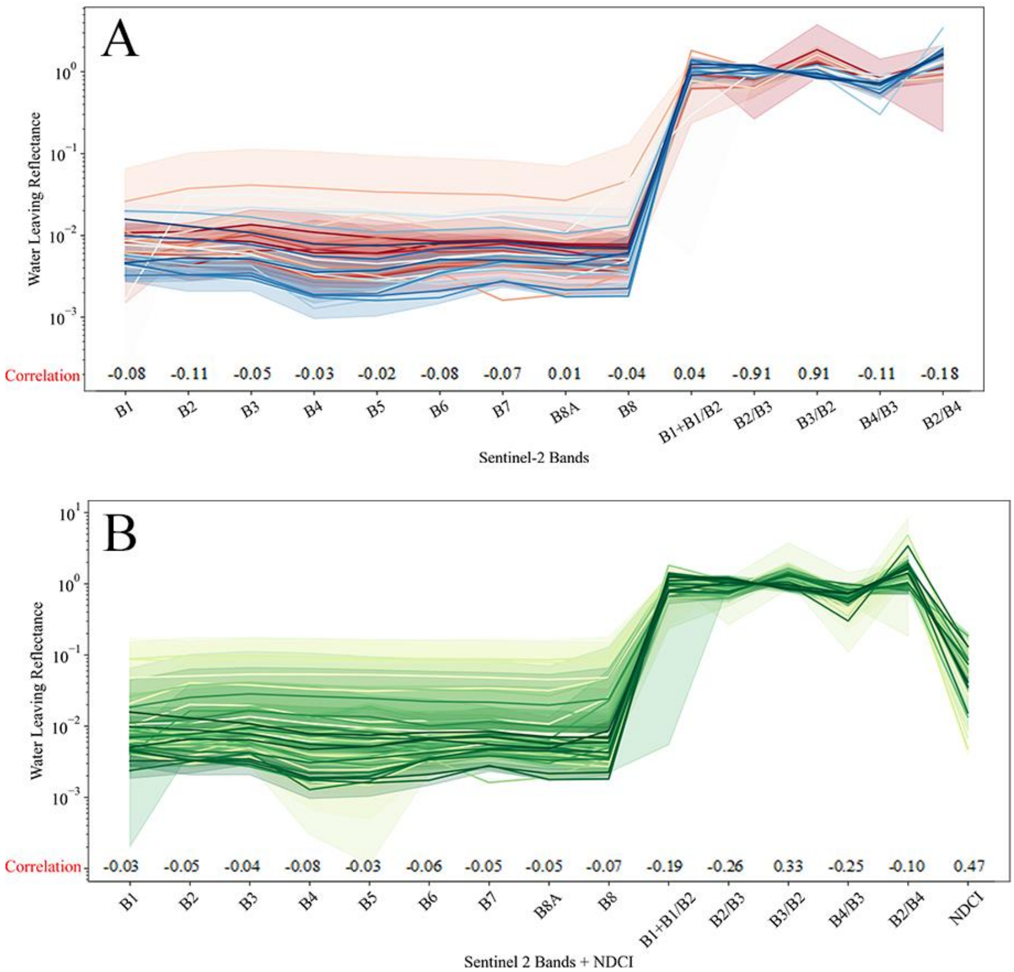

Fig. 3 Remote sensing water leaving reflectance and correlations in different bands of Sentinel-2A satellite data from 115 calibration gauges for A) turbidity B) chlorophyll-a. Note: single bands scales are 0.0001, and NDCI minus values are masked to be compared with Sentinel-2A bands.

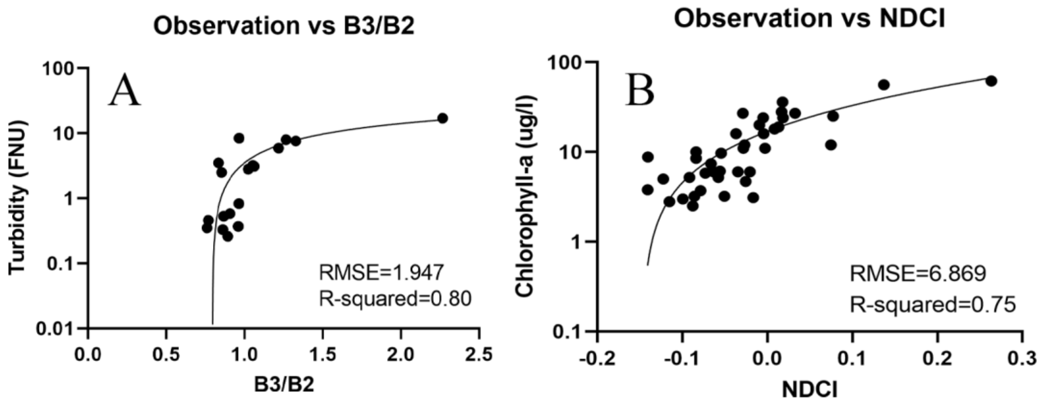

Fig. 4 Scatter plots of field observations versus Sentinel-2A satellite data for A) turbidity (FNU), B) chlorophyll-a (µg/l).

2.5 Performance metrics

Two performance metrics were applied in the calibration section to fit an empirical equation between Sentinel-2 image reflectances and gauge observations. Root Mean Square Error (RMSE) and R-squared (R^2) are two classical metrics to show the goodness of fitting between observations and calibration parameters. Because the observations and calibration parameters are concentrated neither near small nor big values, the RMSE and R-squared parameters are good metrics for evaluating the empirical regression. The RMSE and R-squared are described by the following formulas:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}[\mathbf{z}_i - \hat{\mathbf{z}}_i]^2}{n}} \tag{10}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}[\mathbf{z}_i - \hat{\mathbf{z}}_i]^2}{\sum_{i=1}^{n}[\mathbf{z}_i - \hat{\mathbf{z}}_i]^2} \tag{11}$$

where, $\mathbf{z}_i$ and $\hat{\mathbf{z}}_i$ are observations and calibration parameters, respectively, n denotes the length of observation and $\hat{\hat{\mathbf{z}}}$ is the average value of observations. The perfect model is associated with $\mathrm{RMSE} = 0$, ($\mathrm{RMSE} \in [0, \mathrm{inf})$), and $R^2 = 1$, ($R^2 \in (0, 1]$).

3 Results and discussion

The results of the suggested methodology are presented for the two parameters; turbidity and chlorophyll-a in pixel time series, geospatial maps, and various road sections using the Google Earth Engine (GEE) app.

***3**.1 Turbidity estimation by Sentinel-2A satellite data*

Turbidity is highly associated with the particulate backscattering coefficient and impacts the water surface reflectance (Constantin et al., 2016). High levels of turbidity reduce light penetration and consequently restrict photosynthesis and chlorophyll-a concentration (Wass et al., 1997). Seasonal meteorological factors such as wind speed (WS) and precipitation affect water turbidity by influencing sediment movement (Du et al., 2020; Serra et al., 2020). High precipitation will induce flooding and erosion from surrounding land and increase turbidity in receiving waters (Kasprzak et al., 2017). Also, the surface washout in heavy precipitation increases the transport of total ions (EC), SS, and turbidity in the construction area (Mooselu et al., 2021). Regarding the effect of wind, (Chalar Marquisá and Tundisi, 1999) reported the maximum mixture of particles and organic matter in Lobo lake by turbulence on windy days.

The box plot of the seasonal turbidity variation in different catchments derived from Sentinel-2 is presented in Fig. 5. The estimated seasonality from Sentinel 2 shows that the average turbidity values in fall and winter are higher than those in spring and summer. This is in line with the site-specific climatic conditions with higher precipitation in fall and winter that carry highway construction and operation runoff into the roadside water bodies. Another point in Fig. 5 is a higher variation of turbidity values in the fall semester, which may be related to higher precipitation events and the "first flush" effect of road pollutants after a dry period.

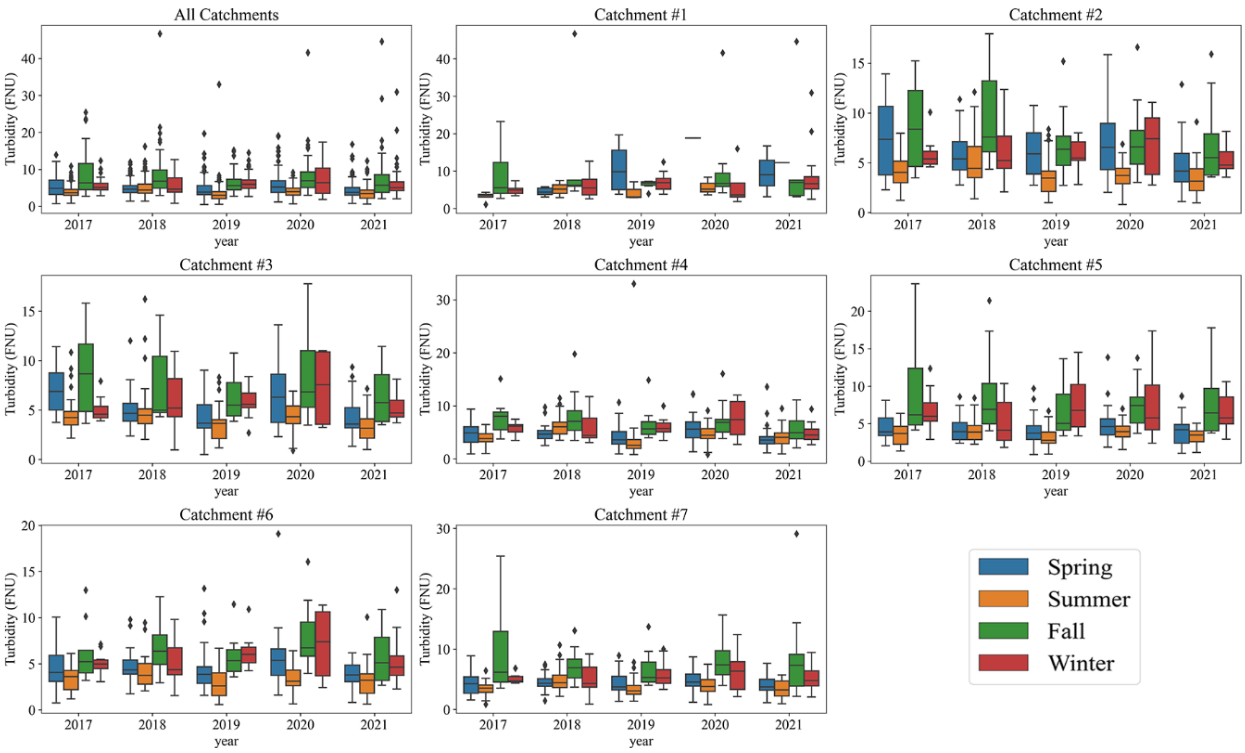

Fig. 5 The seasonal turbidity variation in different catchments derived from Sentinel-2A satellite data.

It seems that the variation of turbidity in various catchment areas during road construction (from 2017 to July 2019) is more affected by the type and size of construction activities. For example, drilling and blasting have been very repetitive activities due to the construction of more than 2 km of tunneling in this project, which increased total nitrogen, turbidity, and suspended solids (SS) in receiving water bodies. In winter 2017, the blasting activities with discharged runoff to catchment #5 increased the turbidity value in monitoring stations (Mooselu et al., 2021). However, climate effects are also an important item. For example, in the summer of 2019, when the majority of the construction activities were completed, and the road was not under operation traffic, the turbidity values in all seven catchments were low. On the other hand, considering the fall and winter seasons in 2020, when the road is in regular operation and the amount of precipitation were higher than during the summer, all seven catchment areas have higher turbidity than other seasons in 2020. When it comes to each specific catchment, the performance of remote sensing data for capturing the turbidity values is reasonable. For example, in catchment #1, the estimated average turbidity increased from 2017 to 2018, which is consistent with the field observations. According to the yearly report of construction activity in E18 Arendal-Tvedestrand (Nye-Veier, 2019), as construction work proceeded in this region, side streams have shown clear signs of being influenced by construction work in the form of increased turbidity and suspended matter in 2018. In catchment #2, the satellite data indicated a decrease in average turbidity values from 2107 to 2018. This is also in line with the field observations. Based on the reports (Nye-Veier, 2018, 2019), most qualitative parameters such as turbidity increased a lot in the side streams in 2017, compared to pre-construction conditions (2015-2016). To reduce the impact of particle transport to receiving waters, silt curtains were used in some places, and there were built three sedimentation basins (ponds) to collect polluted road runoff from some parts of the road, but the performance of these were poor just after construction. In 2018, the measured values, including turbidity and suspended matter in the main and side streams showed a significant decrease compared to 2017, which may indicate that the sedimentation ponds and cleaning measures between the construction area and the stream have an improved effect.

In catchment #3, similar trends were estimated for variation in turbidity during the construction time, in which the overall turbidity values decreased from 2017 to 2018. Higher turbidity values in 2017 than in 2018 was also evident by the field observations. During 2017, there were large bog excavations and mass replacement, stone embankment, earth cladding of embankments, and road superstructure, which affected the receiving streams. The watercourses were also affected by other sources (e.g., grazing areas for cows, agriculture, and diffuse runoff from buildings) in addition to construction work. A permanent sedimentation pond was established in the region in 2017, which protected the main streams in the next periods. It means that in 2018, despite a lot of construction work (i.e., drilling, blasting, mass replacement, filling and casting of the bridge, bog unloading, and lowering of the water level), the content of suspended matter and turbidity significantly decreased for all test points of the catchment in 2018 compared with 2017.

On the other hand, catchment #4, had different trends in which there were little variation from year to year in the various parameters, and the watercourse shows no clear signs of impact of the construction work based on physical/chemical quality parameters. This catchment had small variations in estimated turbidity values during the road construction. It is mentioned in the yearly report from the highway construction that compared with the pre-construction state, there was very little or no change for the vast majority of test points and parameters in catchment #4. Also here, values for turbidity and suspended solids decreased in 2018 compared to 2017. However, there was a discharge of tunnel washing water upstream of the catchment during the road operation, which may have increased the turbidity (Nye-Veier, 2018, 2019).

In catchment #5, the S2A estimation indicates a decrease in turbidity values from 2017 to 2018, which is verified by the field data. Accordingly, all parameters were reduced in 2018 compared to 2017 for the main streams in Mørfjær catchment, but compared to earlier field data (before 2015 and 2016), the values are still high, indicating the effects of construction activities on surface water quality (Nye-Veier, 2018, 2019). The results of remote sensing in monitoring turbidity in catchments #6 and catchment #7 were also consistent with the ground-based measurements. Notably, based on in-situ data in catchment #7, there were no signs that the Longum/Barbu watercourse was generally affected by construction work in 2017. Also, in 2018, there was generally little impact of construction work on the Longum/Barbu watercourse. Another point regarding the estimated turbidity values by the S2A products is decreasing trend from 2019 to 2020, which is generally visible in all catchments which is in line with the yearly report of E18 Arendal-Tvedestrand. Ground-based observations demonstrated that the particle impact (which was significant during the construction phase) sharply reduced in 2020, and in many water bodies, the levels of turbidity and suspended matter have returned to the levels measured during the pre-construction period (2015 and 2016). However, in some sites, turbidity is still higher than that in pre-construction conditions (Nye-Veier, 2021).

Fig. 5 considered all water bodies in each catchment. However, the effects of road on water quality vary by distance from the central line of the road. As suggested by (Forman and Alexander, 1998), road runoff can influence aquatic ecosystems by pollution within 50 m, by hydrological effects within 200 m and by sediments 1 km downstream. To clarify the effect of construction activities on the spatiotemporal variation of turbidity in roadside water bodies, the seasonal variation of turbidity in various distances to the central line of the road (buffer zones of 50, 200, and 1000 m from the road line) are presented in Fig. 6. This figure shows that during construction time (from 2017 to June 2019), the highest turbidity values were estimated during autumn. This could be explained either by the higher precipitation in fall (Nye-Veier, 2018,

2019) which can carry the contamination load to streams and then to lakes. Even during road operation (since autumn 2019), the rising rainfall in autumn increased the turbidity in different buffer zones around the road (Fig. 6 and Fig. S12 in Supplementary Material).

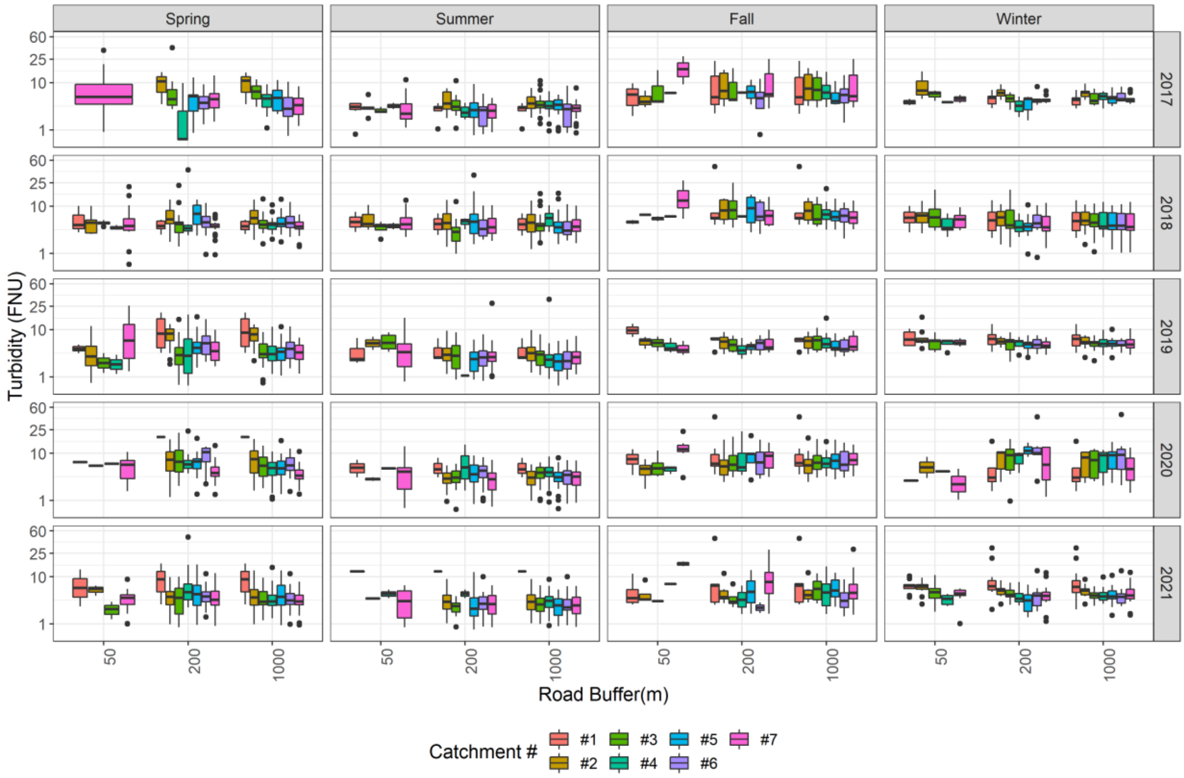

Fig. 6 The seasonal variation of turbidity values derived from Sentinel-2A satellite data in catchment areas for various buffer zones

Additionally, the variation of turbidity during road operation is more predictable than during construction. During operation, the turbidity load on nearby water bodies is likely related to variations in traffic load and precipitation. Considering the type and size of activities in different catchments, the turbidity variation in catchment #5 (Mørfjær) is notable. In the Mørfjær area, in spring 2017, the dominant activities were blasting and area cleaning, which have the highest effect on water quality (Mooselu et al., 2021). Also, in the winter of 2018, the dominant construction activity in catchment #5 was blasting related to bridges and tunnels construction, and such events can highly increase the turbidity values in receiving waters.

The spatial variation in average turbidity values between 2017 and 2021 in all seven catchments are shown in Fig. 7. A part of this variation depends on the distance to the central line of the road and the amount of received contamination load. Also, the type and size of construction activities (during the construction time) and the traffic load (during the road operation) affected the turbidity concentration in roadside water bodies (Mooselu et al., 2021). However, the climatic parameters, especially the intensity and the frequency of rainfall events, have a significant impact on turbidity variation in different catchments.

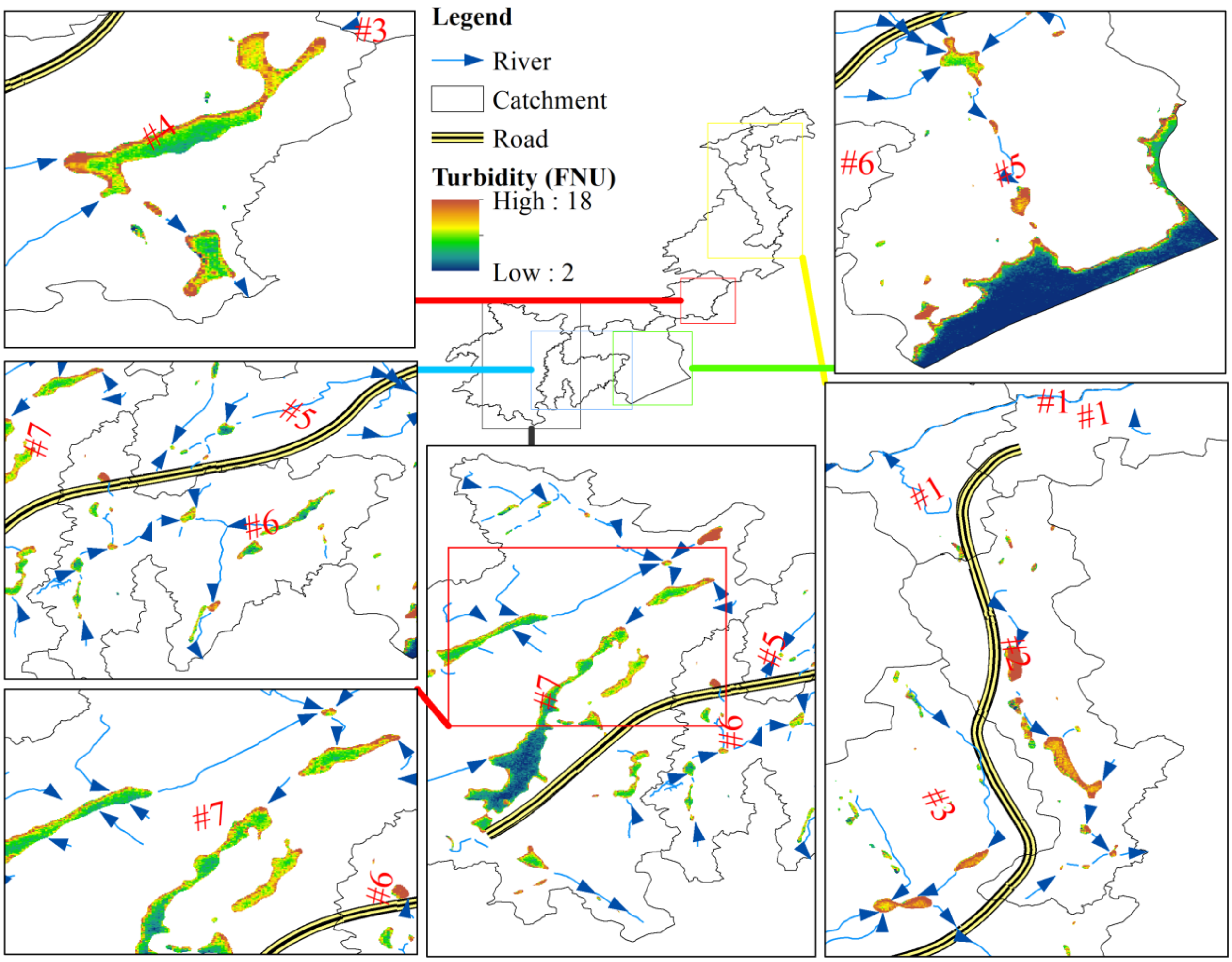

Fig. 7 Spatial map of catchments with average turbidity values in waterbodies derived from Sentinel-2A satellite data (2017-2021) and flow directions

Fig. 7 also shows the direction of streams that carry the road runoff to receiving water bodies. Based on this figure, the turbidity concentrations close to the shore of the water bodies are higher than in central areas. This can be related to transport of particles from land in the boundary area, but also particles dispersed from sediments and shoreside erosion by wind induced waves and turbulence. Besides, in catchment #5, where the stream is discharged to the ocean, turbidity concentration decreases with distance from the shoreline. It is explained by the fact that turbidity acts as suspended solids throughout the water column, and turbid water may exist over various depths. However, since deep water (ocean) bodies look darker from satellite, turbidity estimation by satellite data in shallow water (lakes and coastal water) is more tangible (Stortz et al., 1976; Olmanson et al., 2011; Pertiwi et al., 2021). Also, the average turbidity concentration in catchments # 2 and #3 has higher values than other catchments. In catchments #2 and #3, a lot of construction work was performed close to streams, and it seems that the distance is a dominant factor here. The surfaces of unpaved roads can route fine sediments to streams, lakes, and wetlands, increasing the turbidity of the waters (Reid and Dunne, 1984). Additionally, the shallow lakes in catchments #2 and #3 may be affected by wind with enough power to mix up sediments from shallow areas close to the shore of lakes (Van Berkel et al., 2020). Also, seasonal maps of turbidity are shown in (Fig. S1-S20).

3.2 Chlorophyll-a estimation by S2A

The concentration of chlorophyll-a in water resources indicates the accumulation of phytoplankton. Chlorophyll-a level is a primary symptom for the biochemical status of the water and increase of algae biomass (Vinh et al., 2019). High level of chlorophyll-a indicates high number of phytoplankton and free-floating macroalgae. The concentration of chlorophyll-a in water is affected by the load and bioavailability of nutrients (Anzecc, 2000). Higher water temperature and elevated light levels can also elevate the chlorophyll-a levels (Brewin et al., 2019). However, the relationship between construction activities and the chlorophyll-a level remains to be considered. The seasonal variation of chlorophyll-a in different catchment areas derived from the S2A satellite data is mapped in Fig. 8. As shown, a general trend is detectable in Fig. 8, in which the average chlorophyll-a in warm seasons is higher than that in cold seasons, and the highest average chlorophyll-a level in most catchment areas occurred in spring followed by summer, and the lowest values of the average chlorophyll-a levels are related to the autumn season. Variations in temperature and light intensity are the main reasons for the observed variations in chlorophyll-a concentrations. Also, the highest variation in the average seasonal chlorophyll-a level was in spring and fall, respectively. In general, the concentration of chlorophyll-a in roadside water bodies during road operation was higher than during construction time. Assuming the same climatic situation for the site, it is suggested that higher loads of nutrients were flushed into water bodies by highway runoff during road operation compared to the construction period.

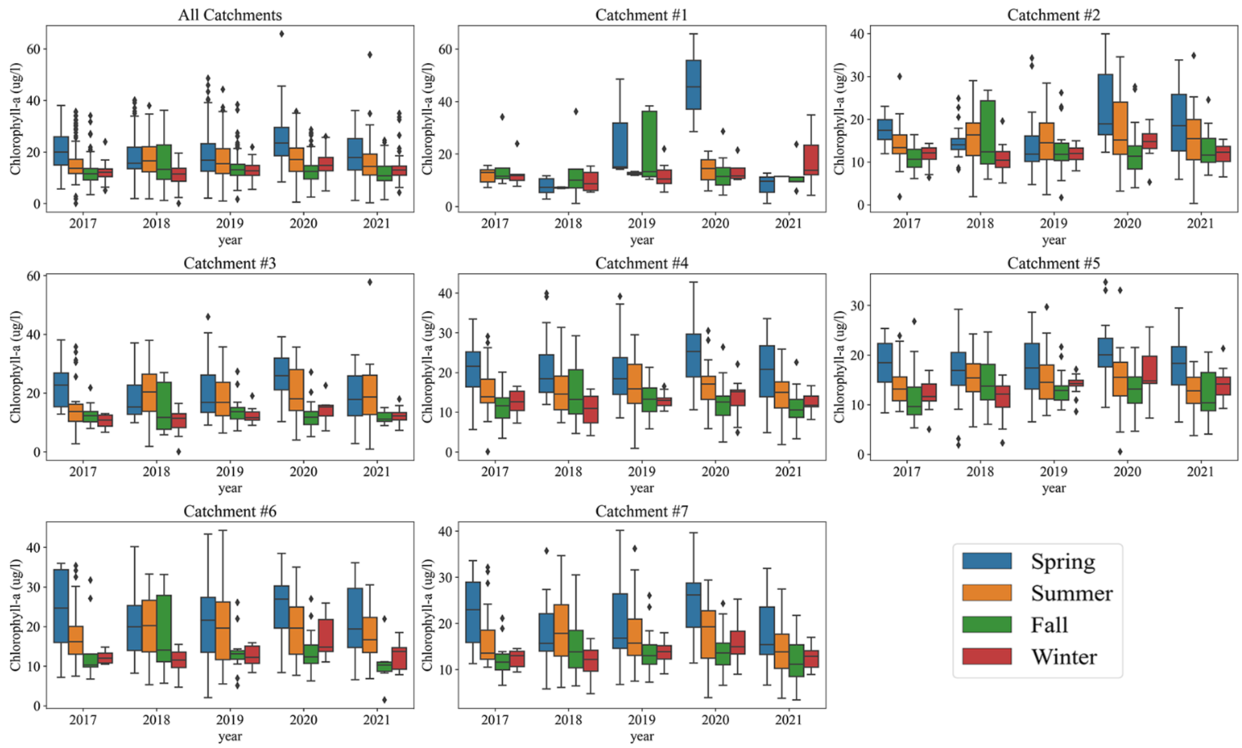

Fig. 8 The seasonal chlorophyll-a variation in different catchments derived from Sentinel-2A satellite data.

In Fig. 8, the highest values of average chlorophyll-a in the selected period (2017-2021) were estimated in spring 2020. As mentioned before, high levels of turbidity can reduce chlorophyll-a concentration (Wass et al., 1997). With that in mind, the Sentinel-2A estimations are consistent with the field observations. It means that the particle impact, which was significant during the construction phase, sharply reduced in 2020 in most roadside water bodies, which may have contributed to increased chlorophyll-a concentrations. The levels of turbidity and the suspended matter returned to the levels measured during the pre-construction period (2015-2016) (Nye-Veier, 2021). Also, the report adds this point that in 2020, the nitrogenous nutrient compounds (NO_3-N, NH_4-N, total-N), and especially nitrate, were still elevated in most water bodies compared to pre-construction and construction periods. In water bodies, degradation of dead plant material can lead to increased levels of phosphorus, and the increase appears to be correlated with particulate runoff from the catchment areas (Nye-Veier, 2021). Elevated levels of bioavailable nutrients (nitrogen and phosphorous) will stimulate algae growth and chlorophyll-a production in water bodies.

There were no direct field measurements of chlorophyll-a during road construction and operation. However, relying on the calibration results and comparing the trends with field observations (e.g., the nutrients and algae level) it could be concluded that the performance of the RS in detecting chlorophyll-a in roadside lakes is also reliable. For instance, in catchment #1, there was strong algae growth during 2020. This is in line with the rise in chlorophyll-a level in periods of 2020 estimated by Sentinel-2A. Also, the average chlorophyll-a in catchment #3 increased from 2017 to 2018 according to Sentine-2A data. Correspondingly, field observations indicated that the main and side streams in 2018 were negatively affected by physical interventions, diffuse runoff from buildings and agriculture, and the concentration of nutrients, including total phosphorus, in both the main course and side streams were elevated compared to 2017 observations (Nye-Veier, 2019, 2018). Another example is catchment #4 that the concentration of average chlorophyll-a increased from 2017 to 2018. Based on in-situ observations, the content of total nitrogen in this catchment increased in 2018 compared to previous years (2015-2017), and algae conditions in 2018 got worst compared to that in 2017 (Nye-Veier, 2019). In catchment #6, the values of phosphorus and nitrate significantly elevated in 2018 compared to 2017. Also, field measurements confirm that the content of turbidity and suspended matter generally decreased in 2018 compared to 2017 (Nye-Veier, 2019, 2018). These factors can increase the concentration of chlorophyll-a in water bodies, as it is also visible in Fig. 8 that the average level of chlorophyll-a estimated by S2A has increased in this period. In 2020, there was a clear growth of algae and a lot of algae was observed in the streams in 2020 than in previous years. This fact is captured by S2A estimations in the form of an increased level of chlorophyll-a for 2020 in Fig. 8.

The temporal variation of chlorophyll-a level in various buffers, i.e., 50, 200, and 1000 m from the central line of the road and in all seven catchments, are presented in Fig. 9. In this figure, by increasing the distance from the central line of the road up to 200 meters, the average values of chlorophyll-a increased in almost all catchments. This might be explained by the hydrological effects of the streams that get the road runoff and pollution from cattle grazing areas and can influence the downstream area (Forman and Alexander, 1998).

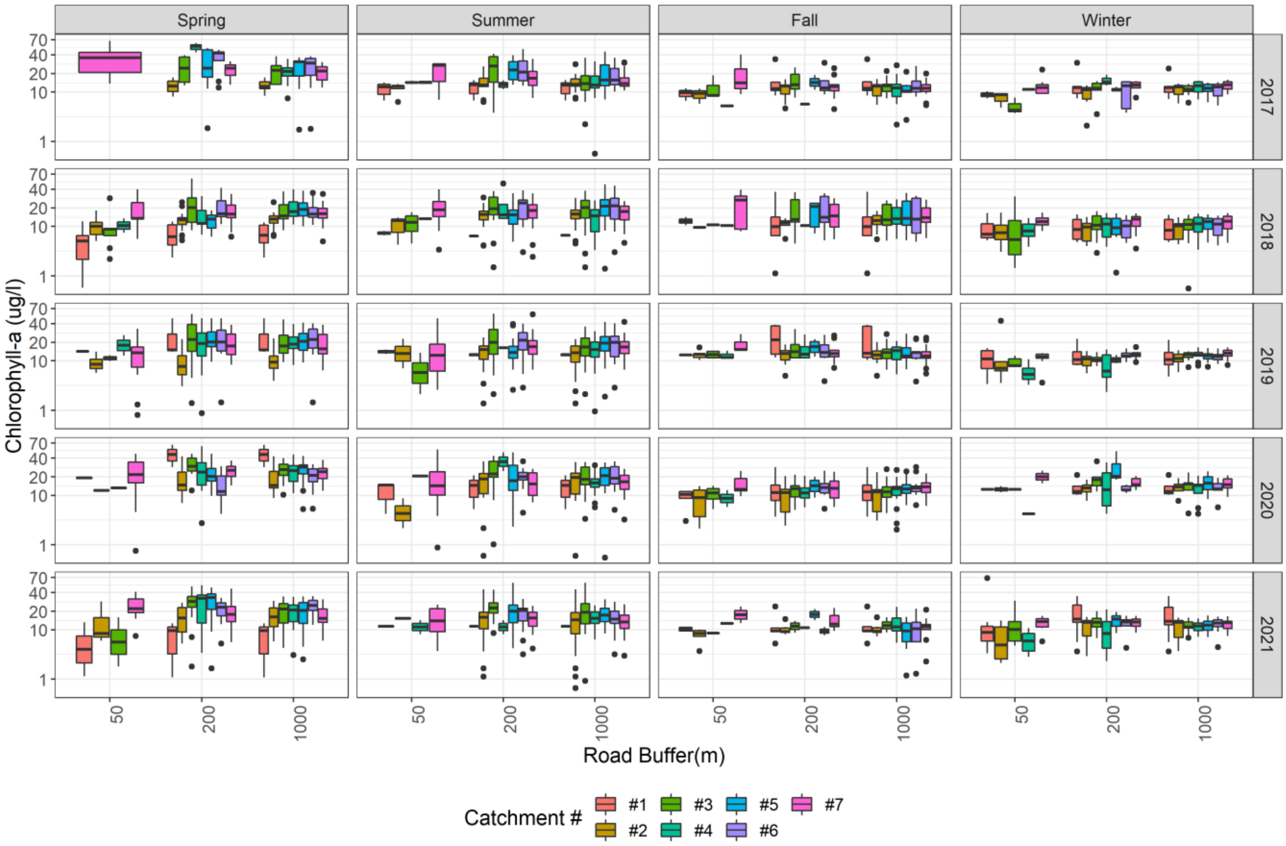

Fig. 9 The seasonal variation of chlorophyll-a in catchments in various buffer zones derived from Sentinel-2A satellite data

Regardless of the distance from the central line of the road in Fig. 9, the variation of chlorophyll-a in spring and summer is more than in other seasons. It seems that the effect of each specific road construction activity, traffic load and erosion on the chlorophyll-a level should be investigated in future studies. Pollutants from roads will affect the nearby chemical environment (e.g., nutrient), which again affects the terrestrial environment. For example, in some woody plants, it has been shown that the concentrations of terpenoids (which is a chemical produced by plants to resist the toxic effects of pollution) (Akimov et al., 1989) and salts (Bogemans et al., 1989) increase, and production of soluble protein and chlorophyll-a decrease (Banerjee et al., 1983; Trombulak and Frissell, 2000) when exposed to pollution produced by vehicles ozone or construction activities (Trombulak and Frissell, 2000).

The spatial variation of average chlorophyll-a between 2017 and 2021 in all seven catchments is demonstrated in Fig. 10. As shown, the NDCI and calibration process were applicable to estimate chlorophyll-a variation on a precise resolution (10 m). The concentration of chlorophyll-a in catchments #5, #6, and #7 is higher than that in other catchments. These elevated values could be associated with the lower turbidity concentration in the same period, as demonstrated in Fig. 7. As shown in Fig. 10, the concentration of chlorophyll-a in water close to the shorelines is lower than that in central areas of the waterbodies. Based on some previous researches, the chlorophyll-a concentration in the roadside terrestrial plants species considerably decreases during the construction period compared to the operation period due to the lower photosynthesis rate in plants near the road (Sarma et al., 2017; Pourkhabbaz et al., 2010; Keller and Lamprecht, 1995). However, the density of vegetation cover (e.g., forest) in the study area limited the solid conclusion from the average chlorophyll-a map (Fig. 10). However, the seasonal maps of chlorophyll-a (Fig. S21-S40) show that in construction periods of the road (2017-2019), the chlorophyll-a concentration is lower than that in operation periods (2020 and 2021). During road construction, nonpoint sources of pollution like nitrate from explosions may discharge in a limited time and location. However, during road operation due to continuous traffic load, the discharge of pollution is non-point and continuous (e.g., air pollution) and may change the aquatic organism by increasing nutrients and sediment leaches from the road for a long time of operation to aquatic ecosystems (Trombulak and Frissell, 2000).

Additionally, the spring and summer seasons have higher chlorophyll-a values compared to winter and fall, which is rooted in the photosynthetic activity of plants in warmer and lighter seasons. These estimations are in line with the seasonal analysis of the catchment. Previous studies claim that chlorophyll-a has been affected by dust originating from construction activities (e.g., establishing pilot roads, excavation, drilling, blasting, tunnel construction, and pavement). The construction dust is more intense than air pollutions during road operation, and decrease chlorophyll-a concentration (Shyu et al., 2012).

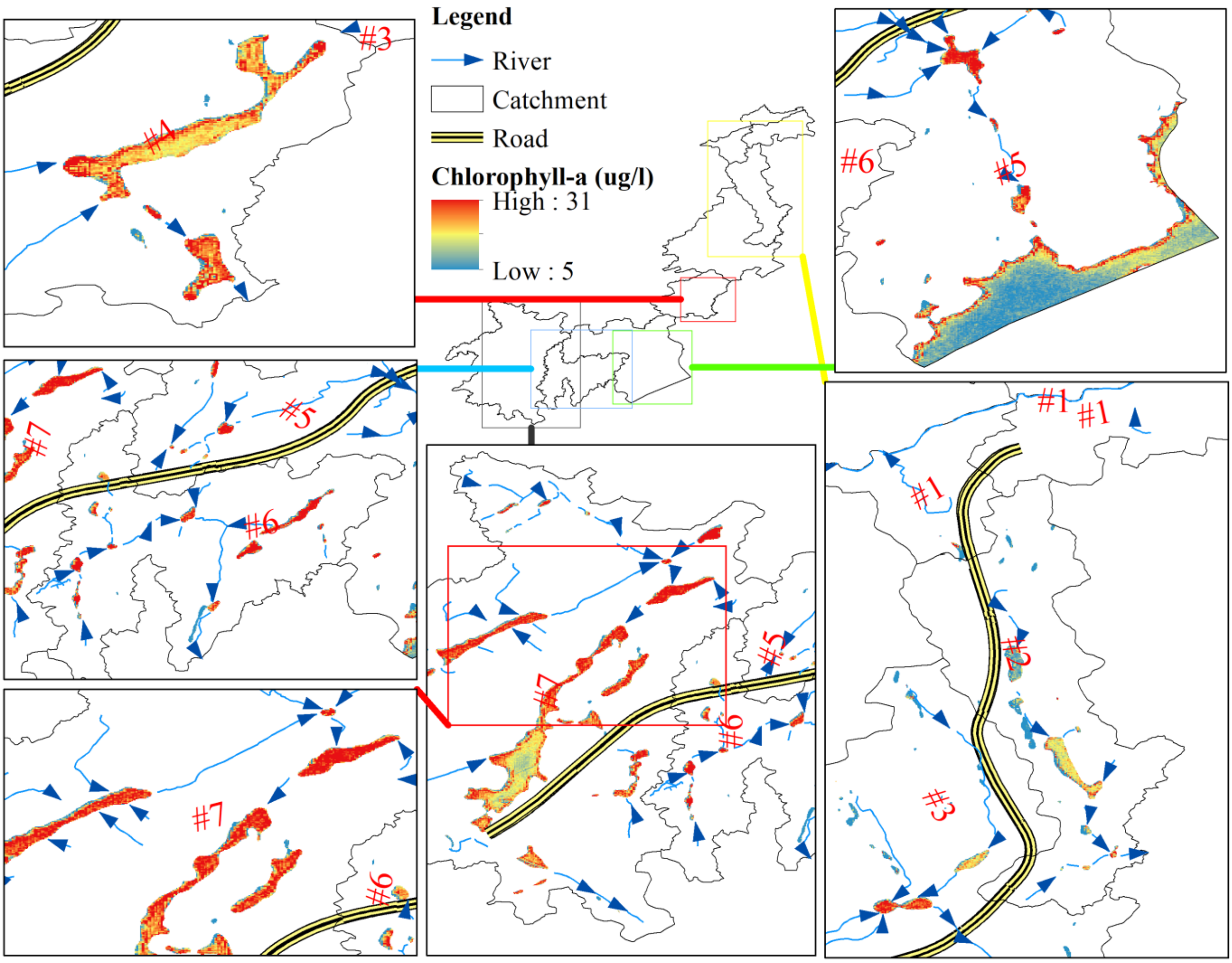

Fig. 10 Spatial maps of average chlorophyll-a values in waterbodies derived from Sentinel-2A satellite data (2017-2021) and flow direction

The results presented here approve the feasibility of satellite data to assess roadside water quality. During road construction and operation, the proposed methodology is efficient because there are not enough ground-based monitoring stations to cover the whole water bodies on a regional scale and along the road path. The methodology could be used for studying impacts of various activities on nearby water bodies, such as pavement activities that may increase turbidity and decrease chlorophyll-a concentrations.

4 Summary and Conclusion

More efficient monitoring of roadside waterbodies during construction work and operation has been proposed by integrating observed data and satellite information. The Sentinel-2 Multi-Spectral Imager (MSI) satellite imagery products were analyzed in the Google Earth Engine (GEE) environment to assess the roadside water quality spatiotemporally. First, the Sentinel-2 MSI images were atmospherically corrected by MAIN algorithms. Then, 115 stations across Norway were analyzed by gauge observations of turbidity and chlorophyll-a to calibrate the remote sensing information. Additionally, the Otsu image segmentation method was used to identify water only pixels, which is in good agreement with observed water bodies. The proposed method applied the B3/B2 bands and the NDCI combinations to calibrate turbidity (R^2 = 0.8 and RMSE = 1.947 FNU) and chlorophyll-a (R^2 = 0.79, and RMSE = 6.869 μg/l), respectively. Finally, proposed empirical equations were used by atmospherically corrected images of Sentinel-2A to estimate turbidity and chlorophyll-a in various buffer zones along the road, and the results were compared to field observations.

This study improves our understanding of the impact of road activities on surface water quality. Hence, the study will be useful for parties involved in planning, construction and operation of road projects, and also for pollution control authorities who are responsible for securing the chemical and biological quality of waterbodies. This research can be continued by developing a machine learning or deep learning model to predict the water quality parameters considering climate change and traffic load. Also, seeing the impact of site-specific uncertainties in modeling and predictions for the future would be a potential direction for further research.

Code and Application Availability

The source codes are available at https://github.com/shahab271069/GEE-Turbidity-Chlorophyll-a-Road/tree/main and an interactive GEE app is available at https://shahab2710.users.earthengine.app/view/roadwaterquality.

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Supplementary Material

Contents

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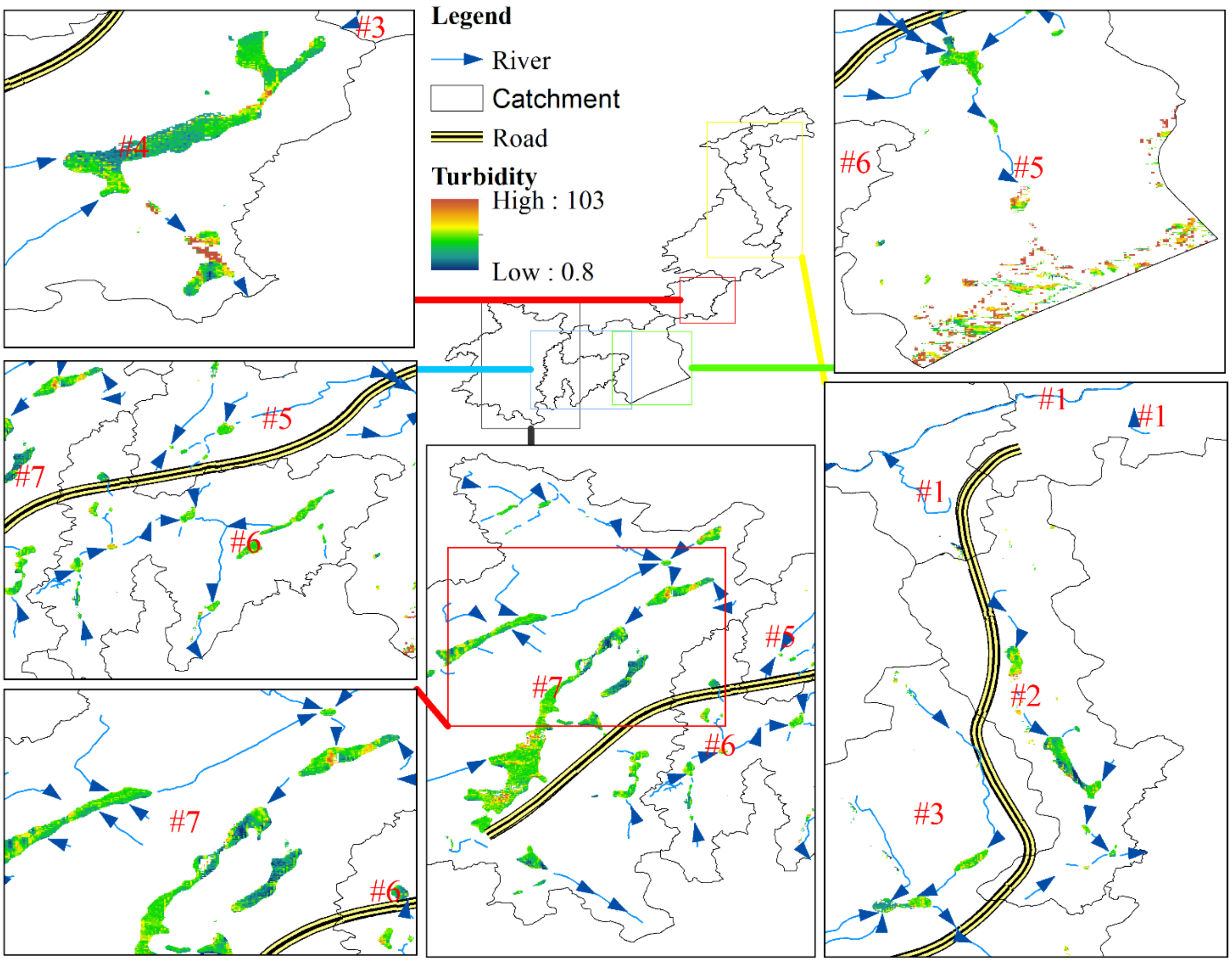
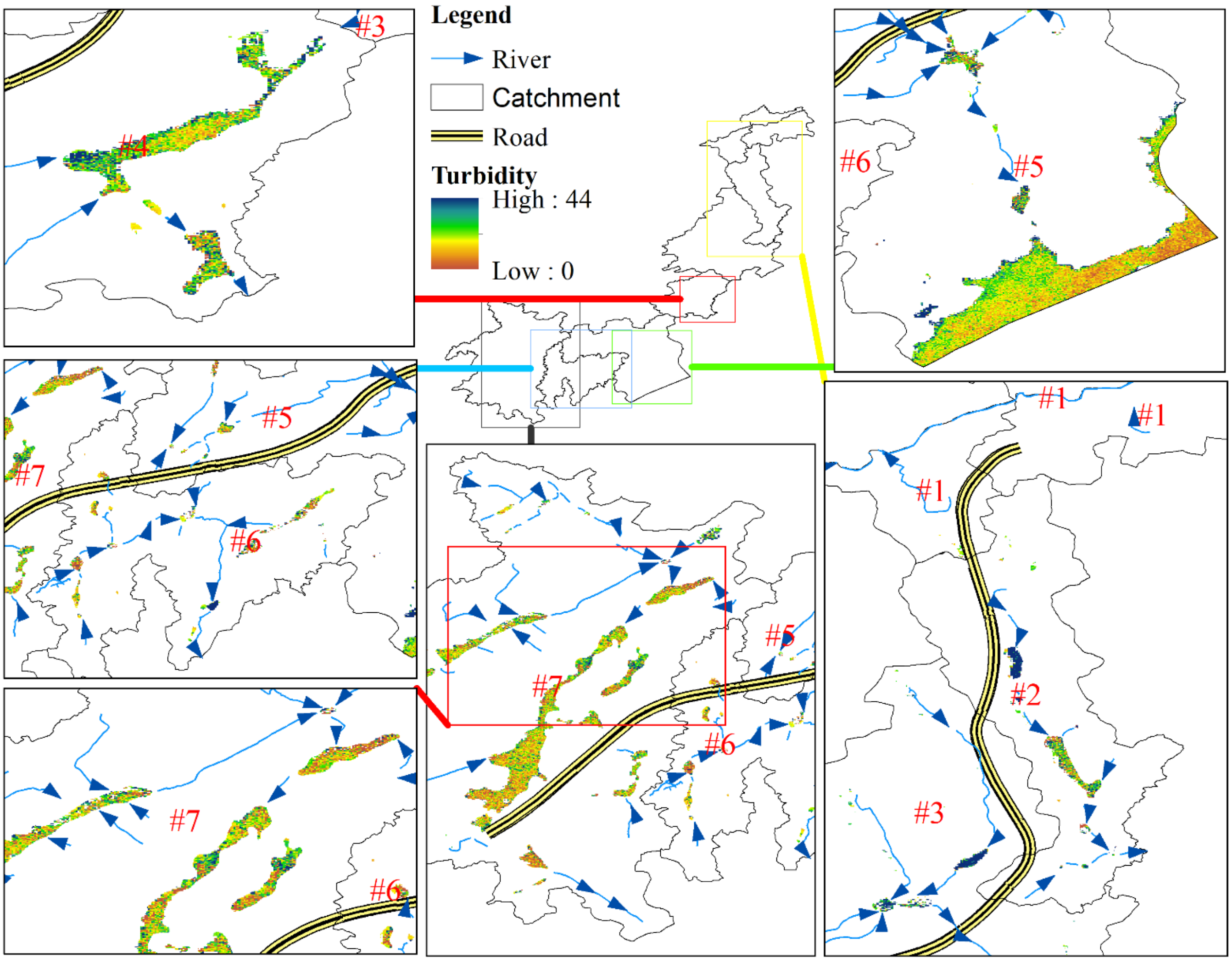


Fig. 1 Average Turbidity 2017 WINTER



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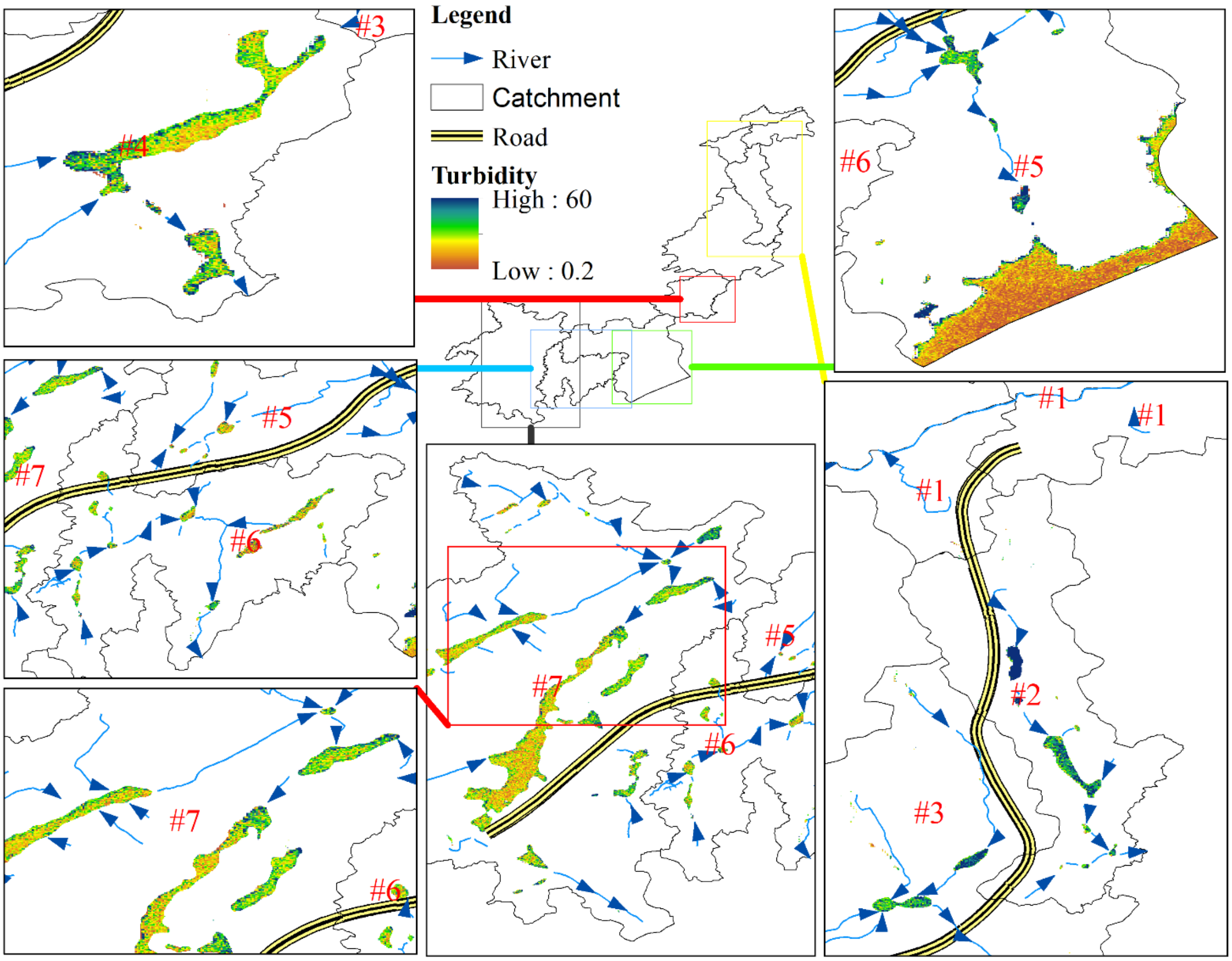

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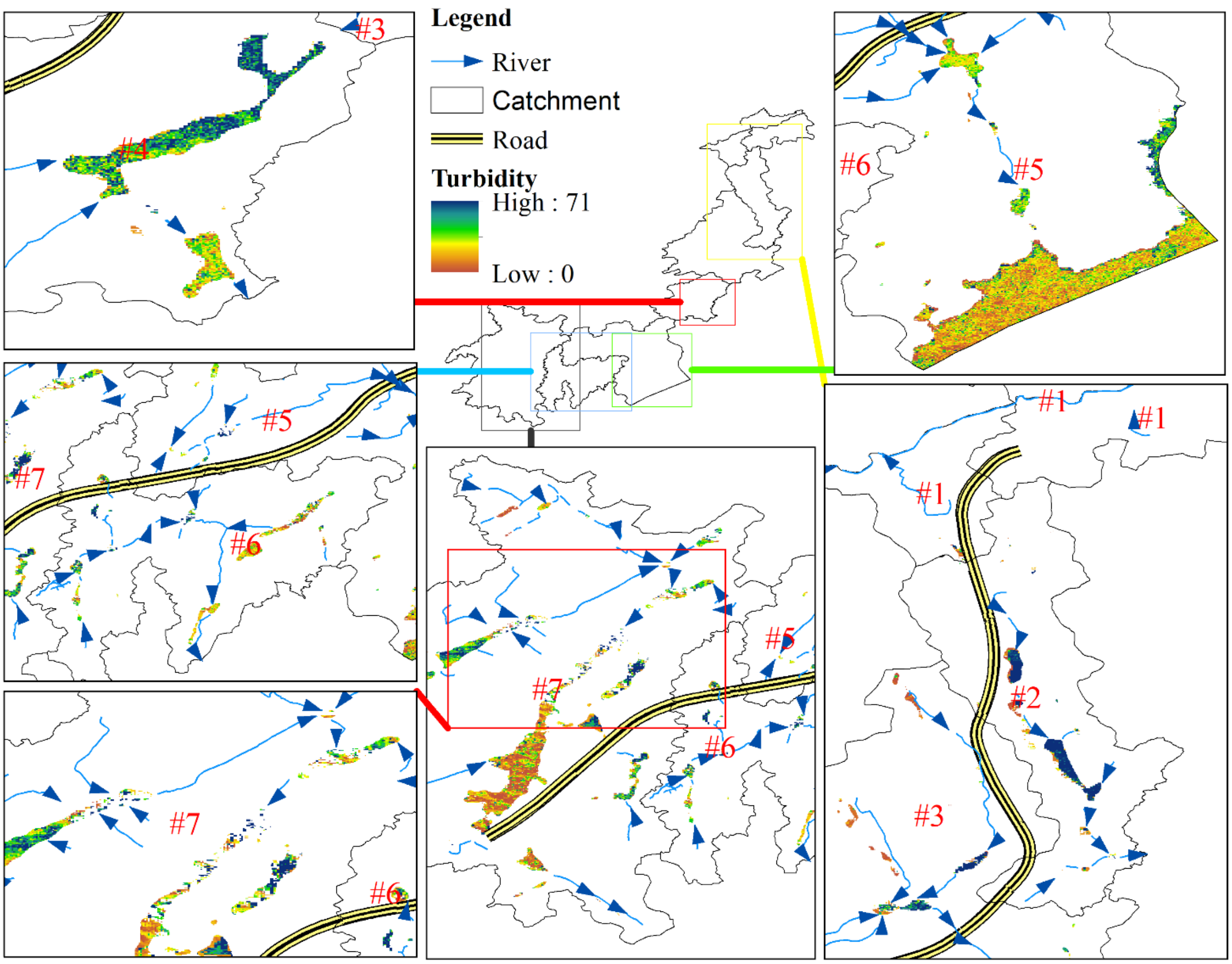

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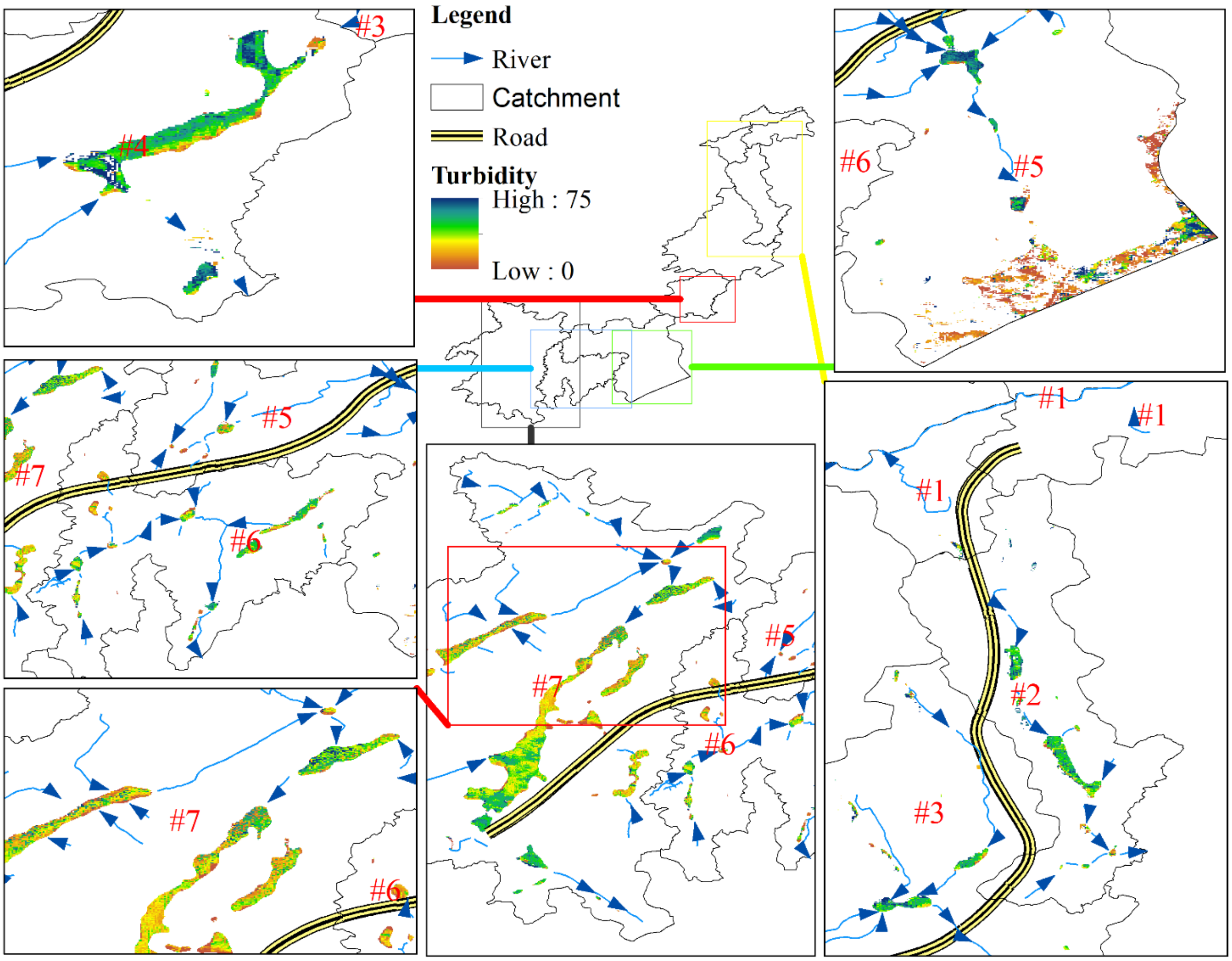

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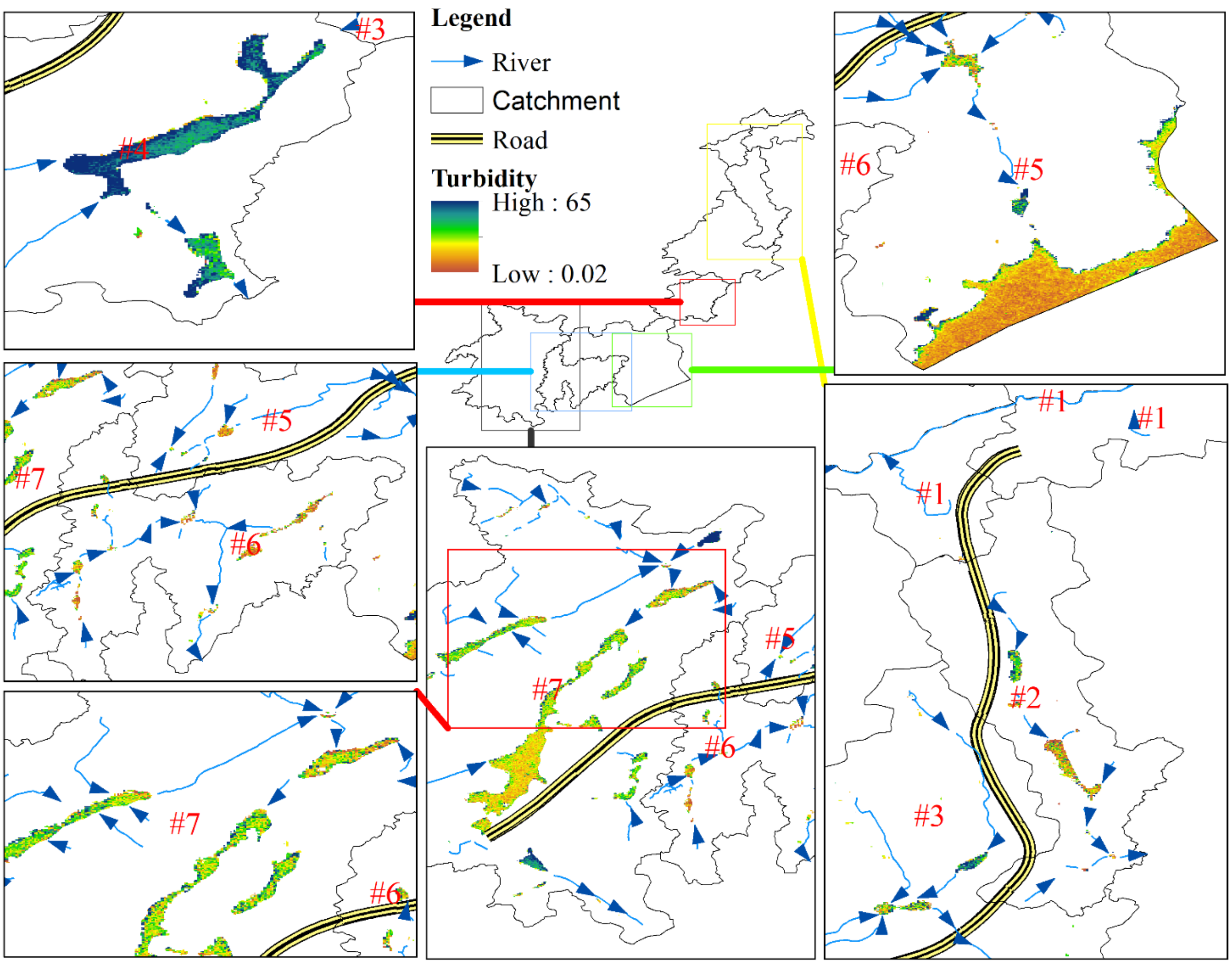

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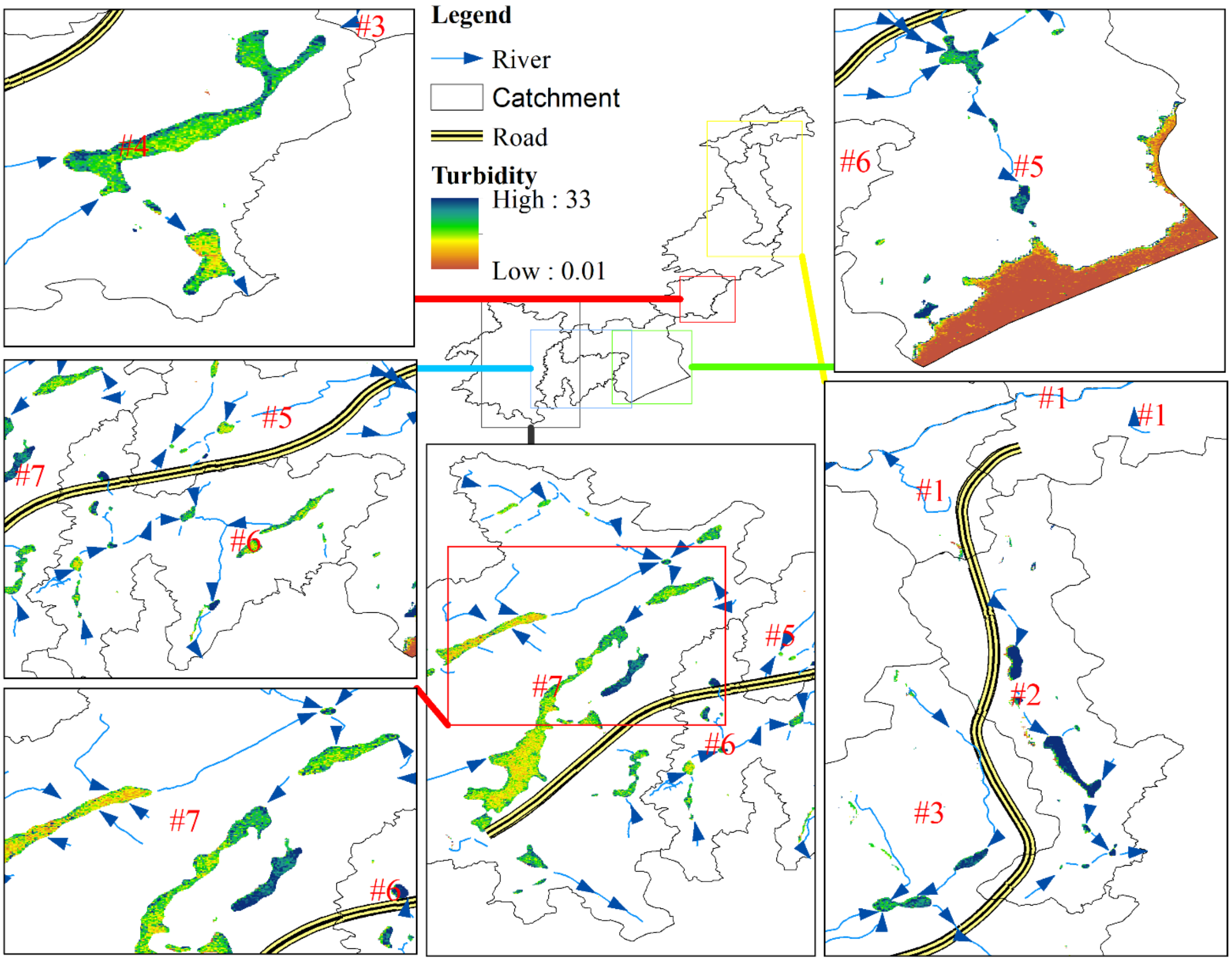

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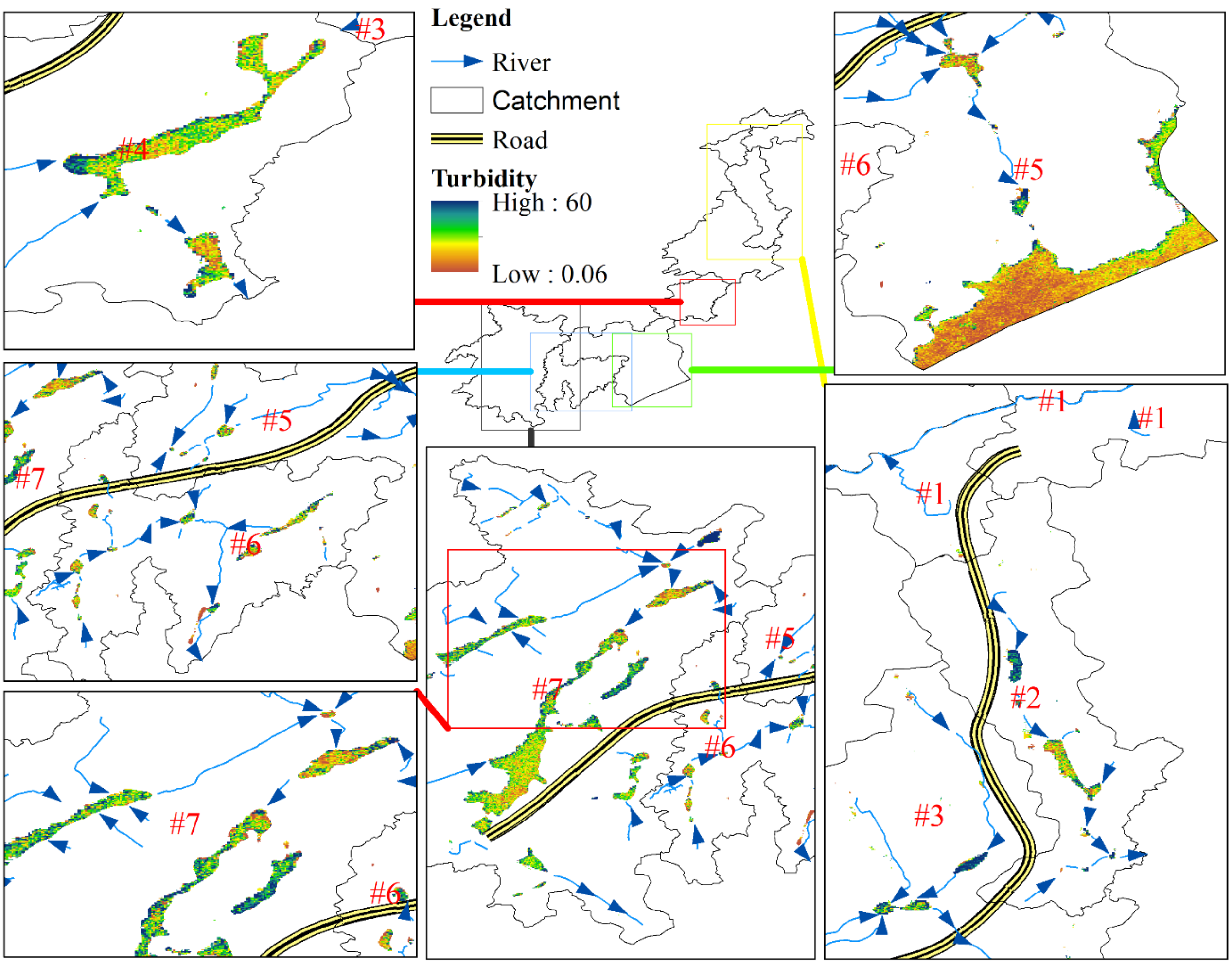

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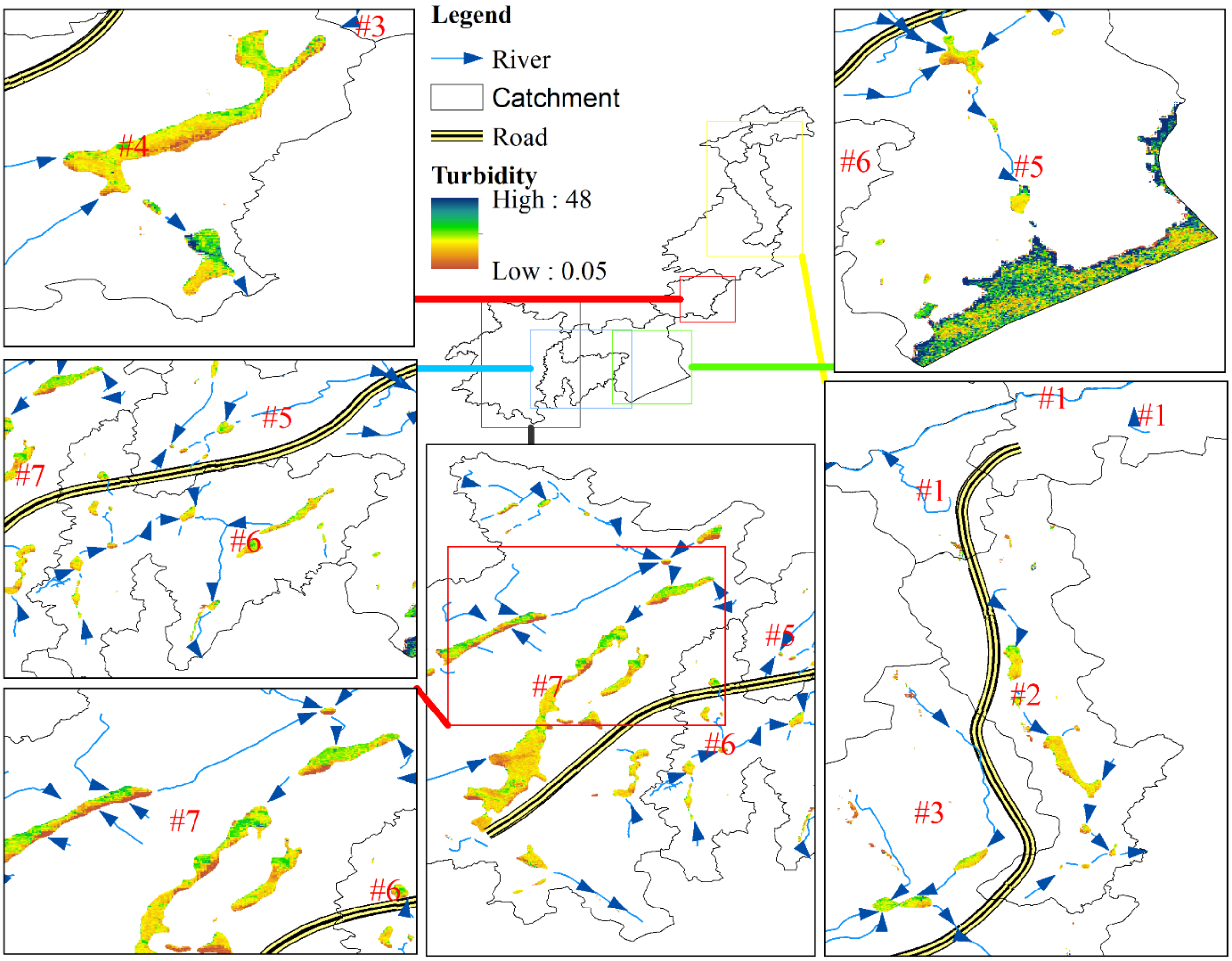

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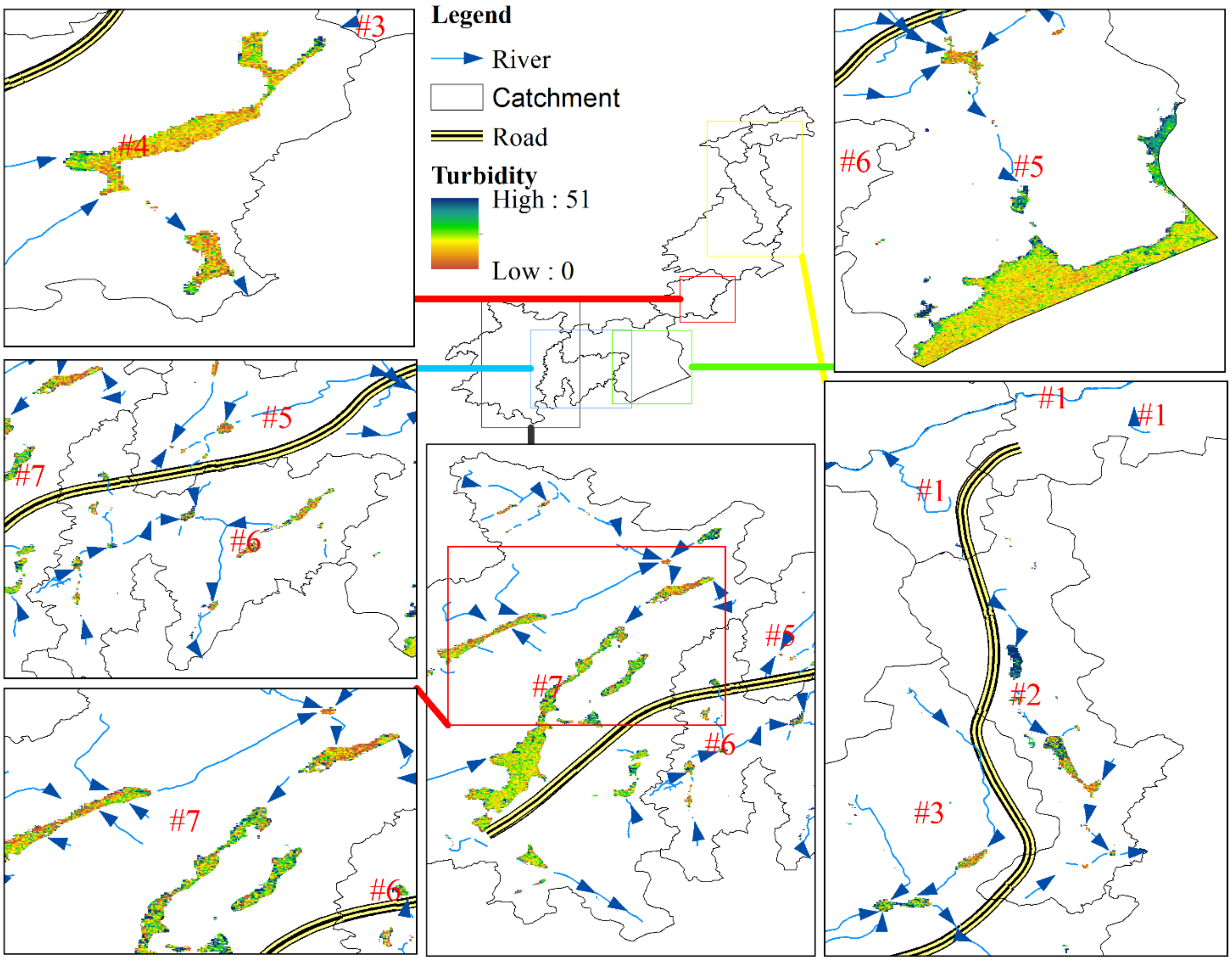

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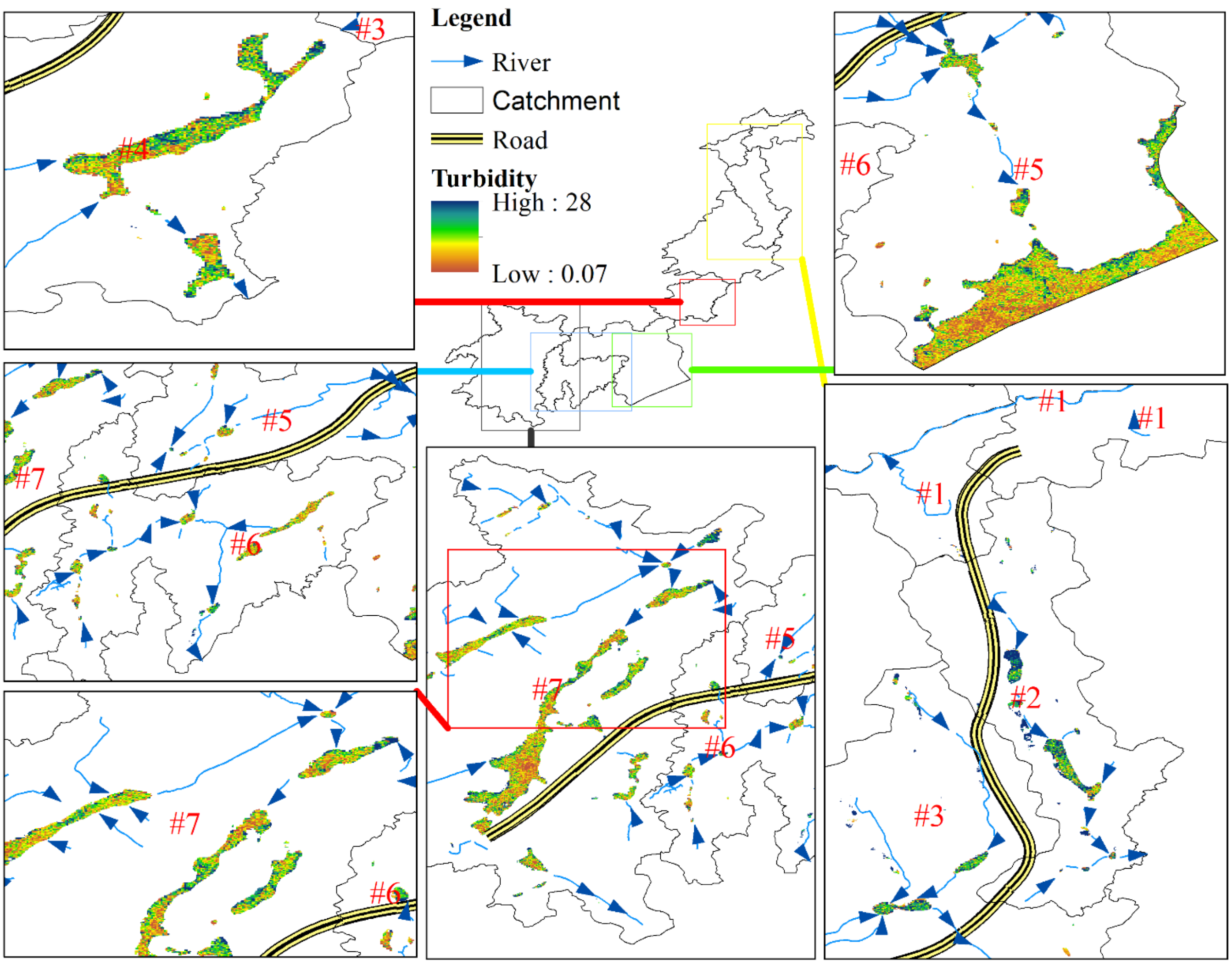

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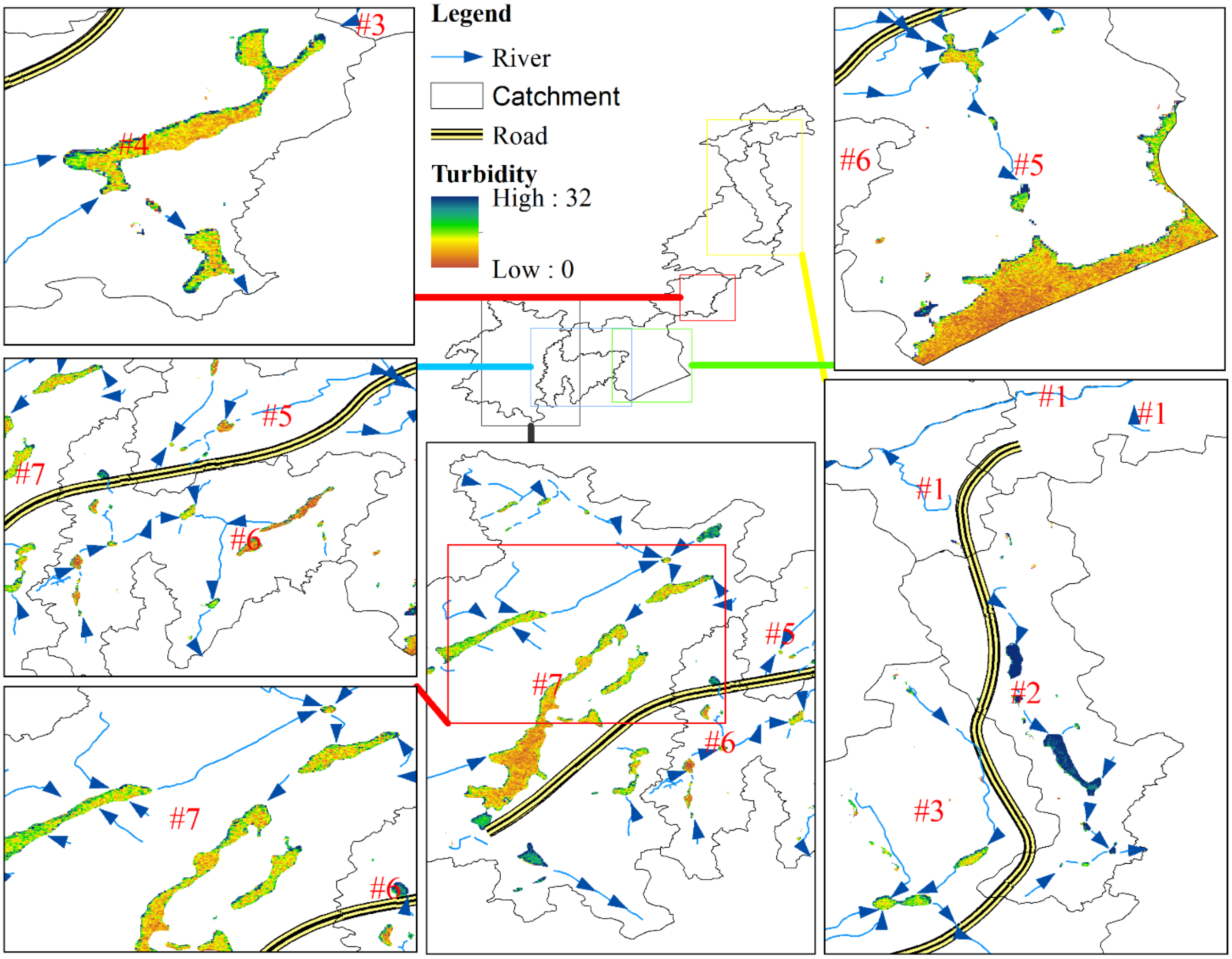

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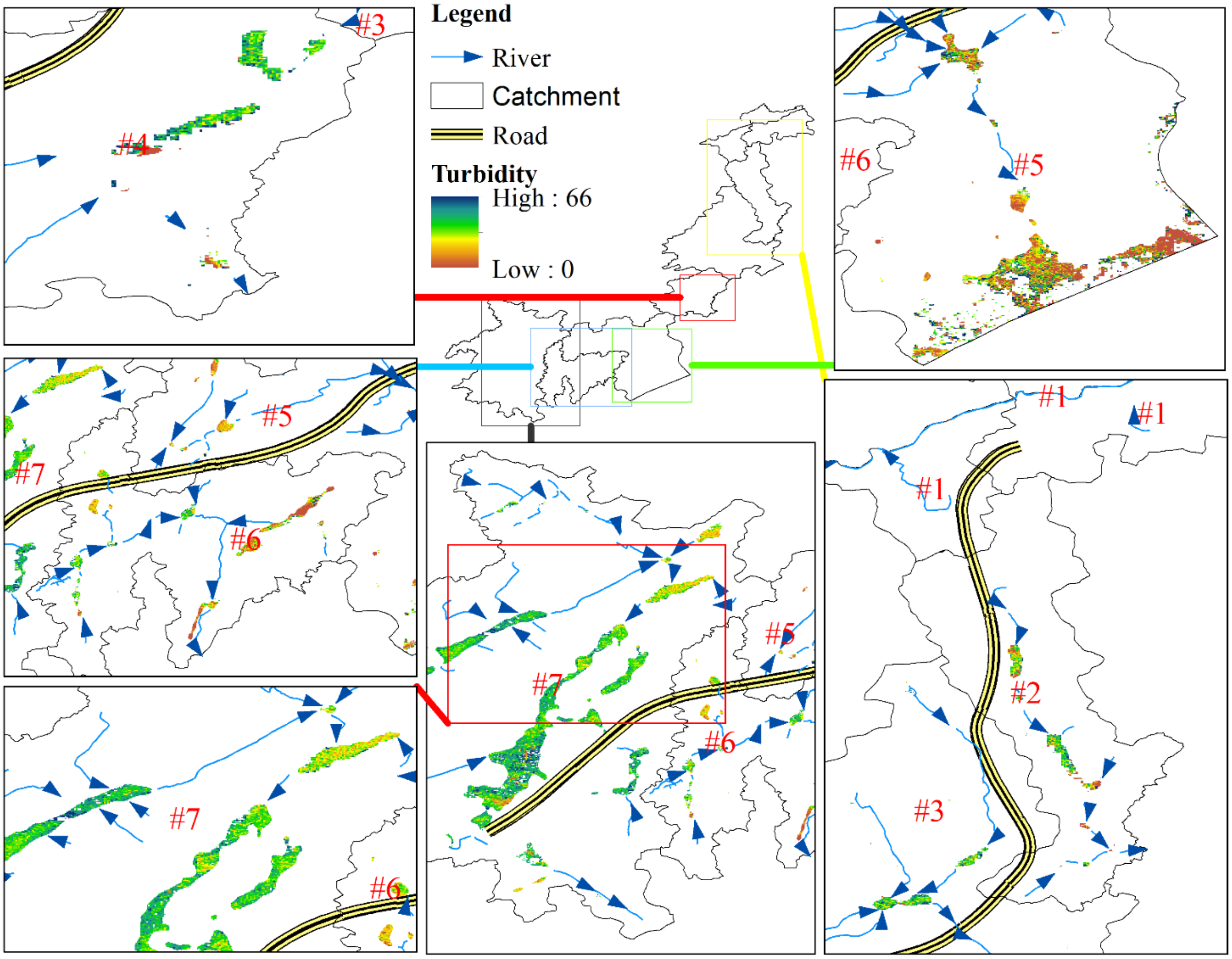

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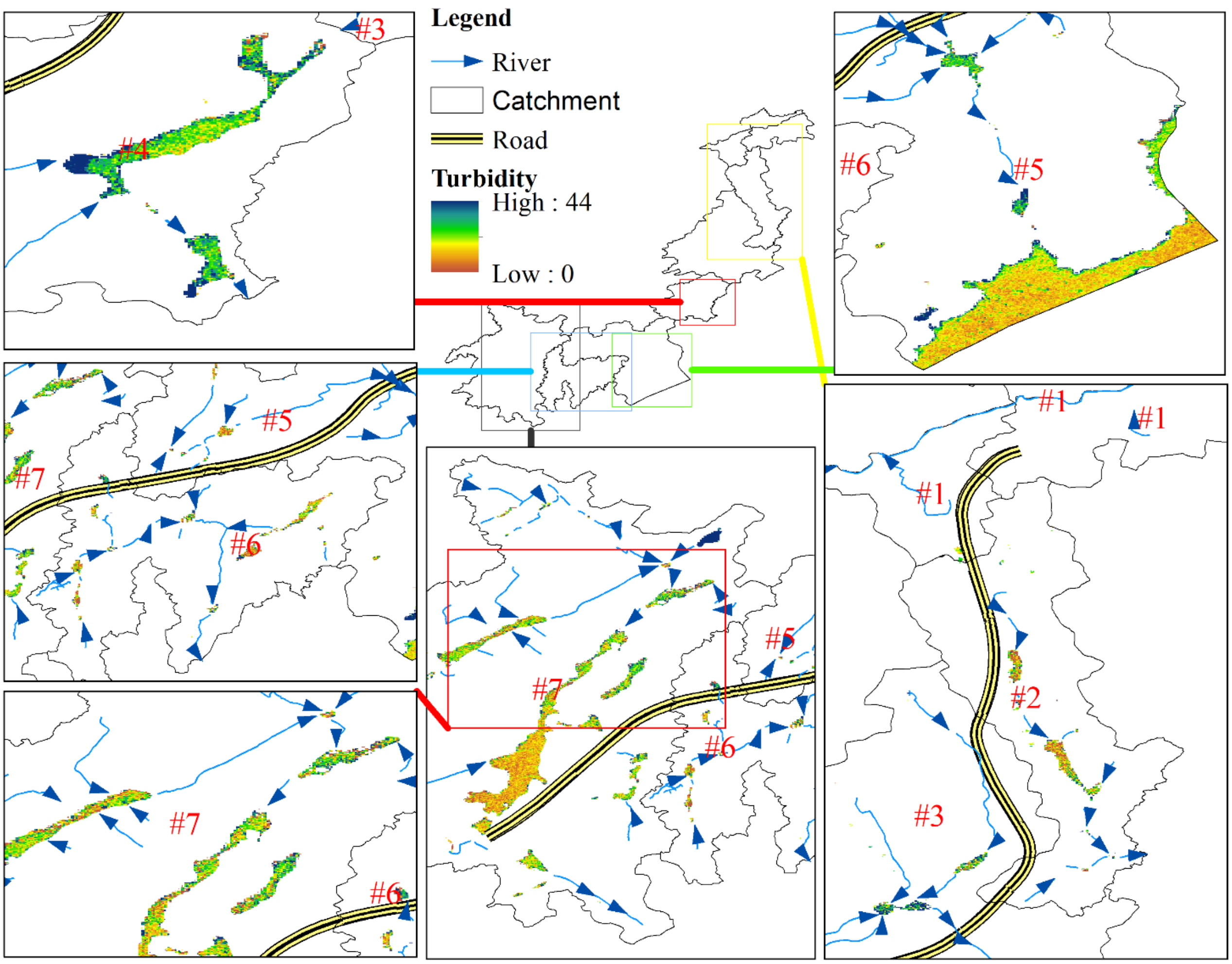

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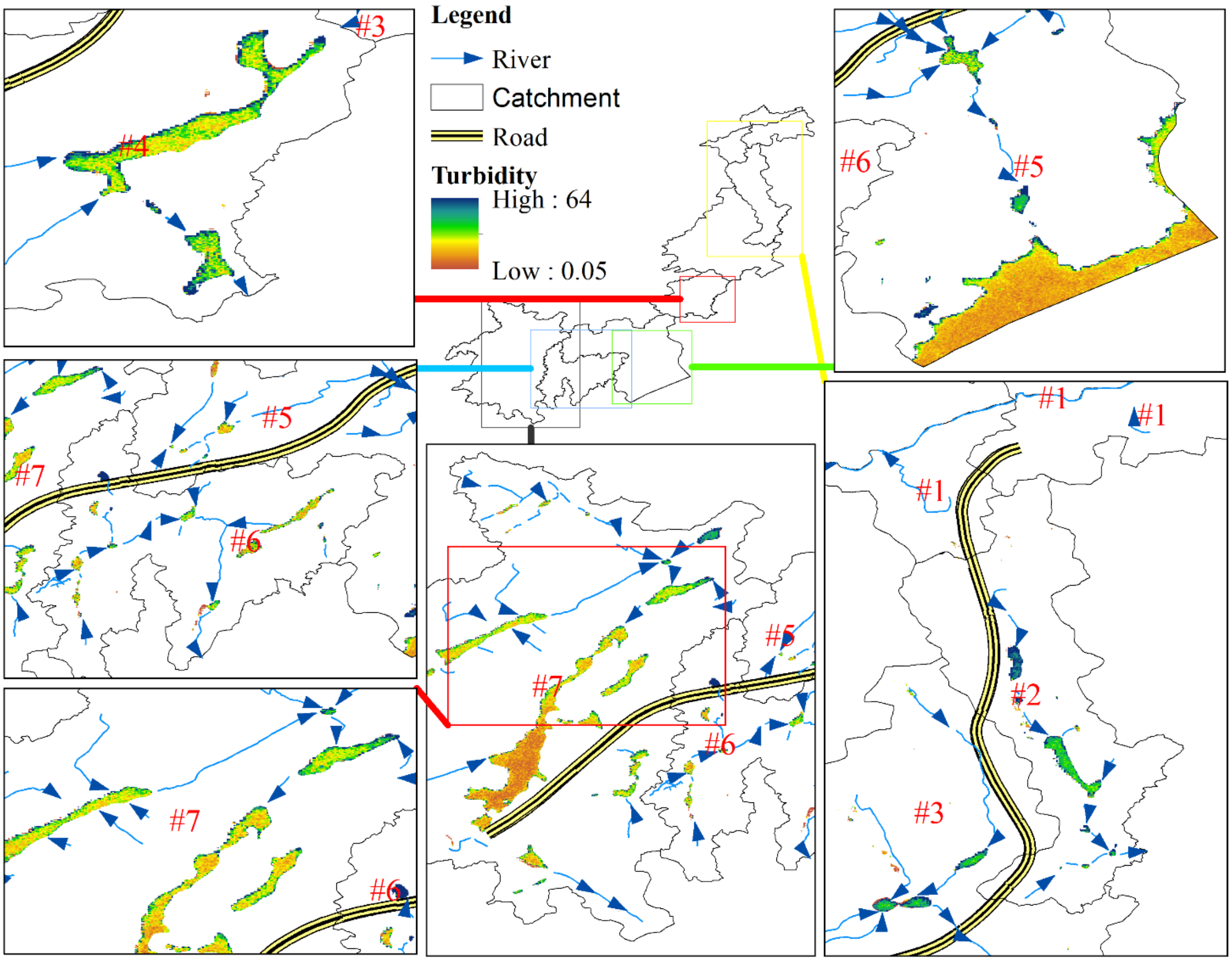

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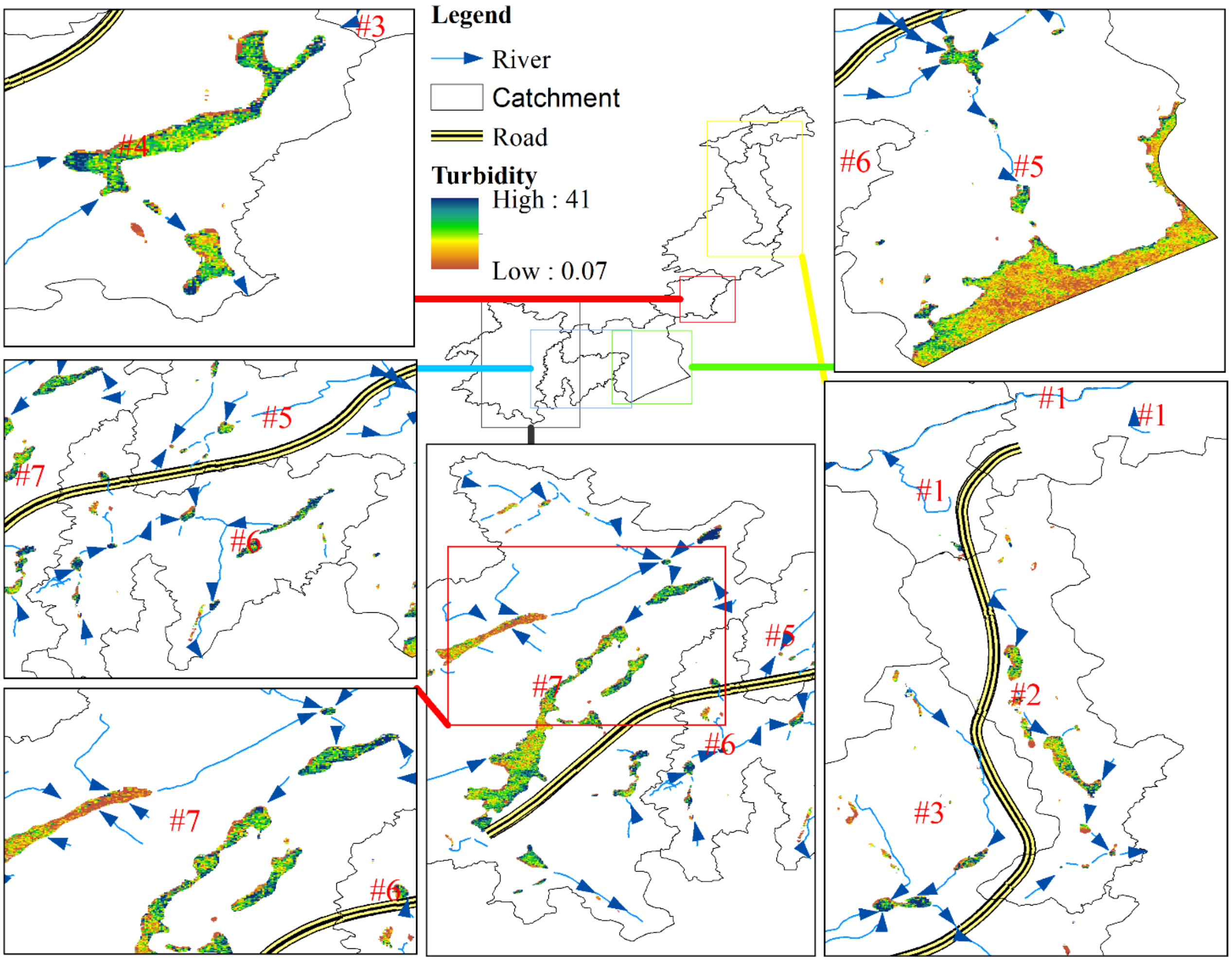

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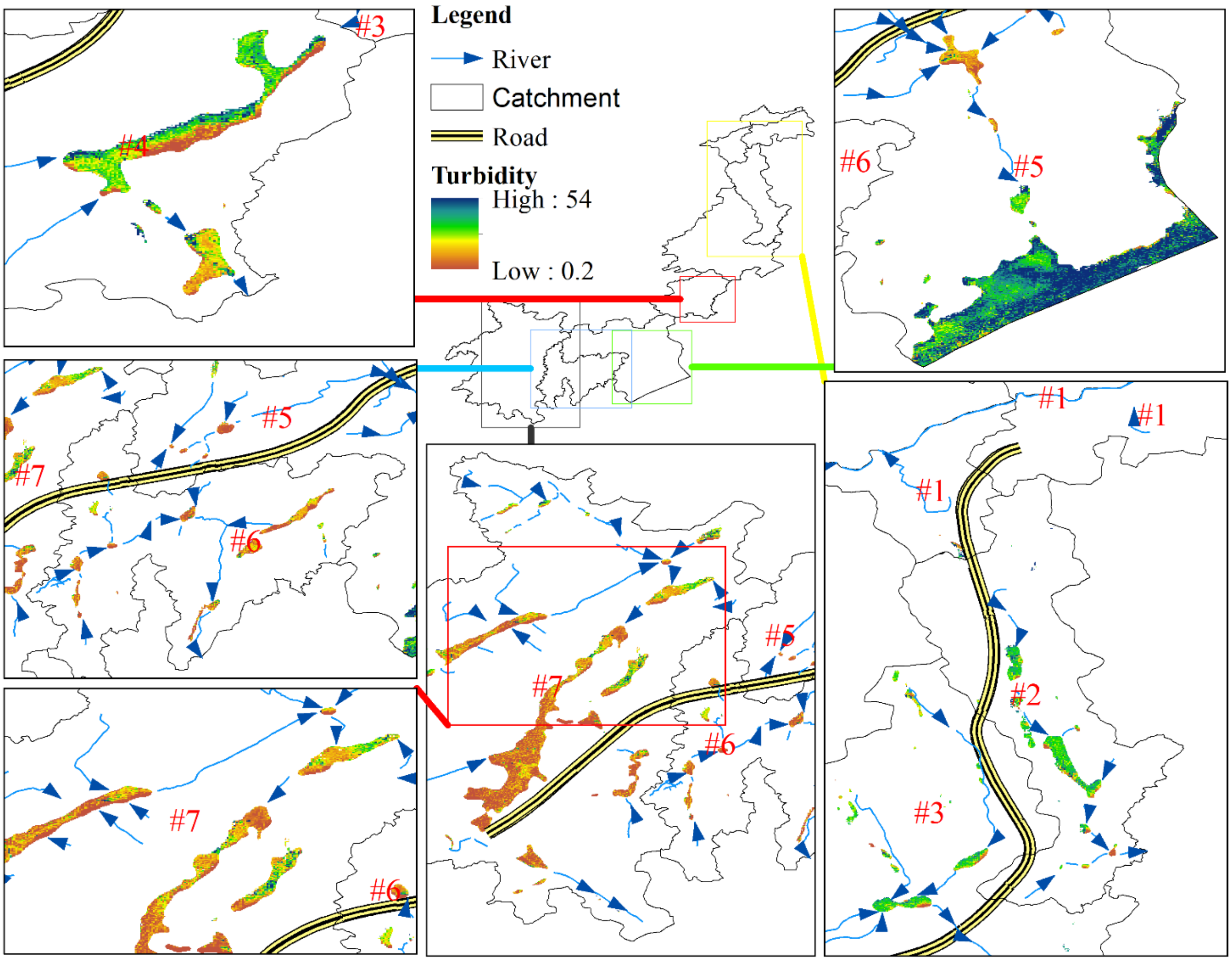

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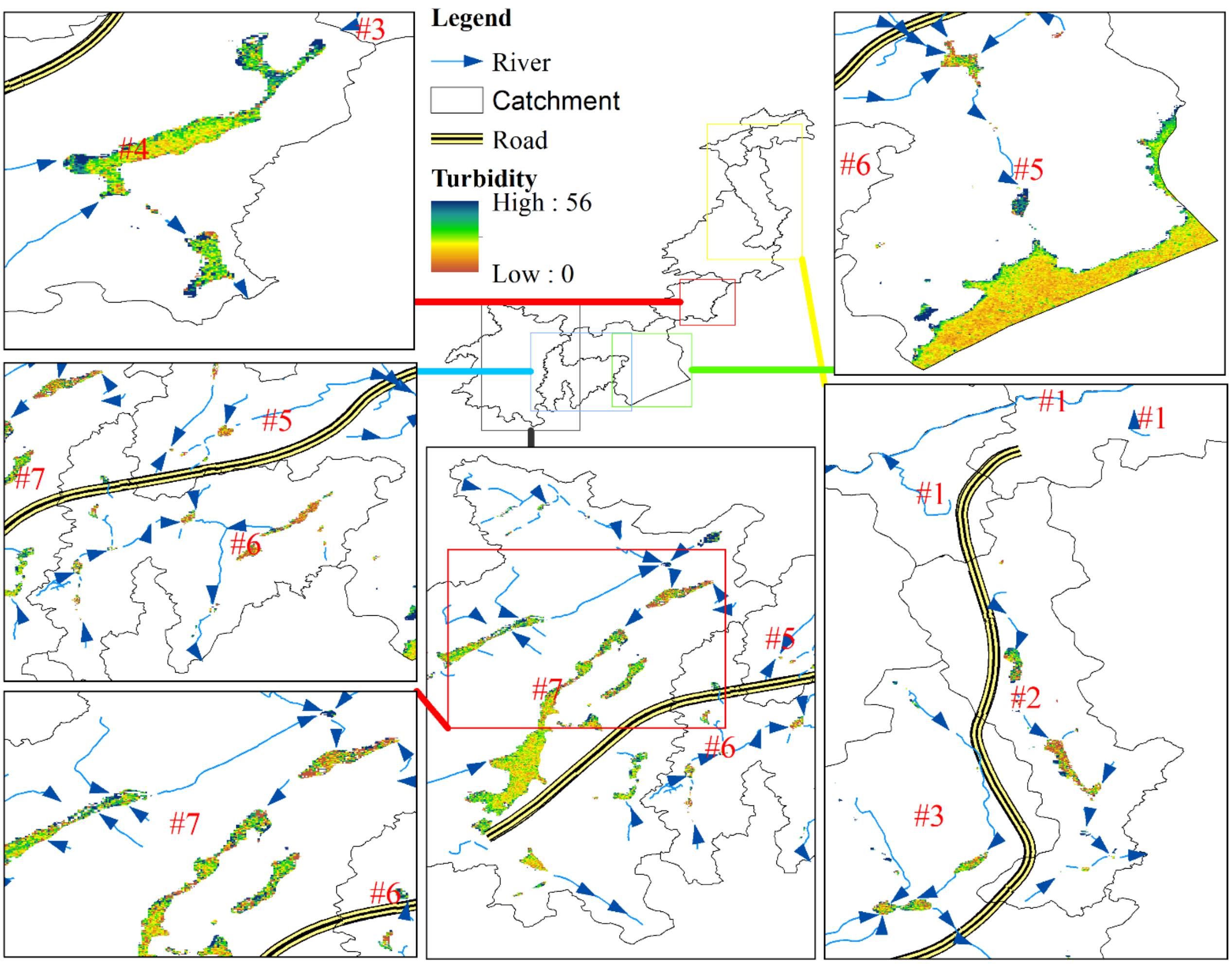

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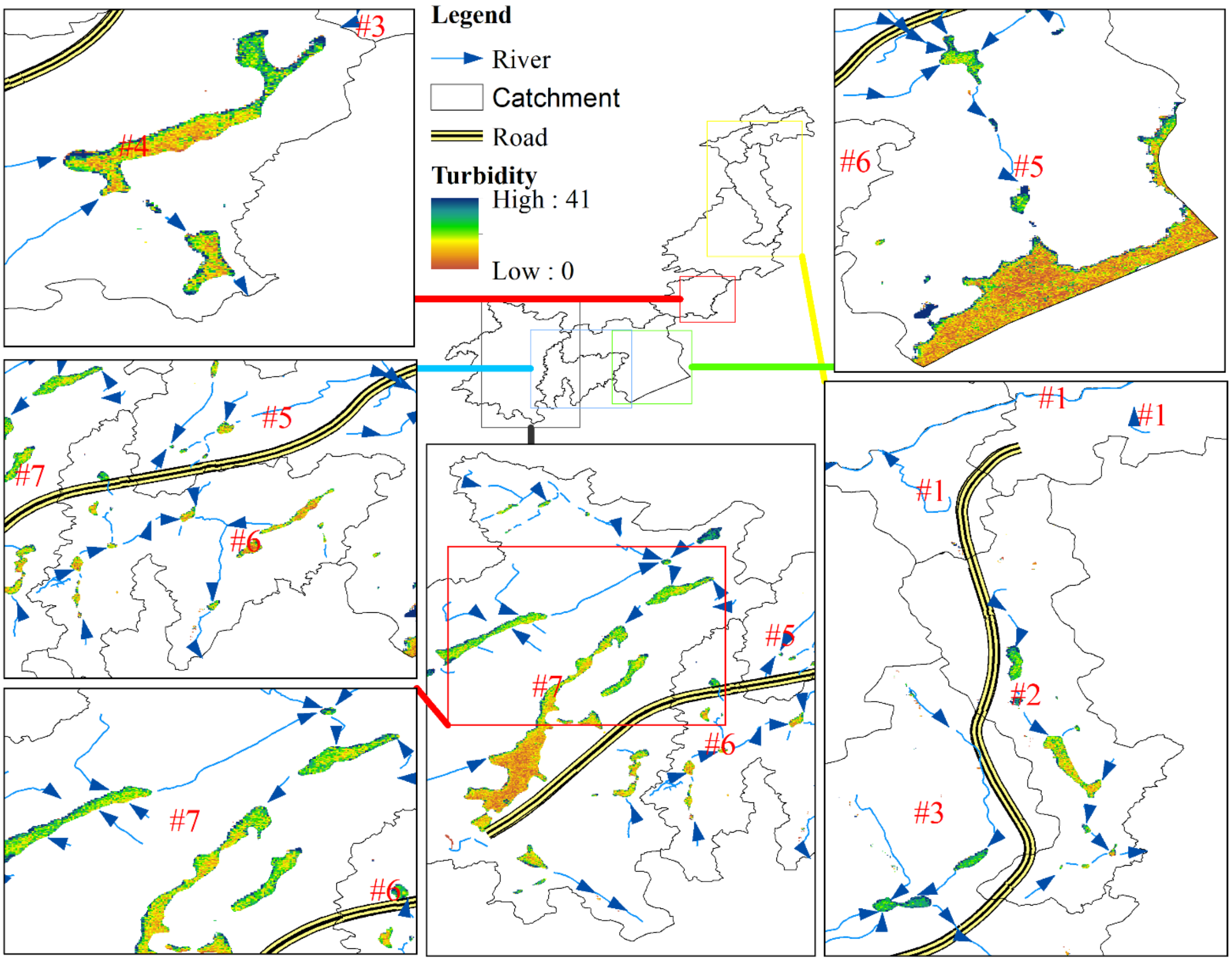

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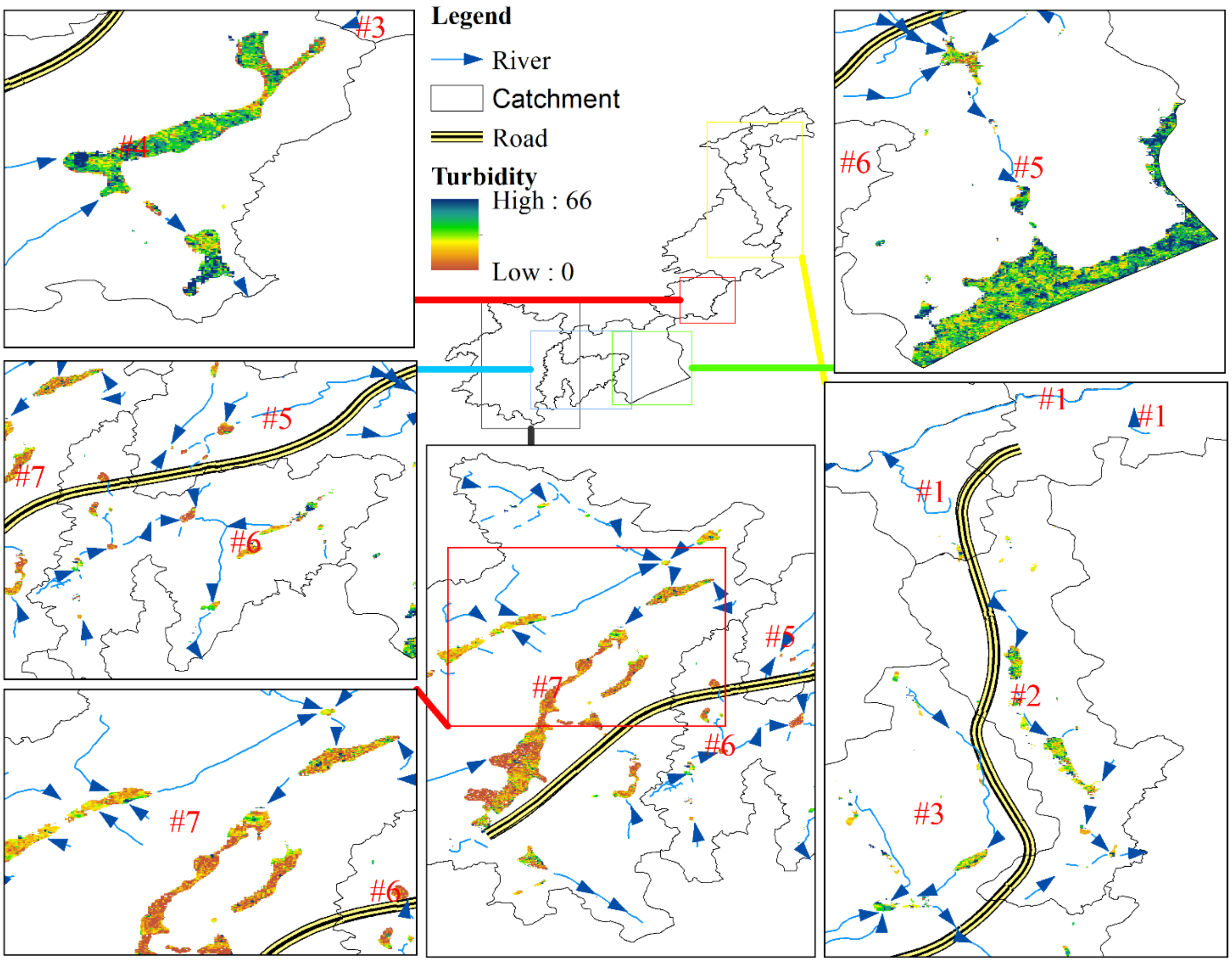

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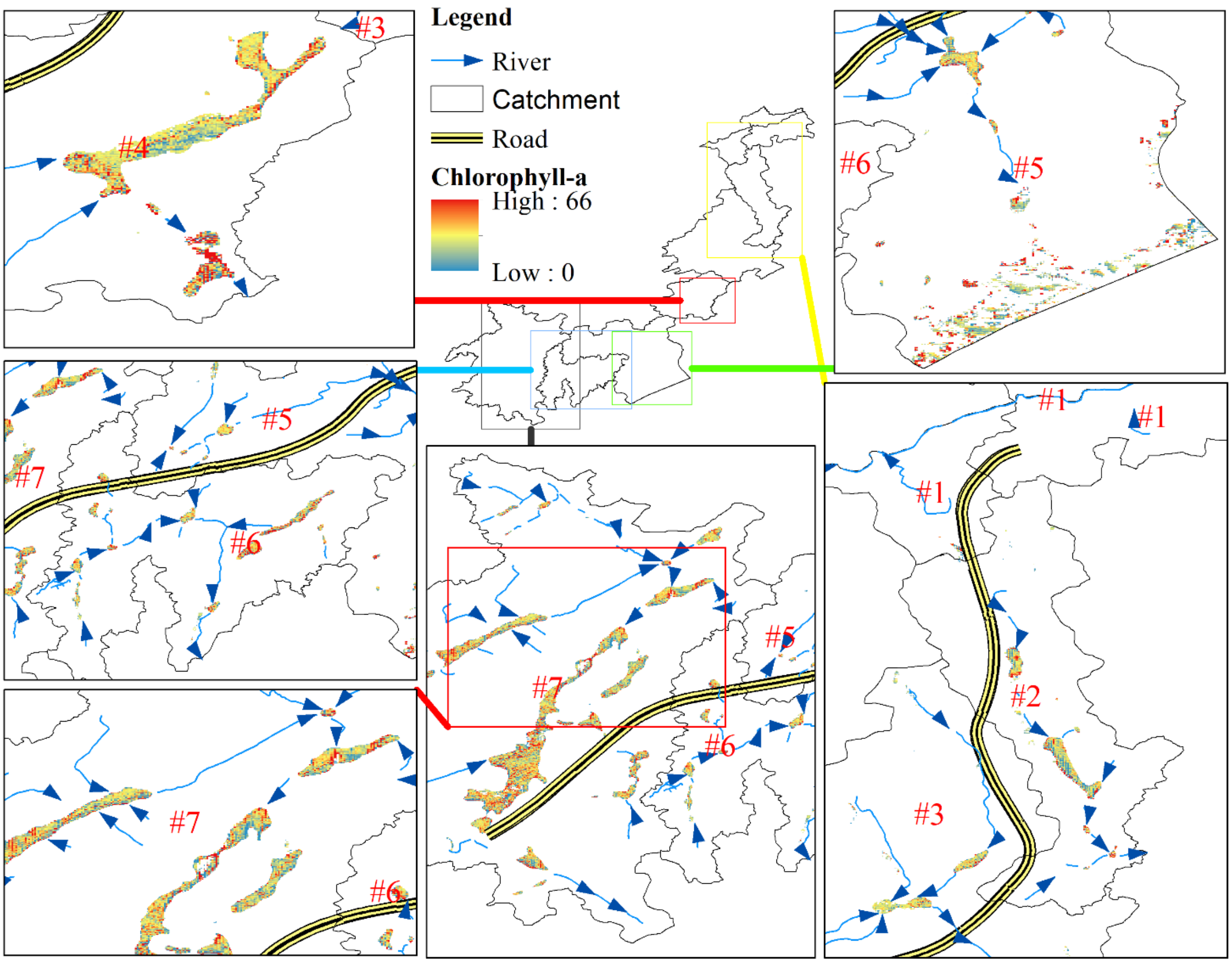

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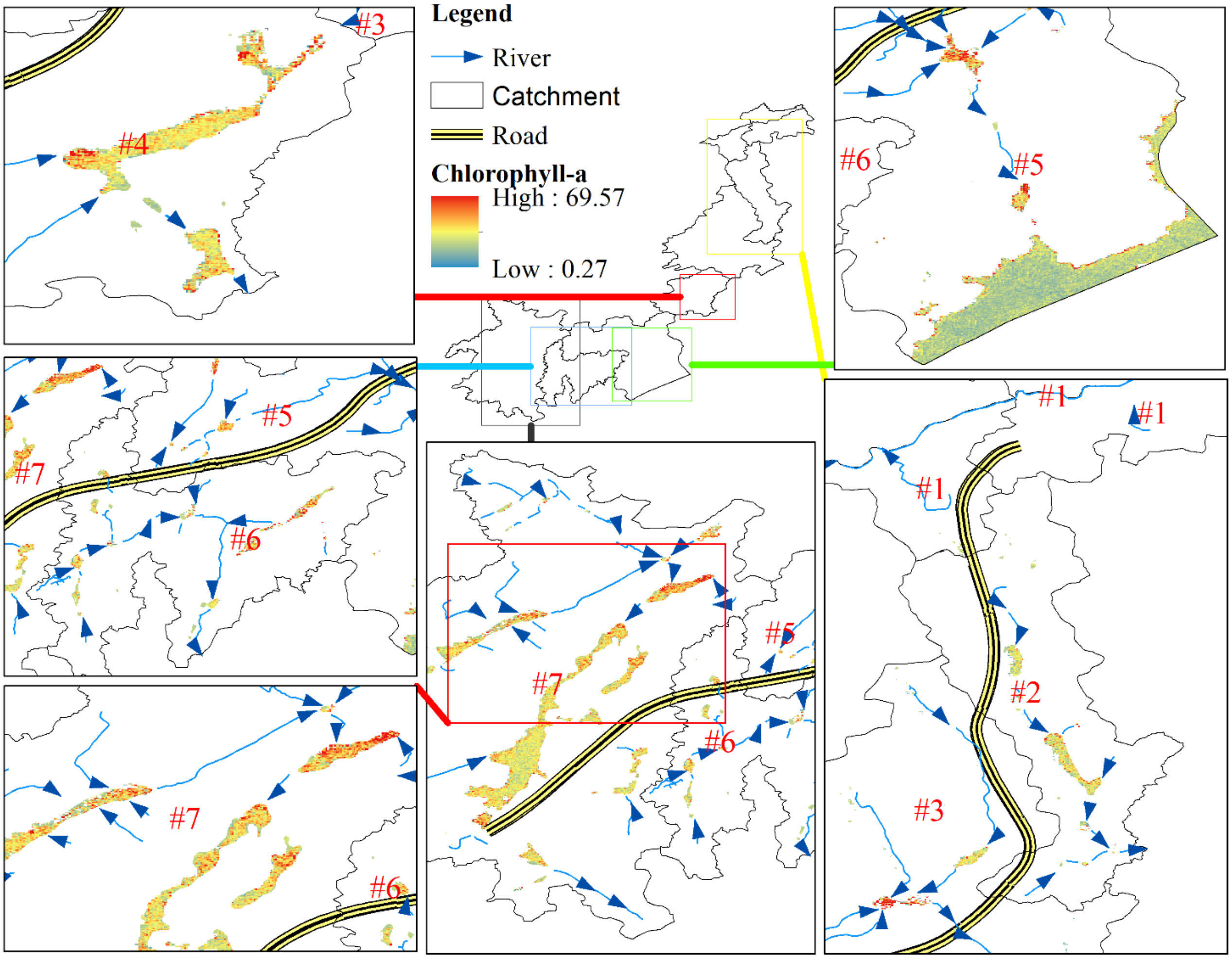

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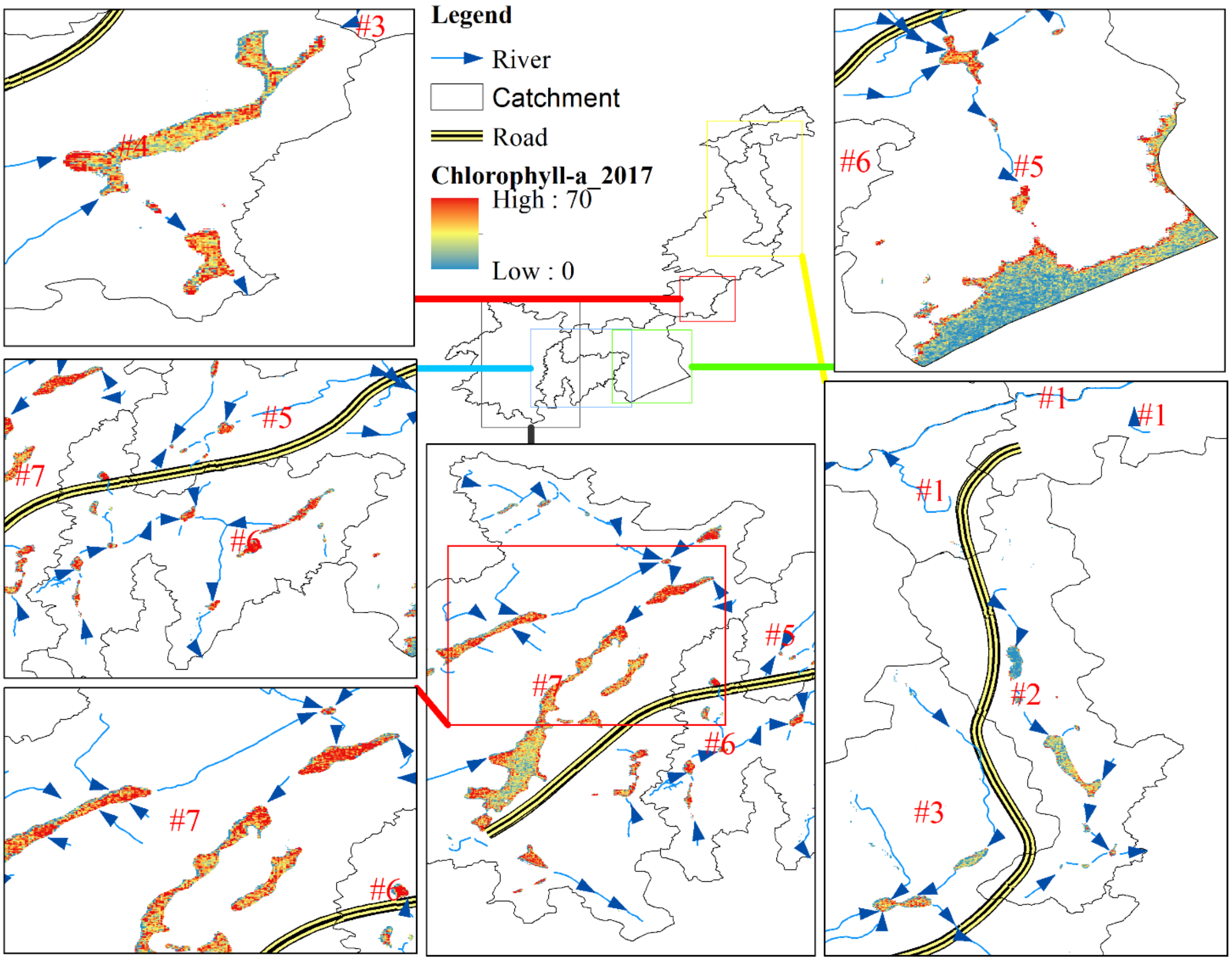

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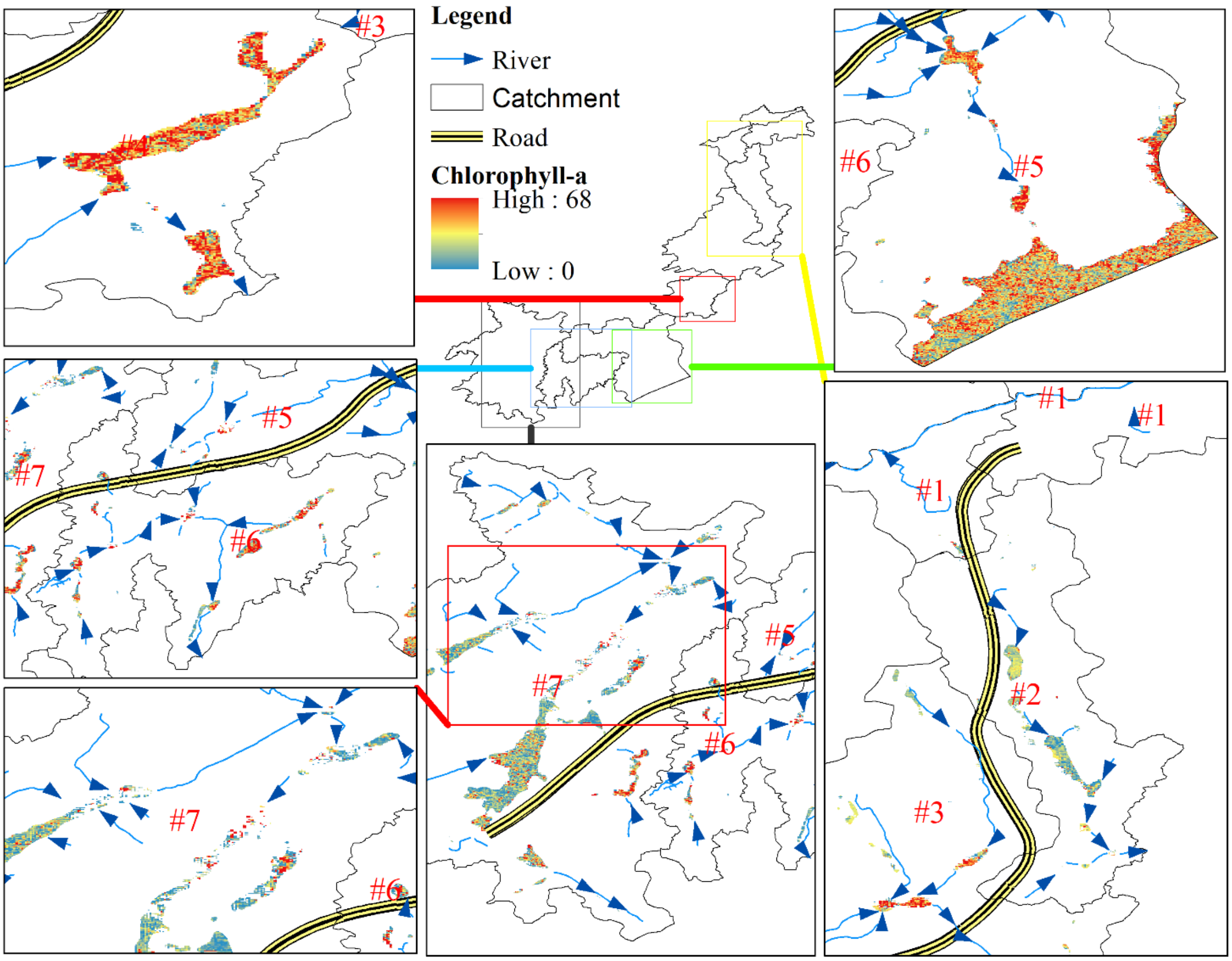

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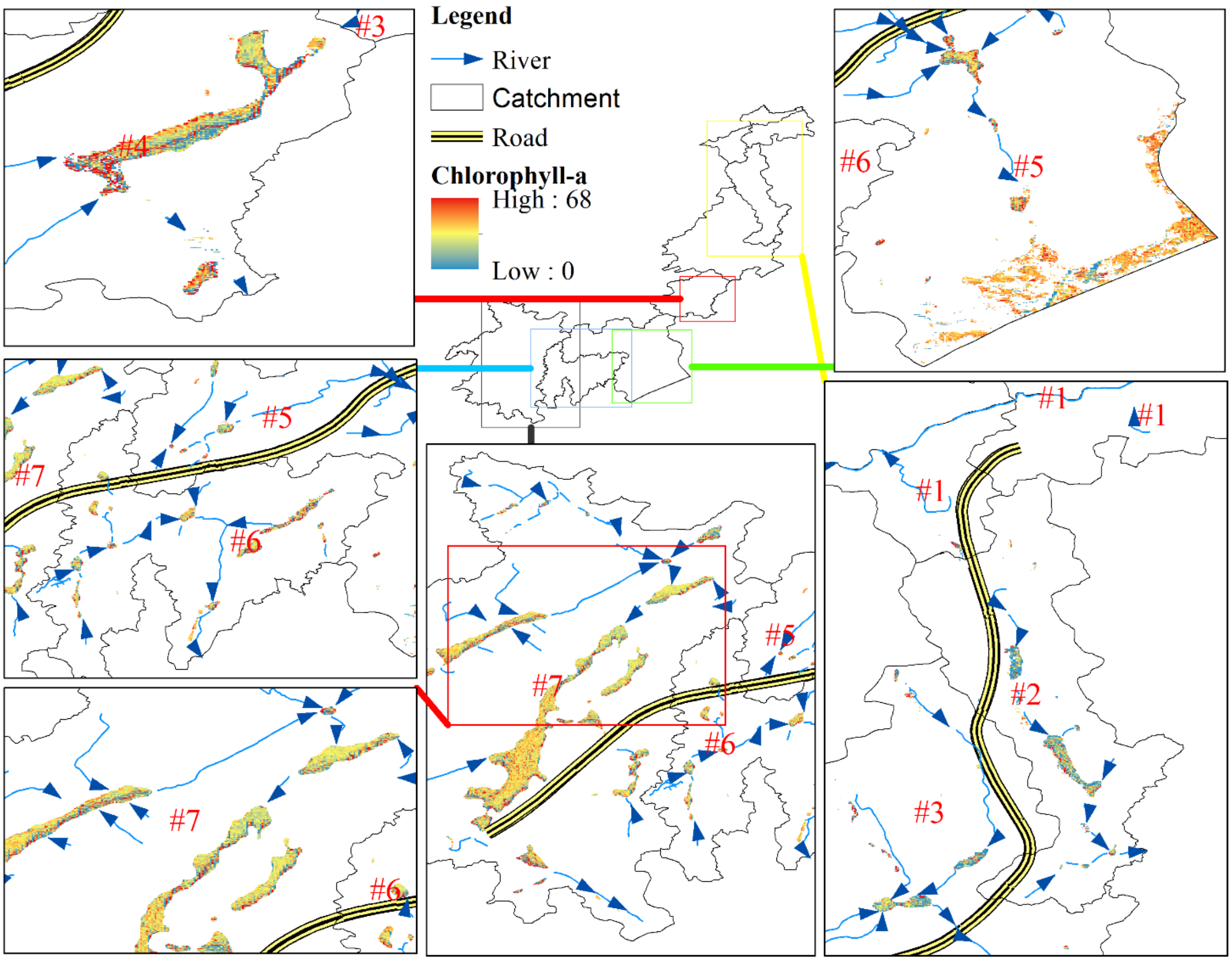

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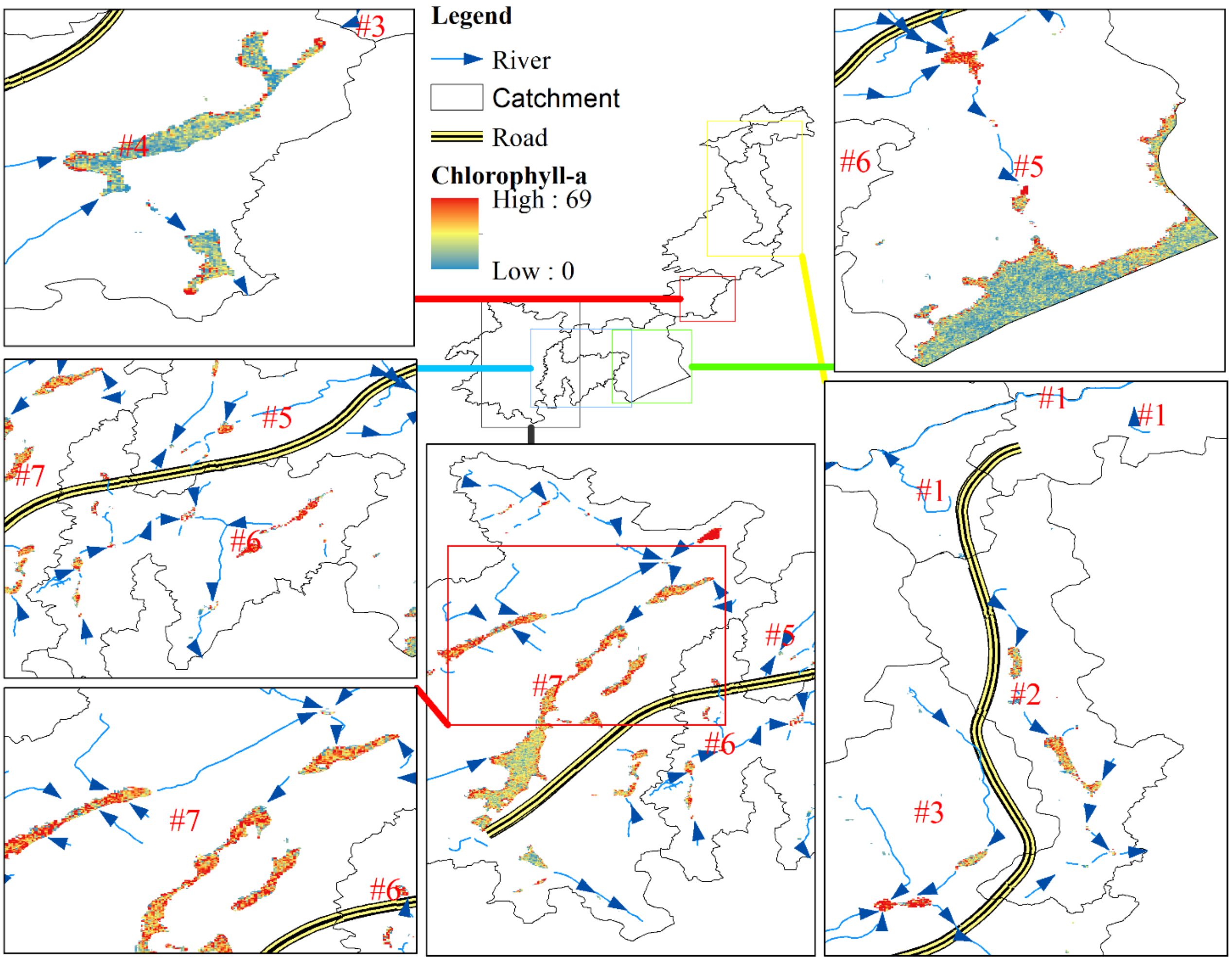

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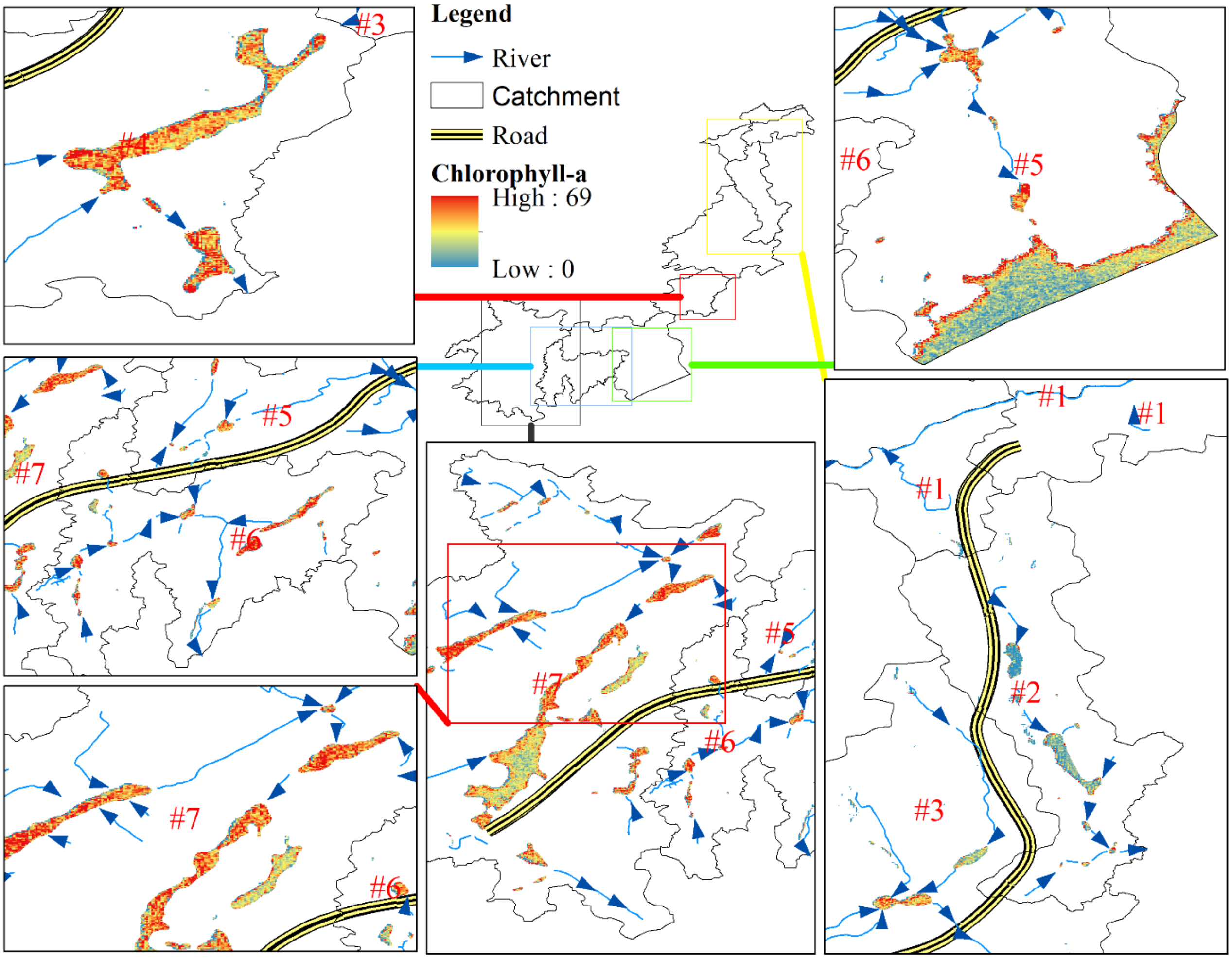

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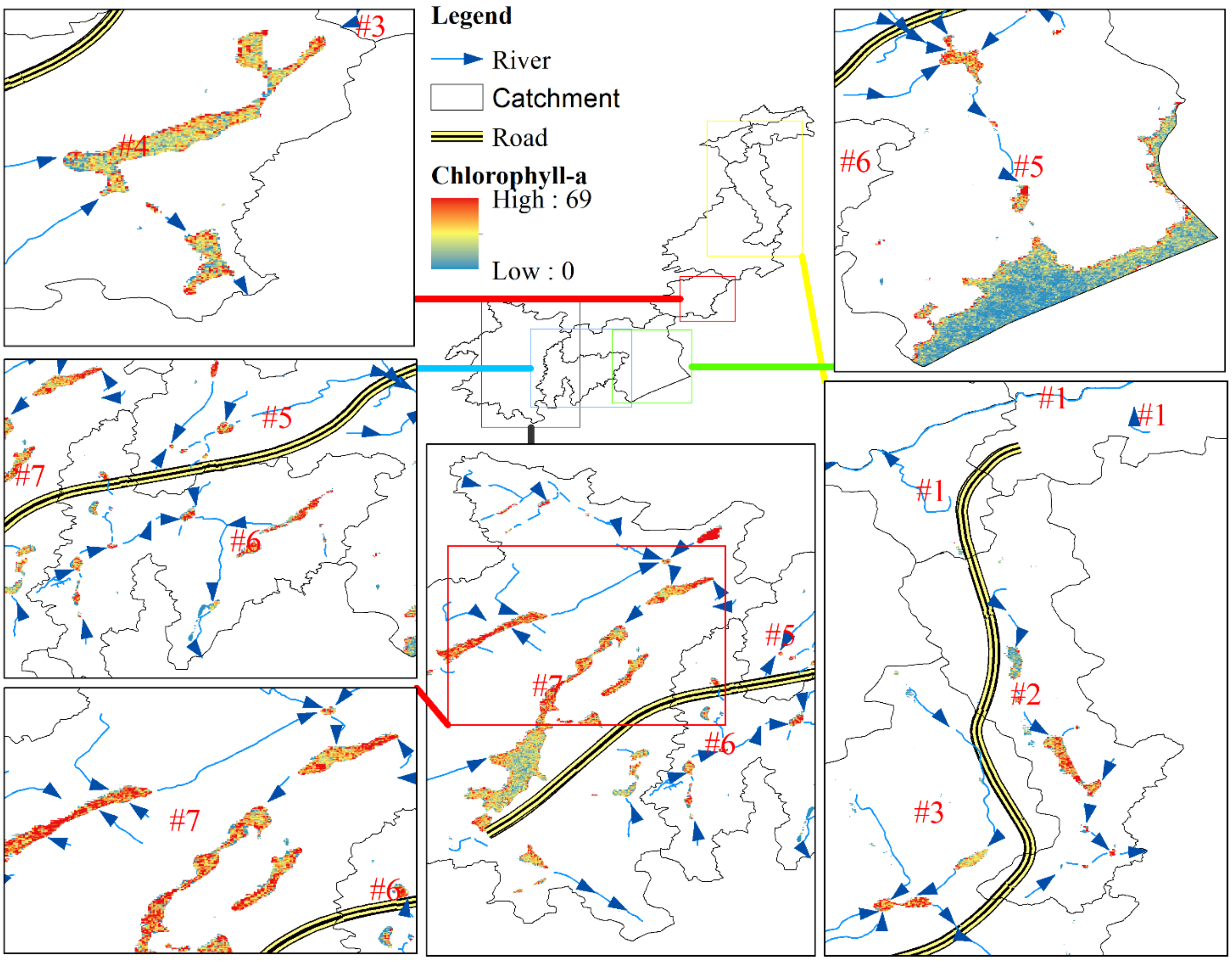

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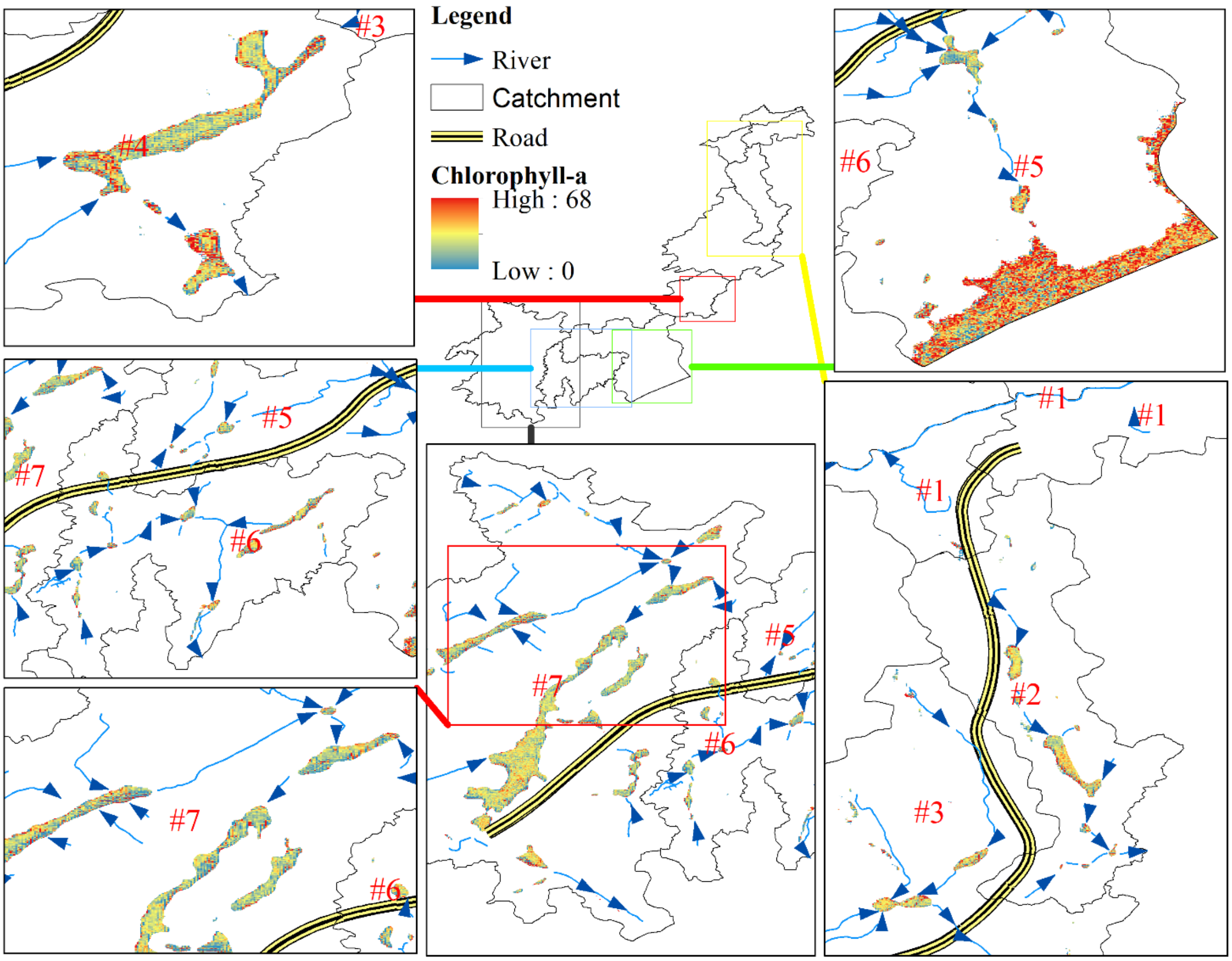

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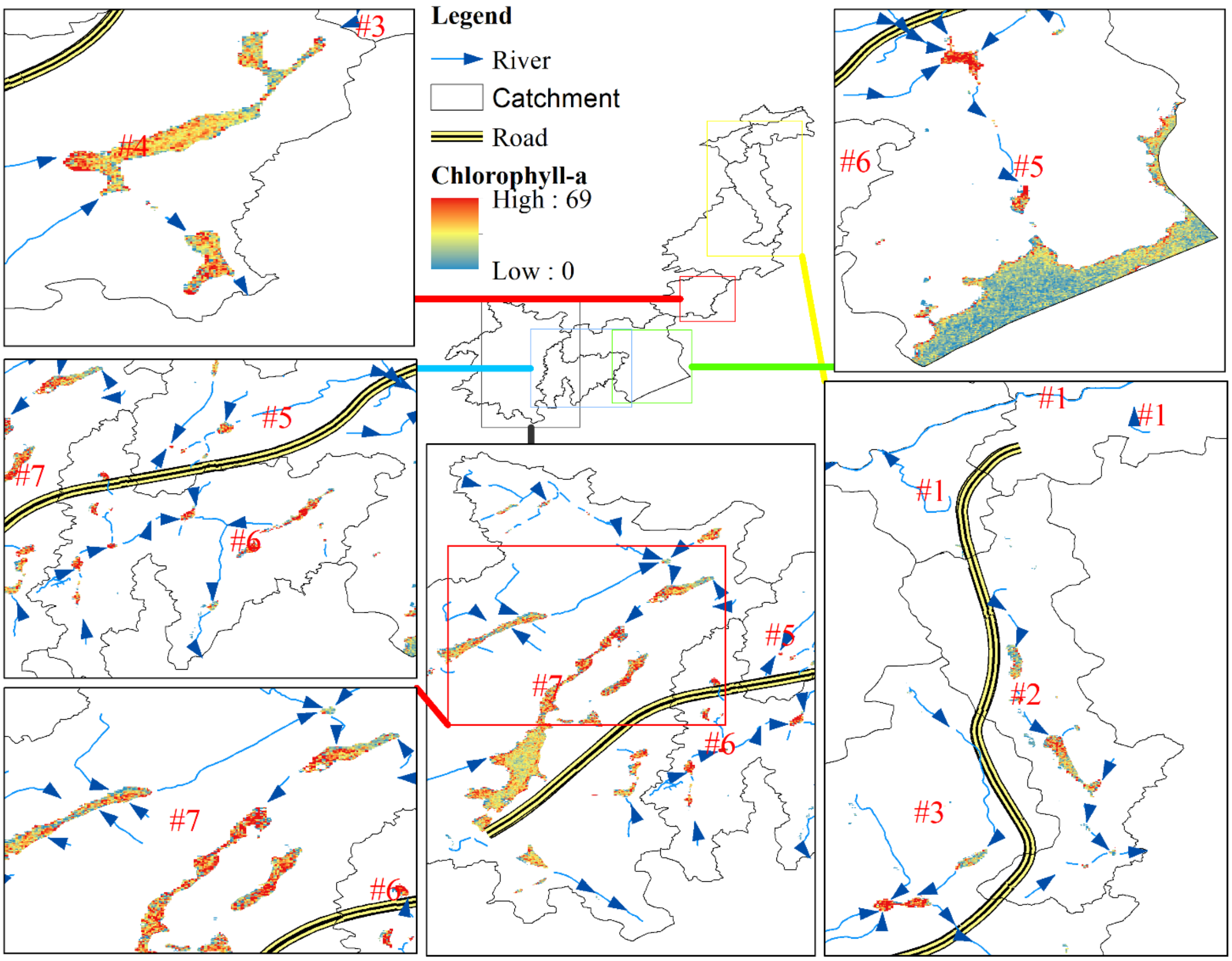

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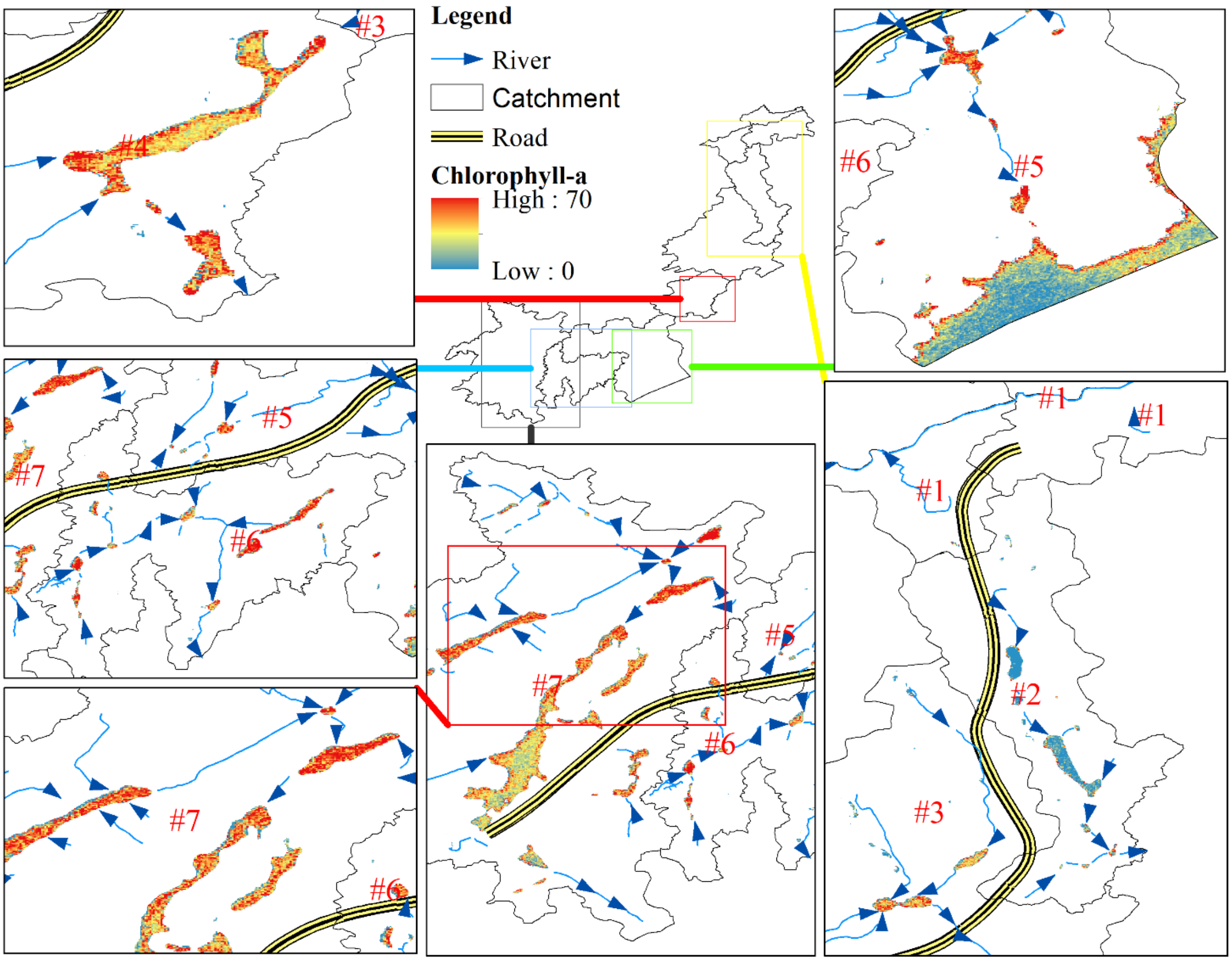

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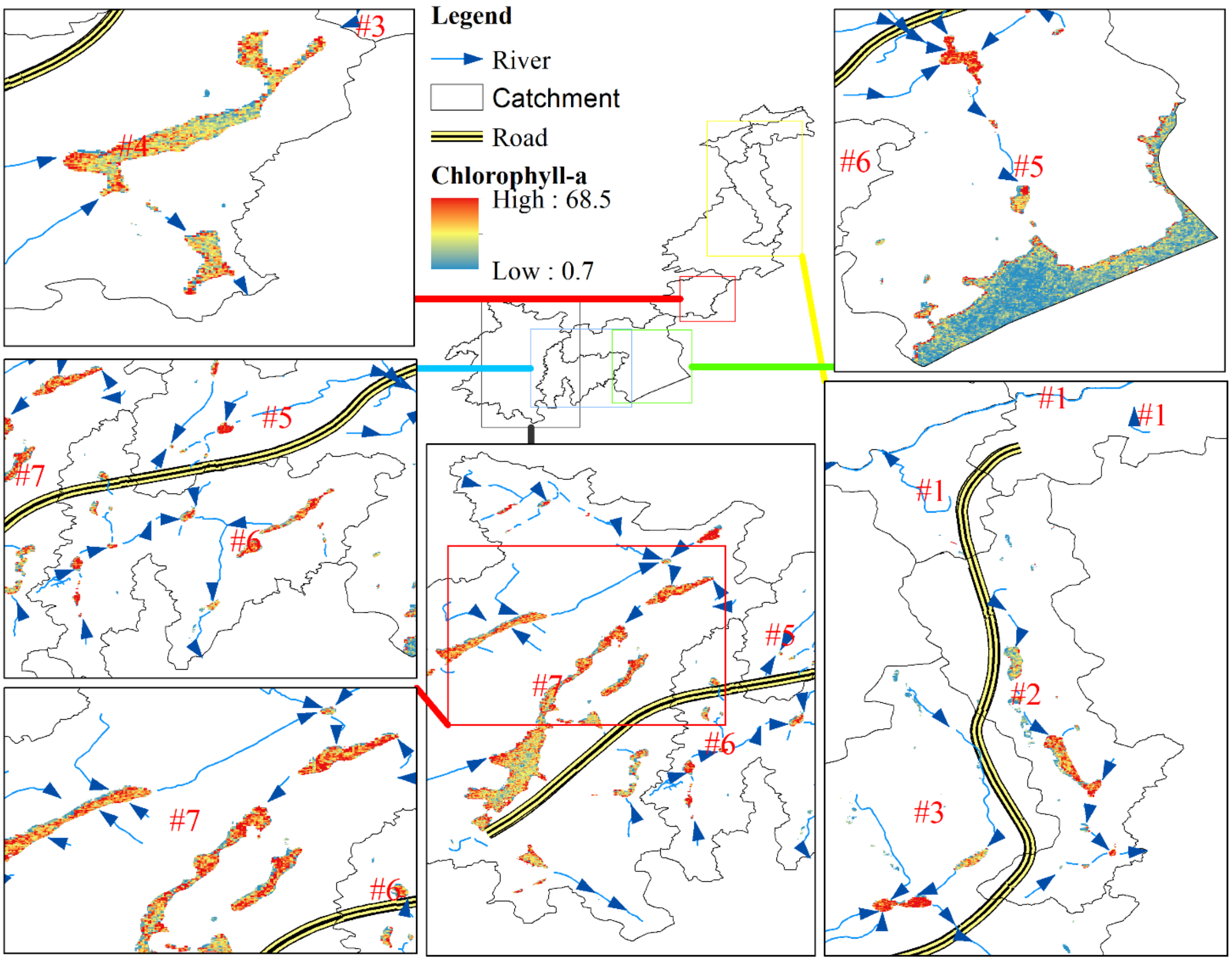

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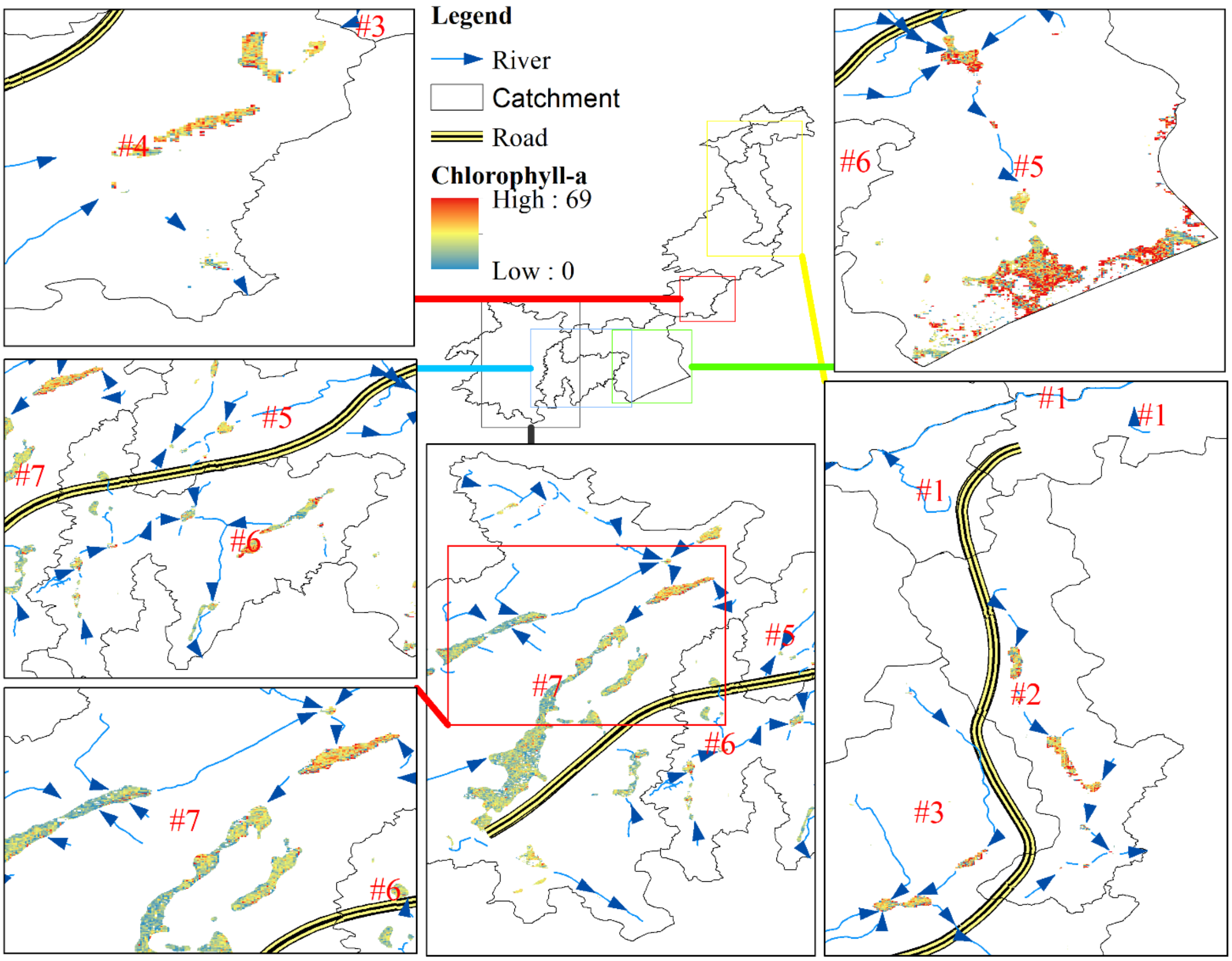

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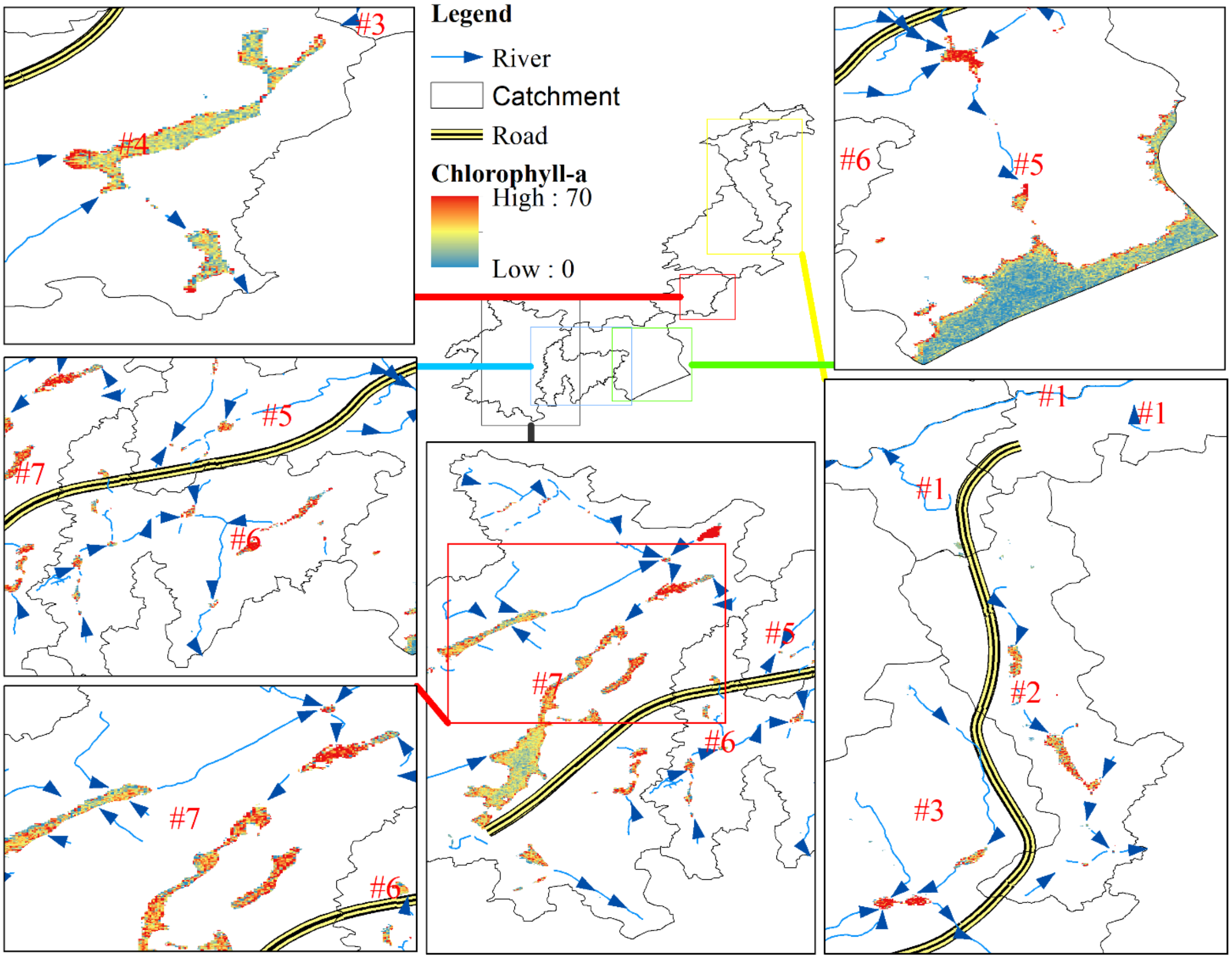

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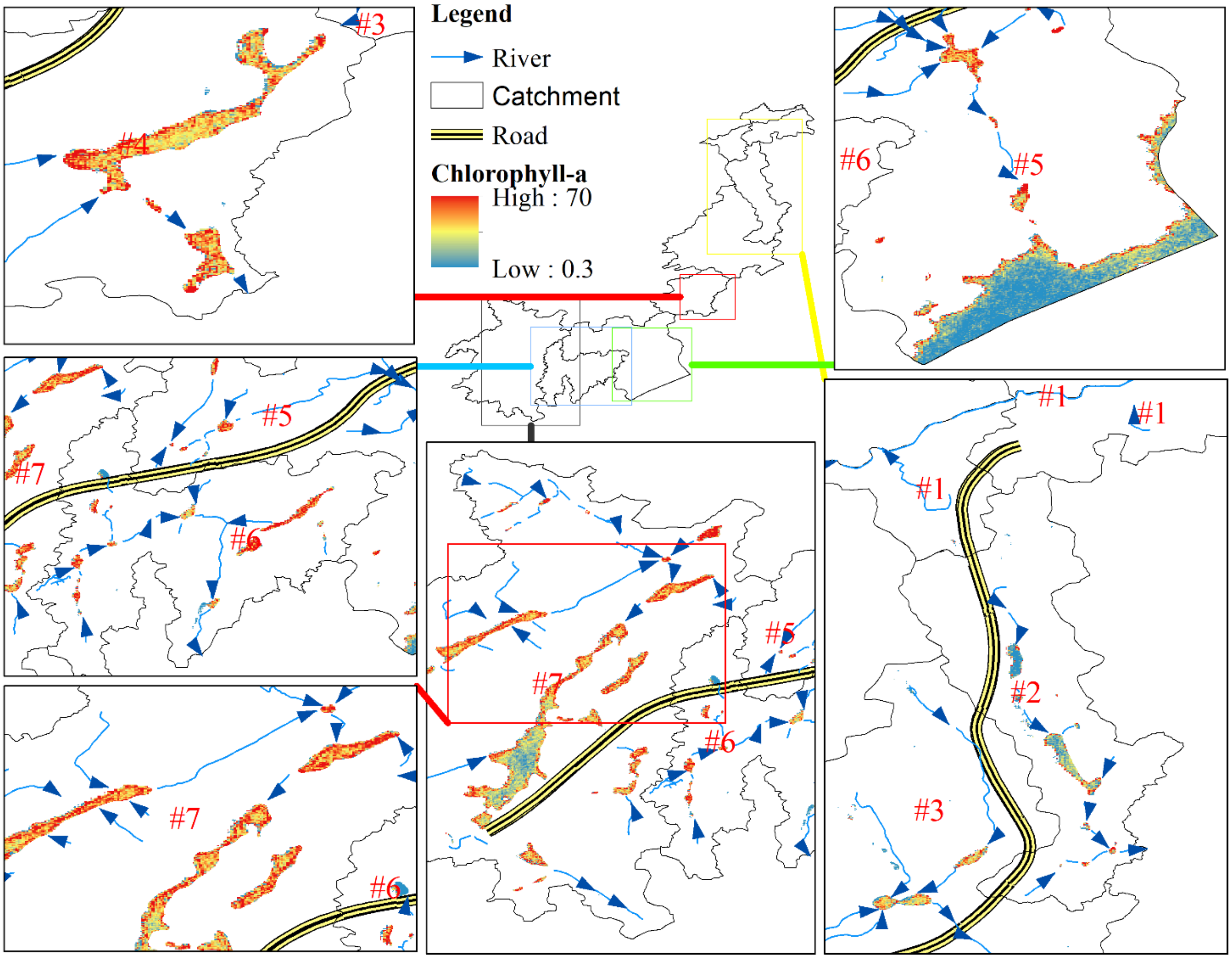

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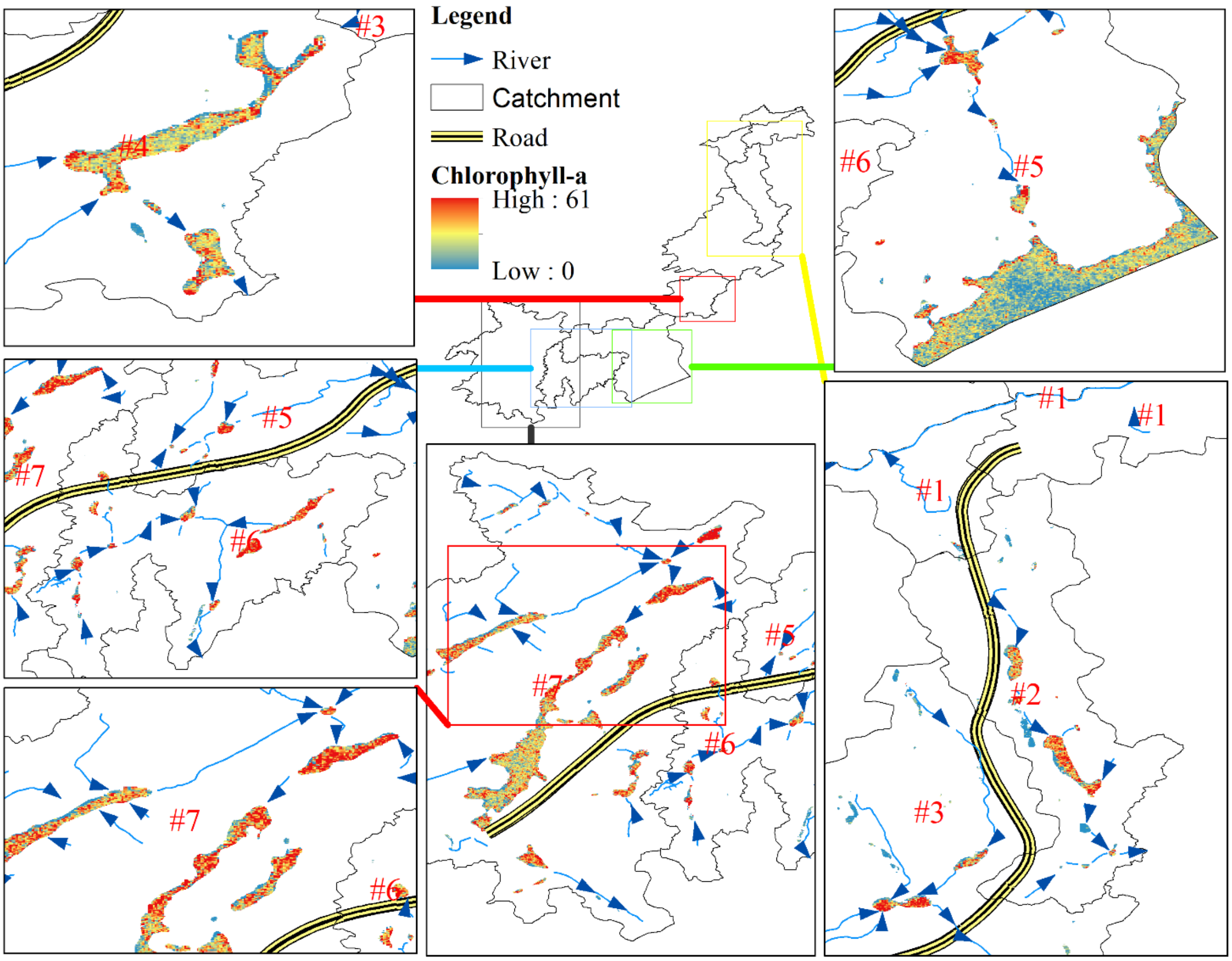

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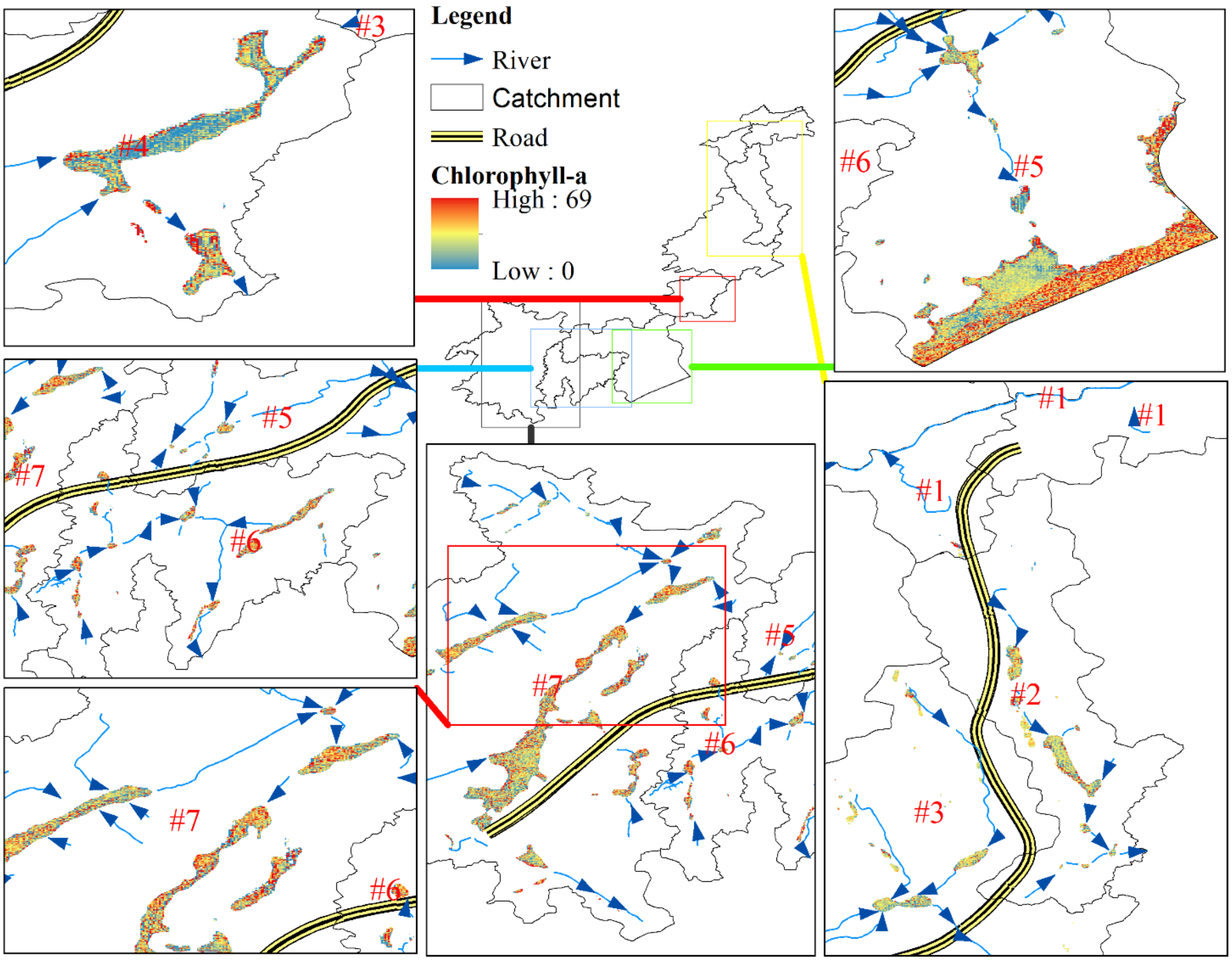


Fig. 37 Average Chlorophyll-a 2021 WINTER

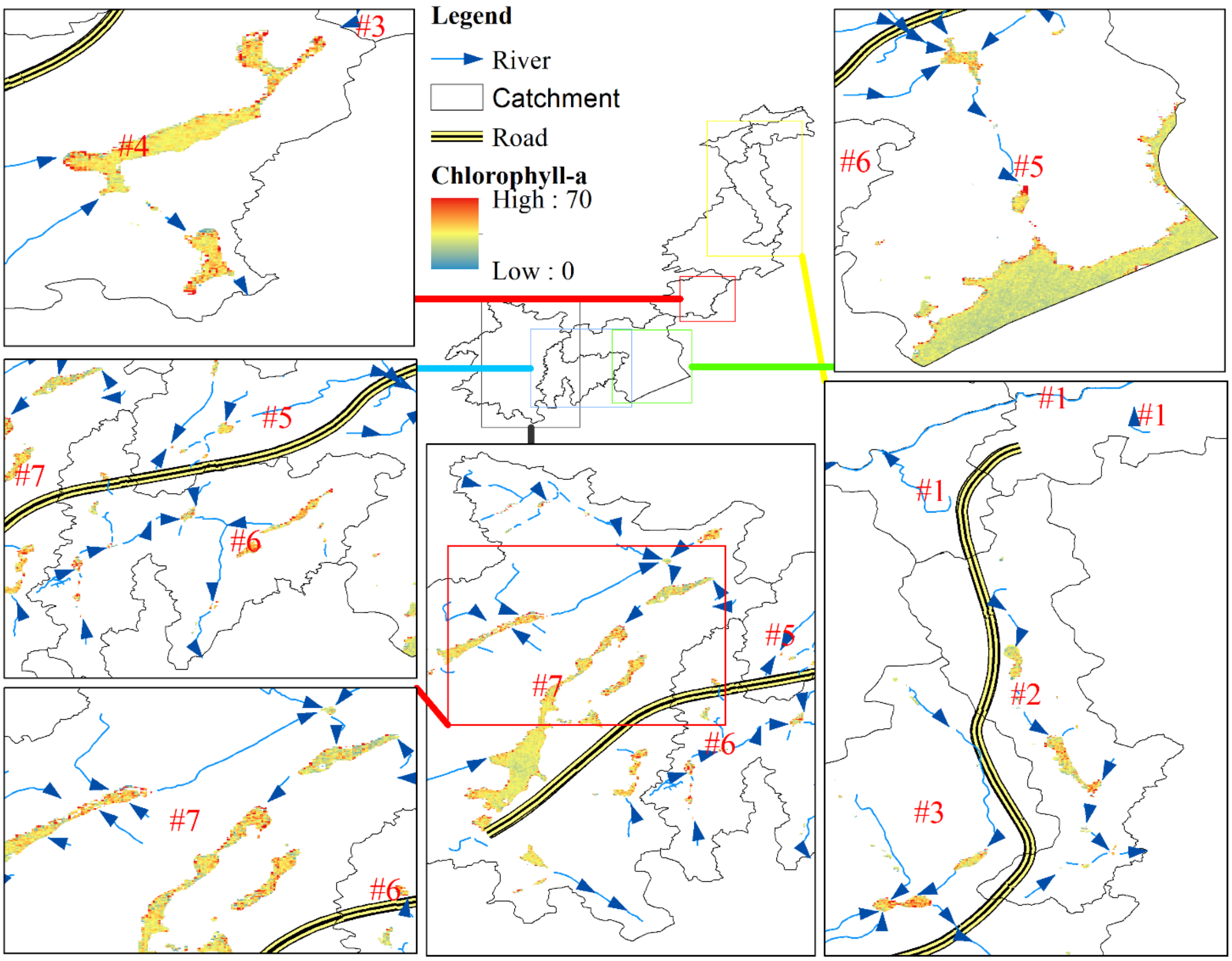
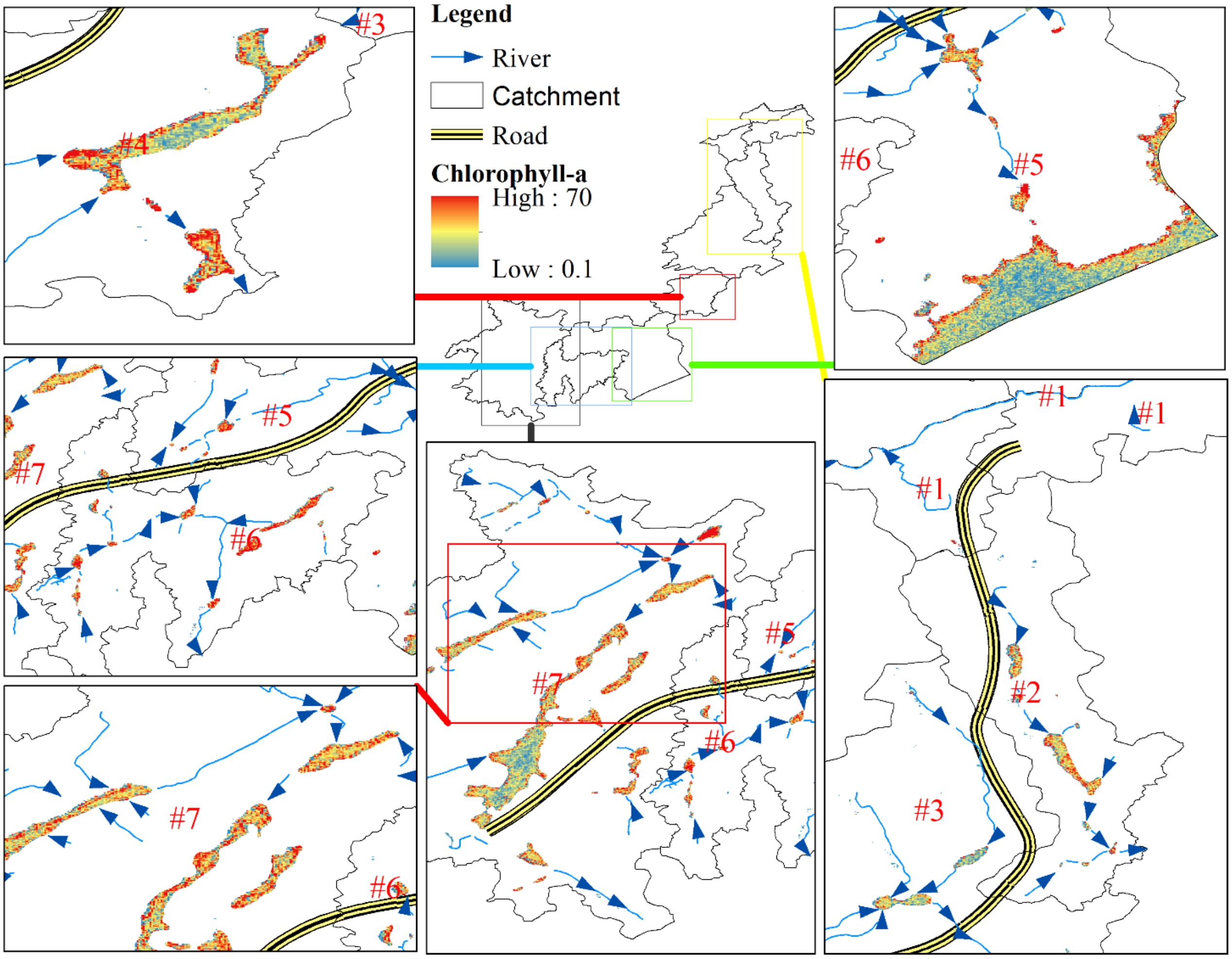


Fig. 38 Average Chlorophyll-a 2021 SUMMER



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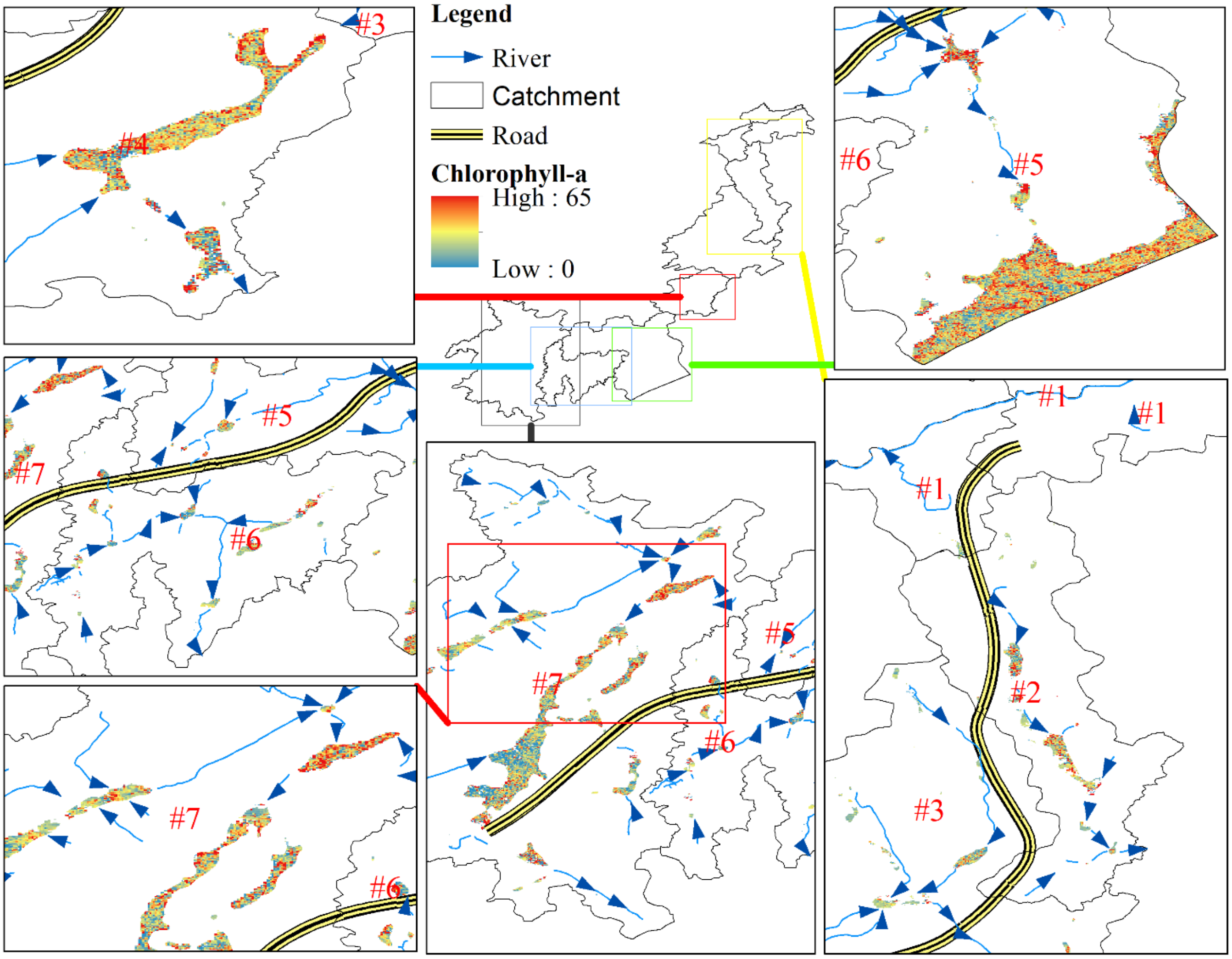

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Paper F

Characterization and Treatment of Tunneling wastewater Using Natural and Chemical Coagulants, by Mehrdad Ghorbani Mooselu, Helge Liltved, Naureen Akhtar. Submitted to Journal of Water Process Engineering (under review)

Characterization and Treatment of Tunneling Wastewater Using Natural and Chemical Coagulants

Mehrdad Ghorbani Mooselu [1*], Helge Liltved [1], Naureen Akhtar [1]

Abstract

Particles and other contaminants are of environmental concern during the discharge of tunneling wastewater to local water bodies. Sedimentation ponds or basins are used to reduce the environmental impacts of particles and particle associated contaminants. In some cases, additional treatment by filtration or chemical coagulation is applied for particle removal. However, there is a gap in the knowledge related to tunneling water characteristics, particularly to the knowledge of heavy metal content and their association to particles. Further, there is a lack of understanding of the link between tunneling wastewater characteristics and the efficiency of coagulants for particle removal. In this research, characterization of tunneling wastewater was carried out by chemical analysis and various techniques for particle characterization, including particle size distribution (PSD), shape and morphology of the particles, and heavy metal pollutants were applied by a laser particle analyzer, scanning electron microscope (SEM), and X-ray energy dispersive spectrometer (EDS), respectively. Based on the characterization, laboratory work was conducted to evaluate the effectiveness of coagulants for the removal of particles and particle associated contaminants. Both natural (i.e., chitosan) and chemical coagulants, including ferric chloride sulfates (PIX-318) and polyaluminium chloride solution (PAX-XL-3103D), were applied in a conventional jar test system. The coagulants' efficiency was assessed by turbidity and suspended solids (SS) removal measures. The results indicated that the optimum coagulant dosages in the jar test caused a high

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treatment efficiency (92-99%) for both turbidity and SS. Also, sedimentation alone shifted PSDs from coarser particle size fractions to finer fractions, and chemical coagulation significantly decreased the volume density of particles. Chemicals decreased the sample volume in the range of 10-100 μm showing that coagulants are highly efficient for particle removal, especially particles smaller than 100 μm.

Keywords: tunneling wastewater, tunnel construction, particle removal, coagulants, chitosan, heavy metals, SEM, EDS

1. Introduction

Tunnel construction is one of the most critical activities for surrounding surface water quality in road construction, which may produce several manufactured and natural water-borne sources of pollutants (Petersen et al., 2016). The characterization of tunneling wastewater highly varies by site-specific bedrock, weather, and applied machinery. Tunneling wastewater with large amounts of suspended particles may also have amounts of particle-bound contaminants (e.g., heavy metals, oil, and PAH). Particles from drilling and blasting might be edgier and sharper than rounded particles (e.g., clay) and thus more harmful for biota by reducing light penetration, changing temperature and spawning conditions, covering the fish foods (e.g., benthic invertebrates), and damaging fish gill tissue (Bilotta and Brazier, 2008).

The tunneling wastewater is generally known with characteristics such as high concentrations of both SS and turbidity (Lee et al., 2014; Liltved, 2014), elevated ammonia concentrations, and high pH value (Yi-Wen et al., 2012). However, the quality and chemical composition of tunneling wastewater are site-specific depending on the geological features of each construction site

(Rustøen, 2015). Suspended solids (SS) is a vital parameter in the characterization of tunneling wastewater. According to the European Inland Fisheries Advisory Commission (EIFAC) 400 mg/L of suspended solids will cause poor fishing (Vikan and Meland, 2013). Turbidity is used as a surrogate measure for suspended solids (Bilotta & Brazier 2008), but the correlation value varies between different suspensions due to particle properties such as shape, color, and reflectivity (Rustøen, 2015). pH is a significant parameter because of its great impact on water treatment processes and also aquatic organisms. Also, the particle removal efficiency of coagulants is affected by pH and initial turbidity (Rizzo et al., 2008).

In a biological context, removing particle-bound contaminants should be accompanied by removing dissolved contaminants since they are more bioavailable in the aquatic biota (Meland et al., 2010). Well-dimensioned sedimentation ponds can purify tunneling water to approximately 400 mg/L SS (Vikan and Meland, 2013). The weakness of sedimentation basins is limited removal of the finer (<20 μm) particles (Li et al., 2006), which poses a risk to the receiving waters (Nyström et al., 2020). Particle contents below 100 mg/L can be obtained by adding coagulants, often in combination with acid (HCl), at the inlet of the sedimentation pond (Vikan and Meland, 2013). Coagulation as a process for the destabilization of the colloidal fraction (include organic and inorganic particulates) (Bratby, 2016) is widely used in drinking water treatment (Fabris et al., 2010; Zemmouri et al., 2013; Muthuraman and Sasikala, 2014; Choy et al., 2016). Also, the coagulation/flocculation processes have been widely applied for the treatment of quite turbid stormwater and highway construction runoff (Trejo-Gaytan et al., 2006; Kang et al., 2007; Sansalone and Kim, 2008; Rounce et al., 2012; Lee et al., 2014; Rustøen, 2015; Nyström et al., 2019, 2020).

Chemical coagulants, especially inorganic coagulants, are popular owing to their superiority in treating turbid water, wide availability, and cost-effectiveness (Duan and Gregory, 2003; Choy et al., 2016). The most widely used coagulants for water treatment are aluminum and iron salts (e.g., aluminum sulfate, ferric chloride, ferric sulfate) (Kang et al., 2007; Choy et al., 2016). However, using chemical coagulants, particularly aluminum, results in excessive amounts of sludge and disposal problems (Renault et al., 2009). There are concerns about elevated aluminum concentrations in the aquatic environment, including drinking water, due to toxic effects on biota and humans (Mclachlan, 1995; Forbes et al., 1997). Recently, environmentally friendly coagulants such as natural polymers have been proposed as an important alternative (Rizzo et al., 2008; Bina et al., 2009). Natural organic polymers named biopolymers are biodegradable and non-toxic to human health (Muthuraman and Sasikala, 2014). Biopolymers are efficient coagulants in low dosage and will therefore reduce sludge volume (Bina et al., 2009; Choy et al., 2016), and their impact on pH and alkalinity is insignificant (Zemmouri et al., 2013).

Despite the importance of tunneling construction for the deterioration of surface water quality, little research has been published on characterization and treatment of tunneling wastewater (Yi-Wen et al., 2012; Lee et al., 2013; Lee et al., 2014). The current study aimed to characterize the tunnel construction wastewater and explore the feasibility of using precipitating agents for the treatment of such water. The novelty of this research lies in the following items

1) Characterizing three types of tunneling wastewater regarding chemical composition, and particle shape, and morphology.
2) Application and comparison of a natural biopolymer (chitosan) to chemical coagulants, including ferric chloride sulfates (PIXs) and polyaluminium chloride solution (PAX-XL60), for treatment of the tunnel wastewater.

3) Using tunnel wastewater collected from construction sites for characterization and to assess the performance of the coagulants

Water samples were collected at different sites during the construction of the new E39 from Kristiansand to Mandal in the southern part of Norway, which is included in the international E-road network.

2. Materials and methods

2.1. Tunneling wastewater

The wastewaters were collected from the tunneling project during drilling operations at the new E39 from Kristiansand to Mandal in southern Norway. A mixture of water from the drilling rigs (water used for cooling of the drilling rigs and removal of cuttings), and water leaking into the tunnel, were pumped out to a sedimentation basin. After sedimentation, most of the water was pumped back into the tunnel for reuse, while a smaller fraction was pH-adjusted and discharged to surrounding surface water bodies. Three types of tunneling wastewater with various turbidity were collected as composite samples in 25-liter polypropylene containers, transported to the laboratory, and stored at room temperature. To achieve the 25-liter composite samples, 0.5-liter grab samples were collected over a time span of approximately 1 hour. When two or more 25-liter containers were collected, the contents were transferred to a common large container in the laboratory, mixed properly, and homogenous subsamples were withdrawn for characterization and experimental testing.

2.2. Coagulants used

Chitosan, a linear cationic biopolymer of high molecular weight, was applied as a natural coagulant in this research. Due to powers of static attraction and adsorption in the molecules, biodegradability, and its polyelectrolytic nature, chitosan is an efficient coagulant to *i)* remove particles (Divakaran and Pillai, 2001; Roussy et al., 2005), turbidity (Pan et al., 1999; Chen et al., 2003; Roussy et al., 2005; Kang et al., 2007; Rizzo et al., 2008; Bina et al., 2009; Nyström et al., 2020), natural organic matter (NOM) and colored substances (Eikebrokk, 1999; Liltved et al., 2001; Chiou and Li, 2003; Bratskaya et al., 2004; Rizzo et al., 2008), *ii)* bacteria inactivation (Chung et al., 2003), and *iii)* metals removal (Juang and Shiau, 2000; Jeon and Höll, 2003; Rae and Gibb, 2003; Rizzo et al., 2008; Zeng et al., 2008; Zemmouri et al., 2013; Rustøen, 2015). The performance of chitosan has been assessed on industrial wastewaters, some studies have been conducted concerning the chitosan efficiency for drinking water treatment (Eikebrokk and Saltnes, 2002; Fabris et al., 2010; Zemmouri et al., 2013), and less is published for road construction wastewater (Lee et al., 2013). Comparing with other commonly used organic coagulants, chitosan requires less dosage and has quicker floc settling velocity, easier sludge treatment, and no secondary pollution (Lee et al., 2013). However, it has a higher cost than the traditional chemical flocculants (Zeng et al., 2008) and releases some organic matter during coagulation (Rizzo et al., 2008).

Chitosan stock solution (0.5%) was prepared by adding 0.5 g of chitosan powder to 100 mL of distilled water and then adding drops of a 30% HCl-solution under continuous stirring until the chitosan was dissolved. Depending on the required amount of chitosan solution, chitosan was transferred to the jar-test experiments by micropipettes (500-5000 μl or 50-1000 μl) for comparing the treatment efficiency of chitosan with the commercial coagulants PAX-XL-3103D and PIX-318 (Kemira Kemwater, Helsingborg, Sweden). The dosages of coagulants were calculated based on the active substance (Fe/Al) using mass percentage and density according to the manufacturer's product datasheet. PAX-XL-3103D is a low-dose, pre-polymerized aluminum coagulant, which can be used for flocculating most waters (e.g., raw water, process water, wastewater, and bathwater). Compared with traditional coagulants, PAX-XL-3103 D is more efficient at removing phosphorus and particles since it reduces the sludge volume and alkalinity consumption and improves the filterability of the settled water (Ghazy et al., 2001). On the other hand, PIXs are effective trivalent iron (Fe^{3+}) based coagulants, which are excellent for drinking water production and wastewater treatment (e.g., color, phosphate, and heavy metal removal, and sludge conditioning). PIX-318 is approved as a precipitating agent in drinking water purification by the Norwegian Food Safety Authority (Rustøen, 2015). Both PAX-XL-3103D and PIX-318 were provided by Kemira (Helsinki, Finland). Notably, chitosan, PAX- XL-3103D, and PIX-318 were stored in a refrigerator in sealed glass bottles, and required concentrations were applied directly in the experiments.

2.3. Particle removal

To assess particle removal efficiency, jar-tests with flocculation and sedimentation were performed. A portable jar testing apparatus (Flocculator, Kemira Kemwater, Helsingborg, Sweden) was used for all jar tests. Six 1000 mL beakers, including one beaker as control, and five beakers were filled with tunnel water and placed in the jar-test apparatus. Each jar-test had a protocol consisting of an initial 45 second rapid mixing phase (200 rpm) in which coagulant was added, followed by 10 minutes of slow mixing (30 rpm) and finally sedimentation for 45 min. This standard protocol was followed and kept unchanged throughout all experiments. Coagulants (either chitosan, PIX-318, or PAX-XL-3103D) were added during rapid mixing (400 rpm), and pH was adjusted to 6±0.2 by diluted HCl solutions. After completing the jar-test cycle (rapid mixing, flocculation, and sedimentation), 500 ml samples were carefully siphoned from the clear phase for analyses. The removal efficiency (%) was defined as the decrease in effluent concentration after using a precipitating agent, compared to the control concentration and calculated as Eq. 1 (Choy et al., 2016):

$$E\ (\%) = \frac{C_1 - C_2}{C_1} \times 100 \quad (1)$$

Where C_1 is control concentration and C_2 is effluent concentration after treatment with the coagulant.

2.4. Analytical methods

Before and after the jar tests, several analyses were performed to characterize the different tunnel waters and evaluate the treatment efficiency. pH, electrical conductivity (EC), turbidity, suspended solids (SS), and particle size distribution (PSD) analysis were measured in the laboratory of the University of Agder according to Norwegian and European Standards. For pH measurements, a pH-meter (VMR pH110) with Ross-Sure flow combination pH electrode (Termo Scientific) was used. The meter was calibrated against two standard buffer solutions (pH 4 and pH 7). EC was measured using a calibrated Hach HQ40d instrument (Loveland, CO, USA), while turbidity measurements were conducted using a Hach 2100Q turbidimeter (Loveland, CO, USA). The SS was determined according to the standard method by filtering known amounts of water through pre-weighed 0.45 µm Whatman GF/C glass microfiber filters. After filtration, the filter was dried at 105 °C for one hour, and SS was determined by calculating the difference in filter weight after and before filtration.

Particle size distribution was analyzed by light scattering using a Mastersizer 3000 (Malvern v3.72) instrument. Representative samples were transferred to a glass beaker equipped with a stirring device to keep the particle in suspension during analysis. For each sample, ten measurements were performed, and the average values were presented. The samples were analyzed in the range of 0.01-2000 μm. In volume-based distribution, the contribution of different particle sizes of total particle mass was assessed by their volume in a sample.

For particle morphology study, a field emission scanning electron microscope (SEM) (JEOL 7200F, Tokyo, Japan) equipped with an energy dispersive X-ray spectrometer (Octane Elect EDS system from EDAX®-AMETEK®) was employed. The microscope was operated at 15kV (accelerating voltage), at a working distance of 10mm. Representative samples for microscopy were collected, and sub-samples for analysis were siphoned from the upper water layer. This methodology allowed for the settling of larger particles, while samples with the remaining dispersed particles were used for analysis. These particles will also be more typical for particles discharged to surface water bodies after treatment of tunneling water. Water containing dispersed particles was drop-casted on a carbon sticky tape. Once the water evaporated, leaving behind dried particles adhered to the carbon tape, samples were coated with a carbon film using the carbon coater (JEOL JEC-530). This step was essential to avoid the sample charging during SEM/EDS analysis. For heavy metal pollutants, samples were analyzed through EDS using TEAM™ software. For each tunnel water type, at least three samples were analyzed.

2.5. Statistics

Duplicate analyzes were conducted for chemical water characterization. For particle size distribution analysis and for the particle morphology study, three or more parallel samples were analyzed. Mean values are presented. The jar-test experiments were repeated three times. Mean values with standard deviations are presented. Where standard deviation bars are not observable on the graphs, they do not extend beyond the dimensions of the symbols.

3. Results and discussion

3.1. Characterization

The chemical characteristics of the three tunneling wastewater before and after 15 min sedimentation are shown in Table 1. For the heavy metals, the maximum admissible concentrations for acute toxic effects to aquatic biota in freshwater bodies have been given by (Agency, 2020), while discharge limits for other parameters, released by the Environment Department of Agder County, Norway, are also presented in Table 1. Water 1 was from a period of low drilling and blasting activity with low concentrations of substances compared to water 2 and water 3; e.g., the TSS content in water 1 was only 4-5% of the TSS of the two other waters. The pH value of water 1 was also totally different from water 2 and water 3 (pH value of 6.4 compared to pH values of 12.7 and 12.2, respectively), which influenced other characteristics, such as metal solubility. Higher solubility is expected at lower pH.

Water 2 and water 3 carried high amounts of mineral solids, with high TSS and turbidity values. The mineral nature of the solids in all waters was evident by the low content of organic carbon (TOC/NPOC) compared to the TSS concentrations. The majority of the solids, particularly in water 2 and 3, were easily removed by short time sedimentation (15 min), as shown in table 1 and table 2. The characterization also shows considerable contents of heavy metals in all three waters. In the waters with high solid content and high pH (water 1 and 2) it was evident that the majority of the heavy metals were associated with particles. By removal of solids by sedimentation, most of the heavy metals were also removed. The removal efficiencies for metals were in the range of 66.7% to 99.5% (Table 2). In spite of the removals by sedimentation, the residual concentrations were still high for some of the metals, particularly Cu and Cr. The concentrations of Cu and Cr exceeded the acute toxicity levels by factors of 6 and 9 in water 1, and by factors of 24 and 36 in water 2, respectively. This means that dilution factors of the same magnitude should be implemented if such water is discharged to local freshwater bodies to avoid toxicity to aquatic biota. However, the risk of toxicity is reduced due to metal association with particles, which limits the bioavailability. However, it should be taken into consideration that the pH-value must be reduced by several units by CO_2-dosing before discharge to comply with requirements. By lowering the pH, increased metal solubility may also take place, with increased risk to aquatic biota. More research should be conducted to highlight the potential metal toxicity of tunnel water, with and without pH adjustment. In published research, the environmental impact of tunnel water has been focusing on high pH values (Yi-Wen et al., 2012), suspended solids, and ammonia (Lee et al., 2013), not on metals.

Among the nutrients, P was present in untreated tunnel waters, ranging from 0.22 to 16 mg/l, while N was in the range of 35 to 180 mg/l. As for the metals, the majority of the P-content was removed with the solids during sedimentation, while N concentrations were more or less unaffected by sedimentation (Table 2). This can be explained by the presence of ammonia-ion (NH_4^+) as the main N-compound in these waters. This dissolved form of nitrogen will not be affected by sedimentation. The processing of the water during the sedimentation trials, i.e., homogenization and transfer of samples, may even explain the small raises in total N in water 1 and 2 by mobilization of particle-associated NH_4^+. The percentage removal of the various constituents after 15 min sedimentation in tunnel waters # 1, 2, and 3 are shown in Table 2.

To have an indication of possible emission of persistent organic pollutants, 16 different priority polycyclic aromatic hydrocarbons (PAHs) were analyzed in water 1 and 3 after 15 minutes of sedimentation. The sum of the 16 PAHs ($\sum PAH_{16}$) was below the detection limit in water 1, while a low concentration of 0.110 μg/L was found in water 3, which consisted of phenanthrene and pyrene in concentrations of 0.091 and 0.019 μg/L, respectively.

Table 1 The characterization of tunneling waters before and after 15 minutes sedimentation

Constituent	Tunnel water 1	Tunnel water 1 after 15 min sedimentation	Tunnel water 2	Tunnel water 2 after 15 min sedimentation	Tunnel water 3	Tunnel water 3 after 15 min sedimentation	Concentration limits [3]
pH	6.4	6.4	12.7	12.7	12.2	12.2	6-8.5
Alkalinity (mmol/L)	0.2	0.04	32	44	38	15	-
Turbidity (NTU)	534	267	6520	640	3824	60	50-100
TSS (mg/L)	317	143	6140	500	8530	124	100
Tot-P (mg/L)	0.22	-	2.4	0.17	16	0.14	-
Tot-N (mg/L)	130	150	35	61	180	160	-
TOC/NPOC[1] (mg/L)	16	8.9	41	46	110	15	-
Hg[2] (µg/L)	-	0.048	0.014	< 0.005	0.008	< 0.005	0.070
As[2] (µg/L)	2.3	1.85	45	3.7	35	0.35	8.5
Pb[2] (µg/L)	7.7	3.5	350	46	210	1.4	14
Cd[2] (µg/L)	1.2	0.068	4.8	0.45	0.86	0.039	0.45
Cu[2] (µg/L)	41	46	1400	190	1200	110	7.8
Cr[2] (µg/L)	39	32	510	125	270	90	3.4
Ni[2] (µg/L)	8.2	4.6	170	11.8	190	2.6	34
Zn[2] (µg/L)	130	165	1300	65	1200	6.5	11

[1]Total organic carbon/ non-purgeable organic carbon, [2]Metals (total), [3]Regarding pH, turbidity and TSS: discharge limits (Environmental Department of the Governor of Agder County, Norway); Regarding heavy metals: concentrations for acute toxic effects in freshwater bodies (Pettersen, 2016).

Table 2. Percentage removal of various constituents after 15 min sedimentation

	% Removal of constituents after 15 min sedimentation		
Constituent	**Tunnel water 1**	**Tunnel water 2**	**Tunnel water 3**
Turbidity (NTU)	50.0	90.2	98.4
TSS (mg/L)	54.9	91.9	98.5
Total P (mg/L)	-	92.9	99.1
Total N (mg/L)	0	0	11.1
TOC/NPOC (mg/L)	44.4	0	86.4
Hg (µg/L)	-	>64.3	>37.5
As (µg/L)	19.6	91.8	99.0
Pb (µg/L)	54.5	86.9	99.3
Cd (µg/L)	94.3	90.6	95.5
Cu (µg/L)	0	86.4	90.8
Cr (µg/L)	17.9	75.5	66.7
Ni (µg/L)	43.9	93.1	98.6
Zn (µg/L)	0	95.0	99.5

The settling velocity of particles expressed as a reduction in turbidity with the time of the untreated tunnel waters (1, 2, and 3) are presented in Fig. 1 (Fig. 1A shows water 1, while water 2 and 3 are shown in Fig. 1B). After 60 min of sedimentation, the reduction in turbidity was 79.0%, 96.8%, and 99.3% for water 1, 2, and 3, respectively. As shown in Table 2, the corresponding reductions after 15 minutes were 50.4%, 90.2%, and 90.4%. From these numbers, the shape of the curves in Fig. 1, and reductions in TSS after 15 min of sedimentation (Table 1 and Table 2), it was indicated that sedimentation is a highly effective treatment process for tunnel water, in particular for waters carrying high loads of suspended solids (water 2 and 3). However, additional treatment is needed to comply with discharge limits regarding particle content (TSS) and metal concentrations, e.g., Cu and Cr.

This study implemented chemical coagulation and precipitation to remove small residual particles with low settling velocity. For efficient treatment and substantially lower chemical dosages, we introduced a two-step treatment process, with 1) pre-sedimentation to remove the majority of the suspended solids (here 15 minutes of sedimentation) followed by 2) chemical coagulation, flocculation, and precipitation to remove the finer solids.

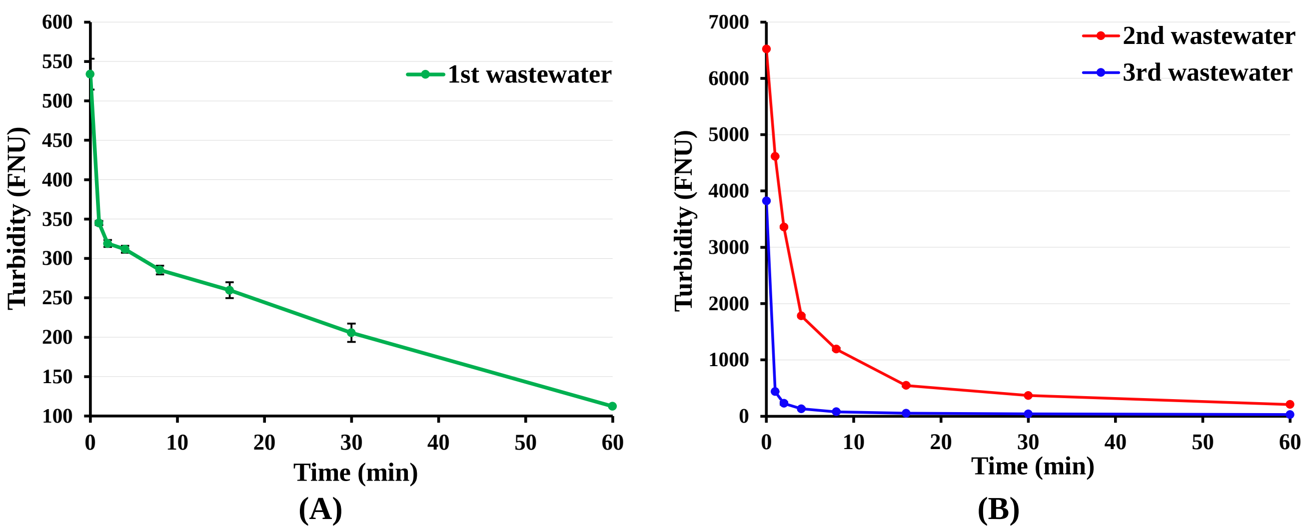


Fig. 1 Settling velocity, as turbidity values versus sedimentation time, for tunnel water 1 (A) and tunnel water 2 and 3 (B)

Fig. 2 displays the SEM images of particles present in tunneling water 1, 2, and 3 before and after sedimentation. Here, only selected images are shown to represent the overall microstructures of each sample. SEM analysis indicated a reduction of the solid content after sedimentation in all three wastewater samples, which is in line with the results presented in Fig.1. The effect was pronounced in water 3, as shown in Fig. 2f, where the density of dispersed particles after sedimentation appeared significantly lower compared to the water without treatment (Fig. 2c). To highlight particle morphology, high magnification images are shown in images a1-c1 (before sedimentation) and d1-f1 (after 15 minutes of sedimentation).

For water 2, there was no such clear reduction in particle density before and after sedimentation when comparing images b and e in Fig. 2. The apparent modest differences in particle densities can be explained by the sampling procedure, which allowed for settling of larger particles before sampling, thereby reducing the differences between untreated and treated waters. It is also important how the SEM images are interpreted before concluding about particle density. At first glance, the density of the particles in water 2 appeared to be higher after sedimentation than before sedimentation (Fig. 2e compared to Fig. 2b). However, a closer inspection revealed that untreated water consisted of large clusters of particles, as evident in Fig. 2b1. On the other hand, the majority of the particles after sedimentation were smaller, and they were distributed in a way to give an impression of high density of particles despite an overall lower volume density in the sample (Fig. 2e, 2e1). Furthermore, the untreated water 2 sample exhibited particles with sharp edges, while particle morphology is more 'rounded' after sedimentation. This suggests that sedimentation treatment is not only efficient in the reduction of the solid content but also in the removal of particles with sharp edges. Similar effects were observed for the other two water samples.

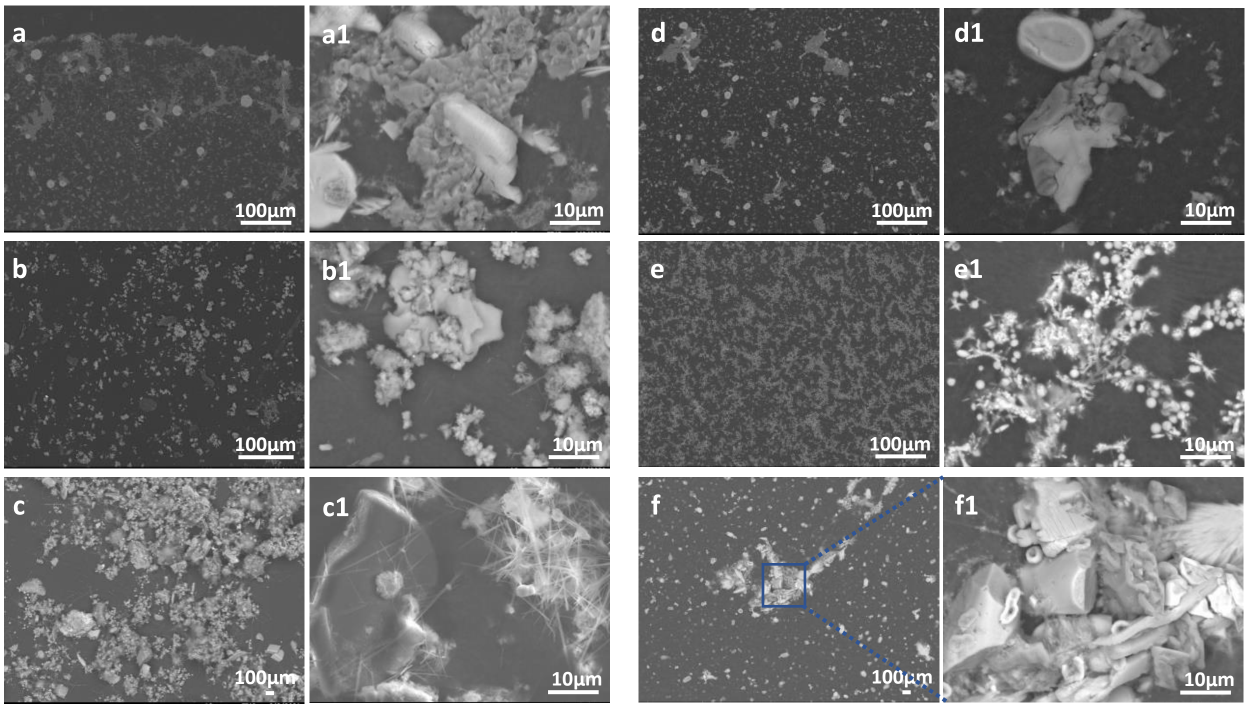


Fig. 2 Images a-c show particles in tunneling water 1, 2, and 3, respectively, before sedimentation. Corresponding high magnification images are shown in images a1-c1. Images d-f show particles from tunneling water 1, 2, and 3, respectively, after 15 minutes of sedimentation, with corresponding high magnification images shown in d1-f1.

EDS analysis, presented in the appendix, showed the presence of As, Pb, S, Cd, Cu, Cr, Ni, Fe, and Ti associated with particles. However, Zn was not found in the EDS in any of the samples, even though the presence was shown in all three waters in Table 1. The absence of Zn in the EDS analysis can be explained by the very small volume of water used for SEM/EDS analysis and the methodology used for sample collection. If Zn is associated with larger size particles, they may have been removed by settling before sampling and will not appear in the SEM analysis. Larger particles are easily removed during the sedimentation process, which leads to a high overall reduction in the content of metal pollutants, especially Zn, as also shown in Tables 1 and 2.

3.2 Chemical coagulation, flocculation, and sedimentation

To follow this two-step treatment strategy, all tunnel waters were subjected to 15 min sedimentation, and the clear phase was used for further coagulation experiments. Due to the higher ratio of finer particles in water 1 after 15 minutes of sedimentation, compared to water 2 and 3, water 1 was chosen for extensive studies of the effects of coagulants. Three different coagulants were tested (PIX-318, PAX-XL-3103D, and chitosan). HCl was used for adjustment of the coagulation-pH to 6.0 ± 0.2. Turbidity values and TSS concentrations versus increasing dosages of the three coagulants are presented in Fig. 3 A and B. It was shown that both PAX and PIX coagulation resulted in lower turbidity and TSS values than the use of chitosan; however, higher dosages were required to obtain the best removal efficiencies. Regarding chitosan, the optimum dosage was approximately 1 mg/l, which resulted in residual turbidity of 30.6 FNU and a TSS concentration of 23.7 mg/l, and removal efficiencies of 93.7% and 92.5%, respectively. At higher dosages, reduced removals were observed. For PAX and PIX, very low residuals for turbidity (3 and 9.9 FNU) and TSS (11.6 and 12.7 mg/l) were obtained at dosages of 3 mg Al/l and 3 mg Fe/l, respectively. Marginal additional removals were observed by applying higher dosages. PAX was regarded as slightly superior to PIX, particularly at lower dosages, and was therefore selected for additional testing with water 3.

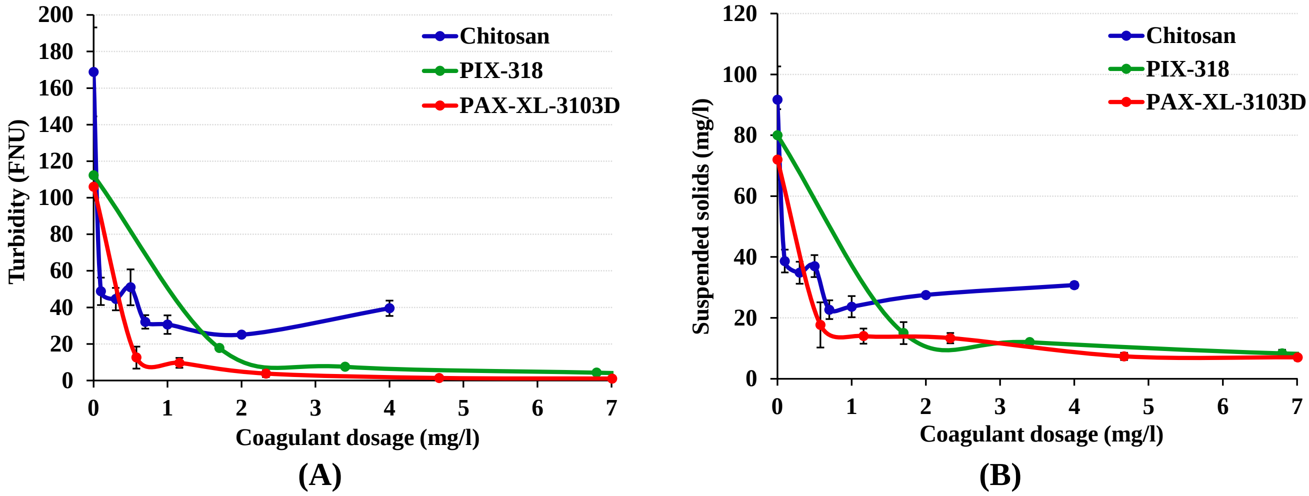


Fig. 3 Turbidity-values (A) and TSS-concentrations (B) in tunnel water 1 versus increasing dosages of chitosan, PIX and PAX.

As indicated in Fig. 4, low residuals of turbidity and TSS were shown by low amounts of PAX in water 3, with an optimum dosage of 2 mg Al/l. The results show poorer removal efficiencies at higher dosage (3 mg Al/l), indicate that overdosing is possible and should be avoided.

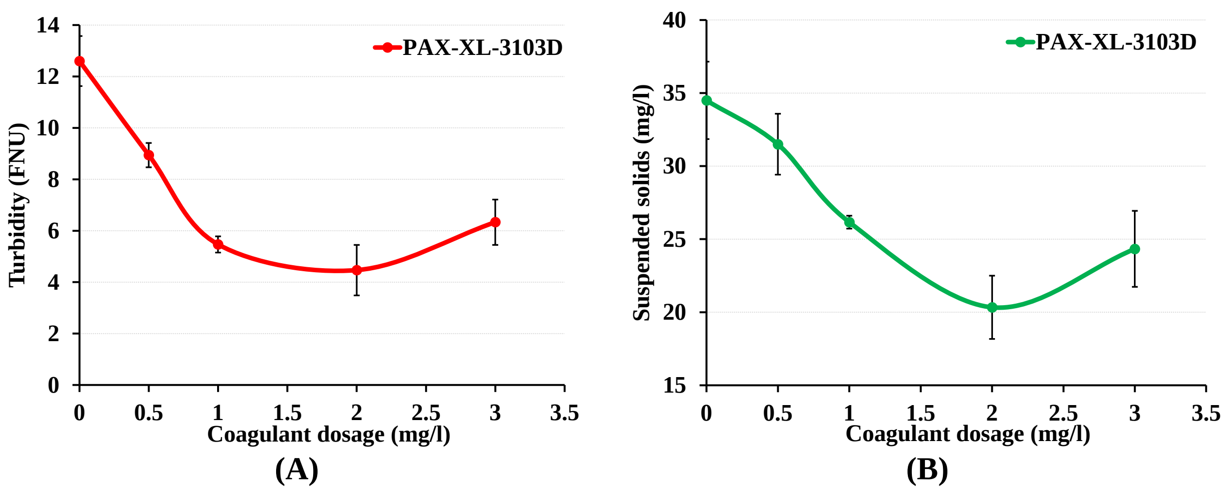


Fig. 4 Turbidity-values (A) and TSS-concentrations (B) in tunnel water 3 versus increasing dosages of PAX.

Fig. 5 displays the SEM images of the water 3 after 15 min of sedimentation (left image) and after coagulation with PAX followed by sedimentation (right image). SEM analysis is consistent with the above results and showed a reduction of the solid content after PAX-treatment and shifting the size distribution towards finer particles due to the removal and/or de-agglomeration of the large clusters of particles. The right panel in Fig. 5 shows some large brighter structures, which might be explained by voluminous unsettled aluminum hydroxide flocs formed as a result of the PAX-treatment.

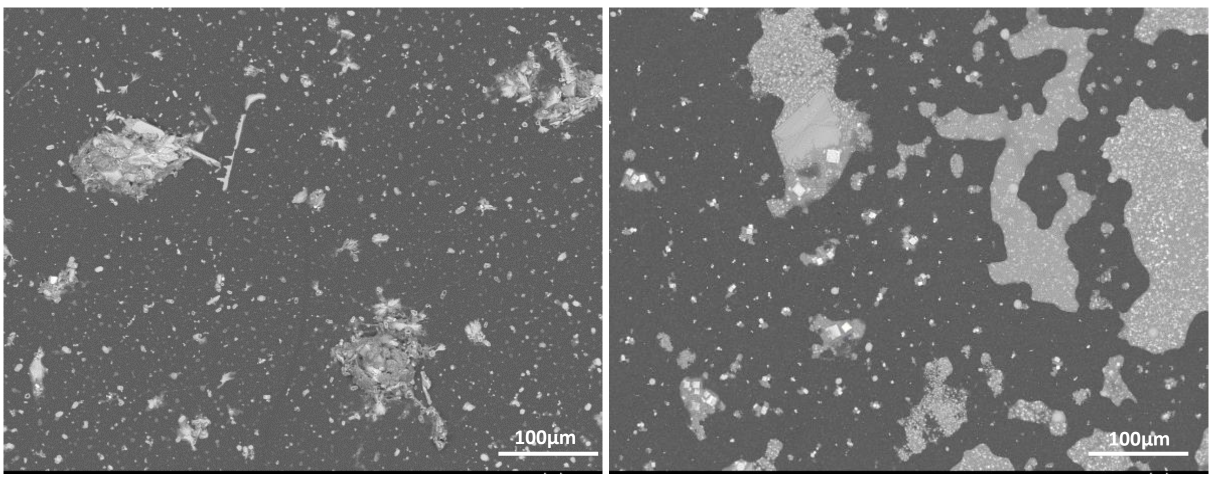
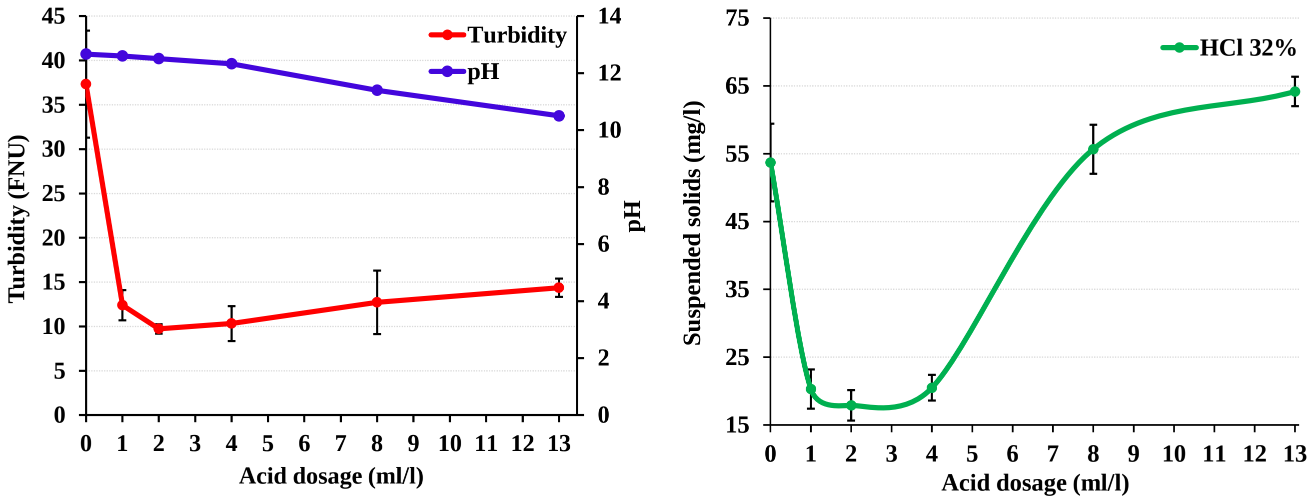


Fig. 5 SEM images of the tunnel water 3 after 15 min of sedimentation (left panel), and two-step treatment (15 min sedimentation followed by coagulation with PAX (2 mg Al/l)) (right panel).

Due to the high initial pH value of tunnel water 2 and 3, it was observed that substantial amounts of acid (HCl) were required to reduce the pH for the best coagulation performance, which was approximately 6 for the chemicals used. It was also observed that the addition of acid alone resulted in good particle removal in jar tests. As shown in Fig. 6, by applying a dosage of 2 ml/l of 32% HCl, the residual TSS was lower than the result obtained in water 3 with the optimum dosage of

PAX (2 mg Al/l) (Fig. 3 B). At higher acid dosages, both turbidity values and SS concentrations increased.



(A) (B)

Fig. 6 Turbidity-values (A) and TSS-concentrations (B) in tunnel water 2 versus increasing dosages of HCl.

Notably, the TSS reduction was highly correlated with the turbidity removal, with a Pearson correlation coefficient of 0.97 based on all the jar-test results. The optimal dosage and removal efficiencies regarding turbidity and TSS from all jar tests are presented in Table 3.

Table 3 Removal efficiency and optimal chemical dosage for the three tunnel waters

Tunnel water	Chemical	Optimal dosage	Turbidity (FNU)			TSS (mg/L)			pH
			Initial	Final	Reduction*	Initial	Final	Reduction*	
1	Chitosan	1 (mg/l)	534	30.6	93.7	317	23.7	92.5	6 ± 0.2
	PIX	3 (mg Fe/l)	534	9.9	98.1	317	12.7	95.9	6 ± 0.2
	PAX	3 (mg Al/l)	534	3	99.4	317	11.6	96.3	6 ± 0.2
2	HCl (32%)	2 (ml/l)	6520	9.7	99.8	6140	17.9	99.7	12.5± 0.2
3	PAX	2 (mg Al/l)	3824	4.5	99.8	8530	20.3	99.7	6 ± 0.2

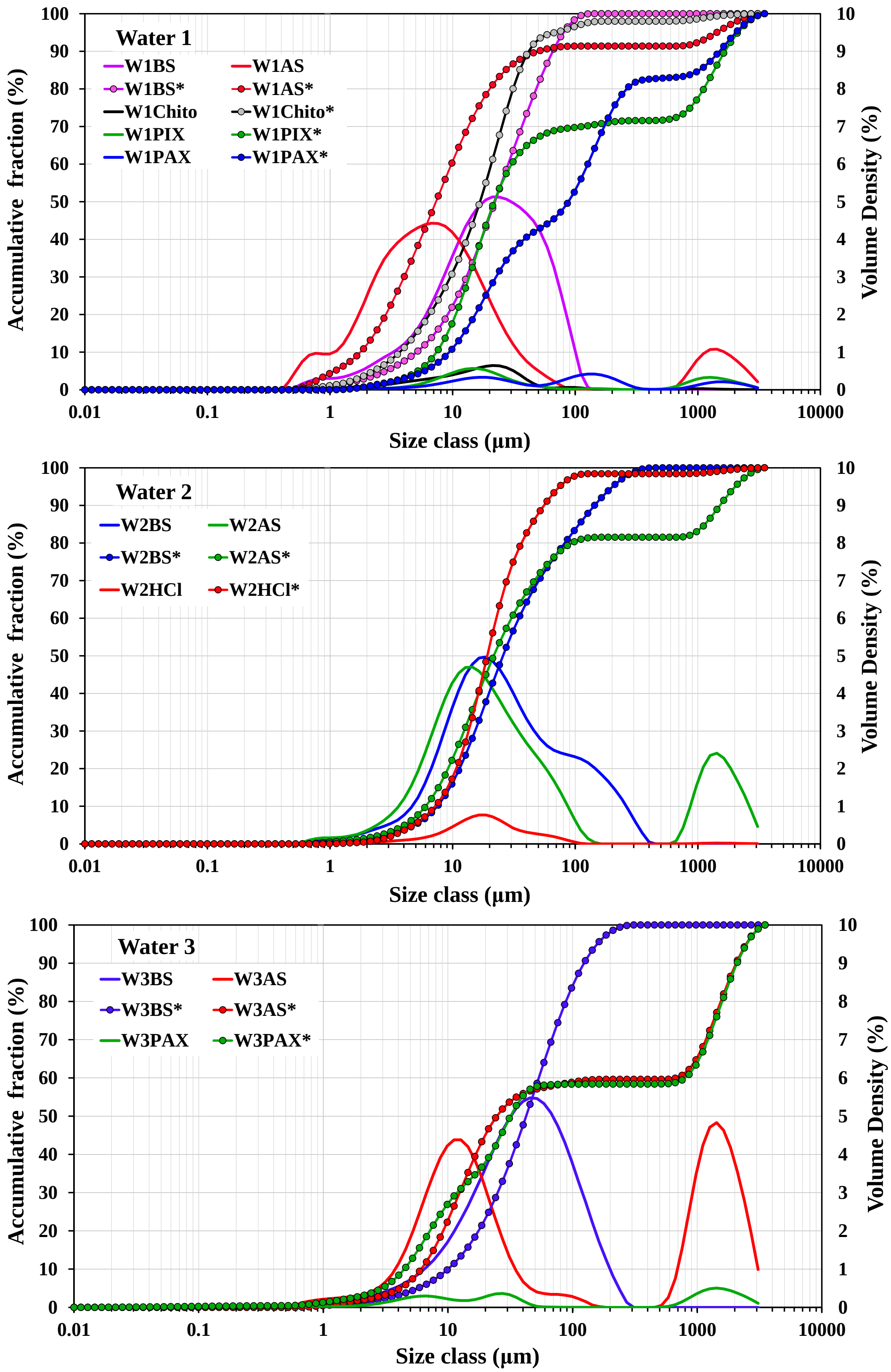
*The reduction percentage (%) was calculated by two digits and rounded down

The two-step treatment (15 min sedimentation followed by chemical coagulation and 45 min sedimentation) showed high removal efficiencies for both turbidity (>93 %) and TSS (>92%) for all chemicals tested, with residual concentrations substantial below discharge limits. The results obtained with PAX and PIX in water 1 were similar, with a slightly lower final turbidity value with PAX. Dosages of 2-3 mg Al/l of PAX (tunnel water 1 and 3) resulted in effluent turbidity and TSS concentrations in the range of 3.0-4.5 FNU and 11.6-20.3 mg/l, respectively, corresponding to removal efficiencies of 96.3-99.7%. The performance of chitosan was slightly lower but still sufficient to comply with discharge limits. The low chitosan dosage required (1 mg/l) implies low sludge production, which is beneficial when it comes to environmental impact and operational costs of treatment facilities. Also, the acid treatment with 2 ml/l of 32% HCl resulted in an outstanding performance regarding overall turbidity removal (99.8 %) and TSS removal (99.7 %). Low sludge production is also expected with acid treatment compared to Al- and Fe-based coagulants.

3.3 Particle size distribution

Besides turbidity and TSS, characterization of tunnel water in terms of the particle size distribution (PSD) and volume density is important to predict environmental impacts and evaluate the effect of treatment. The PSD curves are shown in Fig. 7, in which the solid lines show the density fraction of PSD of the different tunnel waters. The corresponding marked lines indicate the accumulative fraction of PSD. Regarding water 1, comparing the PSD curves before (W1BS) and after sedimentation (W1AS) suggests that 15 minutes of sedimentation shifted PSDs from coarser particles (D50 = 22.1) to finer particles (D50 = 7.3). Interestingly, after sedimentation, some few unsettled larger particles (>1000 μm) made a more substantial amount of the total particle volumes. This was particularly pronounced in water 3 (W3AS), which was the water with the best sedimentation performance (98.5% of the TSS was removed after 15 min sedimentation, as shown in Table 2). The application of chemicals (chitosan, PAX, and PIX) significantly decreased the volume density of particles (Fig. 7). It means that the contribution of different particle sizes (defined by their volume) after using chemicals was decreased. The accumulative fraction of a specific size indicates the portion of the total volume of the tested sample that has an equivalent diameter less than the specific size. With that in mind, in water 1, the accumulative fraction of particles bigger than 70 μm decreased by 15 minutes sedimentation (W1BS* versus W1AS* in Fig. 7). For chitosan, PAX, and PIX, a cumulative fraction decrease was evident for particles bigger than 80, 30, and 1 μm (W1BS* versus W1Chito*, W1PAX*, and W1PIX* in Fig. 7).

In water 2, as also evident in the SEM images in Fig. 2, the PSD analysis demonstrates that 15 minutes of sedimentation shifted the distribution towards finer particles. However, 18.4% of the particle volume was detected in the range of >500 μm (W2BS versus W2AS in Fig. 7). Using 2 ml/L of 32% HCl in the jar test remarkably decreased the particle volume density (W2AS versus W2HCl in Fig. 7). By 15 minutes of sedimentation in water 2, the accumulative fraction for the particles bigger than 70 μm decreased up to 20 % (W2BS* versus W2AS* in Fig. 7). In contrast, HCl treatment increased the accumulative fraction for the particles smaller than 300 μm, and after that, since only 1.6% of the particle volume was related to larger particles, the accumulative curve almost remained constant (W2BS* versus W2HCl* in Fig. 7). Regarding water 3, 15 minutes of sedimentation shifted the PSD towards finer particles and decreased the volume density of particles smaller than 500 μm. However, a notable portion (40.4 %) of the particle volume in water 3 after sedimentation (W3AS) was detected in the range of 500-3000 μm (W3BS versus W3AS in Fig. 7). The optimum dosage of PAX (2 mg Al /L) sharply reduced the volume density (W3AS versus W3PAX in Fig. 7).



Water 1
W1BS
W1BS*
W1Chito
W1PIX
W1PAX
W1AS
W1AS*
W1Chito*
W1PIX*
W1PAX*
Accumulative fraction (%)
Volume Density (%)
Size class (μm)
Water 2
W2BS
W2BS*
W2HCl
W2AS
W2AS*
W2HCl*
Accumulative fraction (%)
Volume Density (%)
Size class (μm)
Water 3
W3BS
W3BS*
W3PAX
W3AS
W3AS*
W3PAX*
Accumulative fraction (%)
Volume Density (%)
Size class (μm)

Fig. 7 The differential volume curve of samples. $WiBS$ and $WiAS$ show the i^{th} water before and after sedimentation. The marked lines indicate the accumulative fractions. Legends: BS = before sedimentation, AF = after sedimentation, HCl = optimum dosage of acid (HCl), Chito = optimum dosage of chitosan, PAX = optimum dosage of PAX, PIX = optimum dosage of PIX, * = accumulative volume distribution.

In water 3, the accumulative fraction curve of 15 minutes sedimentation and the curve of optimum dosage of PAX were almost the same. This does not indicate a lack of particle removal by PAX treatment, but similar removal in all size fractions, so the size distribution before and after remains almost constant. Compared to the sample before sedimentation, the accumulation fraction curve shows a substantial decrease of approximately 40% in particles >50 μm (W3BS* versus W3AS*, and W3PAX* in Fig. 7). Larger size particles, as shown by Mastersizer, could not be seen in SEM. Such larger particles may have been excluded from the samples by settling or loss in other ways. SEM analysis was done on a very small volume of the wastewaters.

In volume-based PSDs, the distributions of particle sizes are often defined by D10, D50, and D90 in μm. These terms are defined as follows:

- D10: The portion of particles with diameters smaller than this value is 10%
- D50: The portions of particles with diameters smaller and larger than this value are 50%. Also known as the median diameter.
- D90: The portion of particles with diameters below this value is 90%

The shape of the particle distribution curve can be described by the span, defined as D90-D10/D50. In Table 4, values of D10, D50, D90, and the span are given before and after sedimentation and after coagulation. In water 2 and 3, the span was raised substantially after sedimentation. This is mainly because D90 significantly increased during 15 minutes of sedimentation (Table 4). Water 3 had the highest increase in the span value.

Table 4 Typical diameter parameters of PSD for the tunneling wastewater (μm)

Sample[1]	D10	D50	D90	Span[2]
Water 1 before sedimentation	5.07	22.1	65.6	2.7
Water 1after sedimentation	1.76	7.31	49.8	6.6
Water 1 with chitosan[3]	3.7	16.7	41.8	2.3
Water 1 with PIX[3]	7.38	21.8	1660	75.8
Water 1 with PAX[3]	9.37	87.9	1500	17
Water 2 before sedimentation	7.49	25.7	144	5.3
Water 2 after sedimentation	6.03	21.6	1520	70.1
Water 2 with HCl[3]	7.2	19.2	55.7	2.5
Water 3 before sedimentation	10	42.4	123	2.7
Water 3 after sedimentation	6.10	24.7	2050	82.7
Water 3 with PAX[3]	4.46	31.8	2090	65.6

[1]Average of ten measurements. [2]In volume-based size distribution, span is defined as (D90-D10/D50). [3] For the optimum dosage from the jar test.

Regarding water 1, the application of chitosan did not significantly change the span. But PIX and PAX sharply increased the D90 and consequently amplified the span. This is also in agreement with the results of Fig. 7 (see W1BS vs. W1Chito, W1PIX, and W1PAX). Contrarily, using the HCl 32% for water 2 decreased both D10 and D90 and consequently reduced the span (see W2BS vs. W2HCl in Fig. 7). Given water 3, the D90 and span of the PSD curve before sedimentation were dramatically raised when PAX was applied as a coagulant in the jar test. This result agrees with the PSD analysis in Fig. 7 (W3BS vs. W3PAX). To analyze the particles' size range, the PSD results were categorized in five intervals, including <1, 1-10, 10-100, 100-1000, and 1000-10,000 μm. Fig. 8 shows the particle size ranges' variation before and after sedimentation and after using different chemicals.

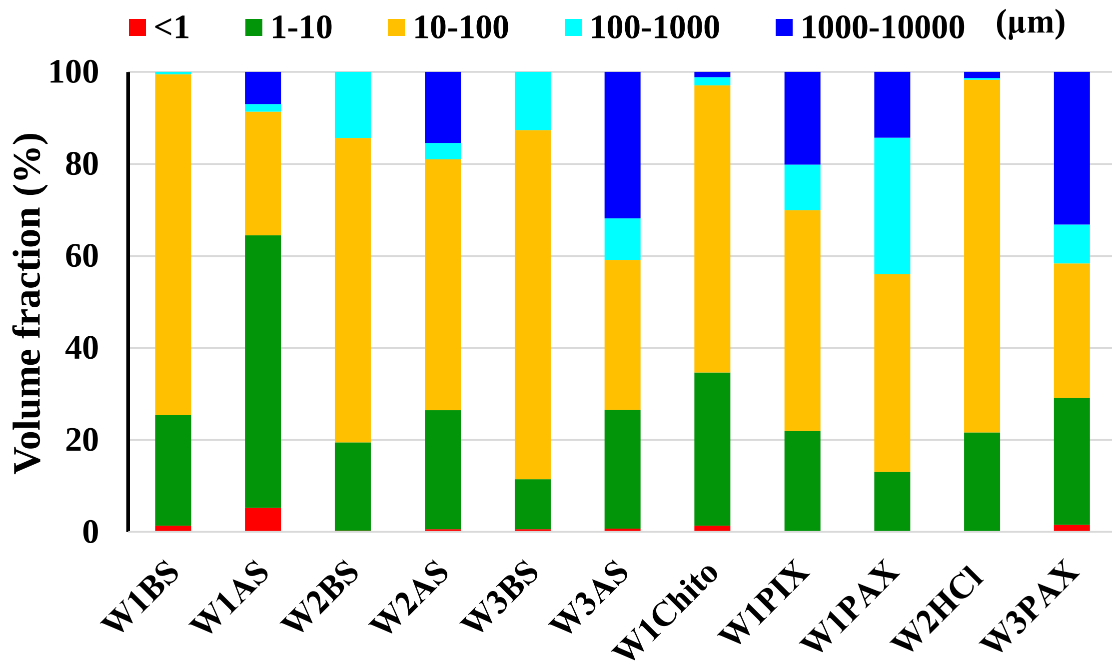


Fig. 8 Particle size variation in tunneling wastewaters before and after sedimentation ($WiBS$ and $WiAS$ show the i^{th} wastewater before and after sedimentation. Wi is the i^{th} wastewater). Legends: BS = before sedimentation, AF = after sedimentation, HCl = optimum dosage of acid (HCl), Chito = optimum dosage of chitosan, PAX = optimum dosage of PAX, PIX = optimum dosage of PIX.

In water 1, before sedimentation, 74% of the sample volume had the particle size in the range of 10-100 µm. By 15 minutes of settling, the largest portion of the sample volume (59%) was in the range of 1-10 µm. The application of chitosan, PIX, and PAX decreased the sample volume in the range of 10-100 µm by 11.7, 26, and 31%, respectively. Therefore, coagulants are efficient in particle removal, especially for particles smaller than 100 µm. For water 2 before sedimentation, the largest part of the sample volume was in the range of 10-100 µm (66.1%). Sedimentation (15 minutes) lessened this volumetric part of the sample by 11.6%. HCl 32% reduced the volume fraction of the sample in the range of >100 µm by 12.7 %. However, for the range of 10-100 µm, the application of HCl 32% caused an increase of 10.5%. In water 3, before sedimentation, the largest volumetric part of the sample is in the range of 10-100 µm (75.8%). During 15 minutes of settling, this part was reduced by 43.2%, and at the same time, the volumetric part of the sample in the range of 1000-10000 μm grew by 31%, which might be explained by some few large particles with low settling velocity, contributing significantly to the total particle volume. During the jar test and using PAX for coagulation, the volumetric part of the sample in the range of 10-100 μm was significantly reduced (by 46.6%), showing this coagulant is highly efficient to remove the particle in this range. However, the sample's volumetric portion in the range of 1000-10000 μm increased by 33.2% in this case, which again can be explained by some few lightweight particles not removed by sedimentation. Al- and Fe-coagulants are known to produce voluminous hydroxides particles in water, which are the principal agents for particle removal. However, some large unsettled hydroxide flocs may have interfered with the PSD analysis.

There is a consistency between our results and other studies in the literature. However, the characterization of the tunneling wastewaters is site-specific. For example (Lee et al., 2013) used turbidity for evaluating the performance of chitosan in tunneling wastewater treatment. The results showed removal efficiencies of 98% and 99% for turbidity and TSS, respectively. Also, (Liltved, 2014), assessed the chitosan efficiency for treatment of tunneling wastewater and introduced chitosan as a coagulant with high efficiency at low dosages (82% and 74% for turbidity and TSS), and low sludge production.

4. Conclusion

The aim of this study was to characterize tunneling wastewater and evaluate the performance of sedimentation and the use of different coagulants on particle removal. Accordingly, the characterization of three different tunneling wastewaters was carried out by chemical analysis and various techniques for particle characterization, including particle size distribution, particle morphology, and metal content by a Laser particle analyzer, a scanning electron microscope

(SEM), and an X-ray energy dispersive spectrometer (EDS), respectively. Laboratory work was designed to evaluate the effectiveness of coagulants for particle removal from the waters. Both natural (i.e., chitosan) and chemical coagulants (i.e., PIX-318 and PAX-XL-3103D) were applied in a conventional jar test apparatus to remove particles. The following conclusions were derived from the chemical and microstructure analysis, and the jar test results.

1. Short-time sedimentation alone substantially reduced the particle content (suspended solids and turbidity) and particle-associated pollutants, including heavy metals in the tunneling waters used in this study. However, our results indicate that sedimentation alone is not sufficient as the suspended solid concentration remained higher than the discharge limit of 100 mg/L in all waters, no nitrogen removal was evident, and the concentrations of some heavy metals, in particular Cu and Cr, severely exceeded the concentrations for acute toxic effects in freshwater bodies (Norwegian Environment Agency 2020), indicating that high dilution factors are required when discharged to local freshwater bodies. In addition, pH adjustment is required before discharge.
2. Improved removal efficiencies were demonstrated by chemical coagulation followed by sedimentation. The optimum coagulant dosages in jar tests led to treatment efficiencies in the range of 92-99% for turbidity and SS. The optimum dosages of chitosan, PIX, and PAX for water 1 after pre-treatment (15 min sedimentation) were 1 mg/l, 3 mg Fe/l, and 3 mg Al/l, respectively, while a dosage of 2 mg Al/l gave the best results in water 3. It was also evident that acid dosage alone (2 ml/l of 32% HCl) improved particle removal.
3. Fifteen minutes of sedimentation shifted the particle size distribution from coarser-size fractions to finer particles. The size fraction of 10-100 μm were reduced in all three waters, indicating a rapid sedimentation rate for such particles. The application of chemicals for

coagulation as an additional treatment step significantly decreased the volume density of the particles. The application of chitosan, PIX, and PAX decreased the particle volume in the range of 10-100 μm by 11.7, 26, and 31%, respectively, showing that coagulants are highly efficient for particle removal, especially particles smaller than 100 μm.

4. Tunneling water without treatment exhibits particles with sharp edges. Sedimentation and chemical treatment seem to remove the majority of these particles, resulting in waters with smaller and more 'rounded' particles. The particle shape is a critical issue related to negative impacts on aquatic biota, especially fishes.

The results of this study suggest that the proposed two-step method (15 minutes of sedimentation followed by coagulation and sedimentation) is highly efficient for particle removal in tunneling wastewater and a promising treatment option to comply with discharge regulations. This study contributes to the characterization of tunneling wastewater and puts a step forward in understanding the efficiency of coagulants in particle removal of tunneling wastewater.

Acknowledgments

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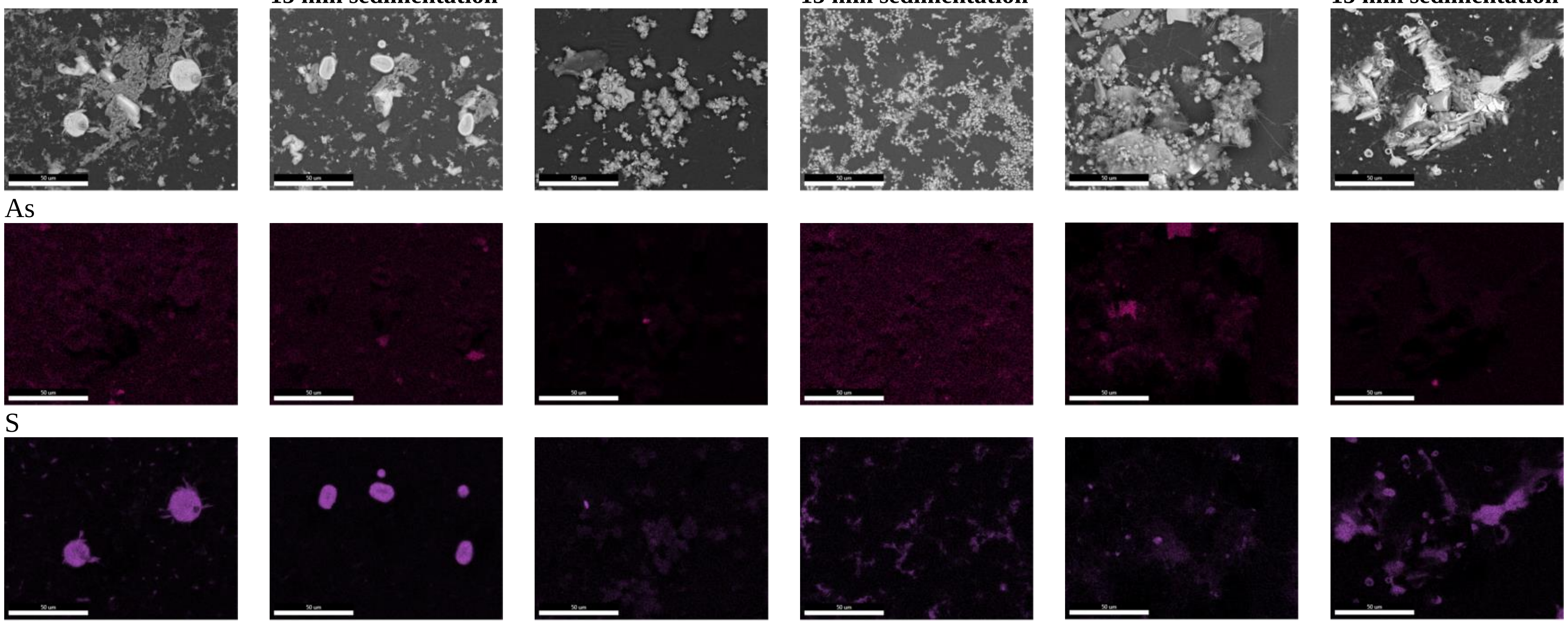
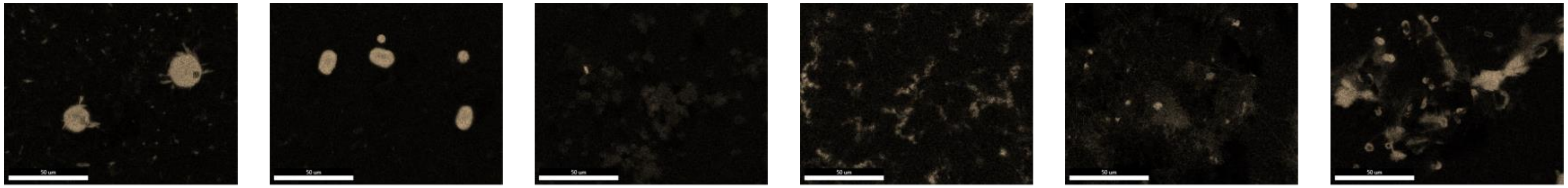
Supplementary Material





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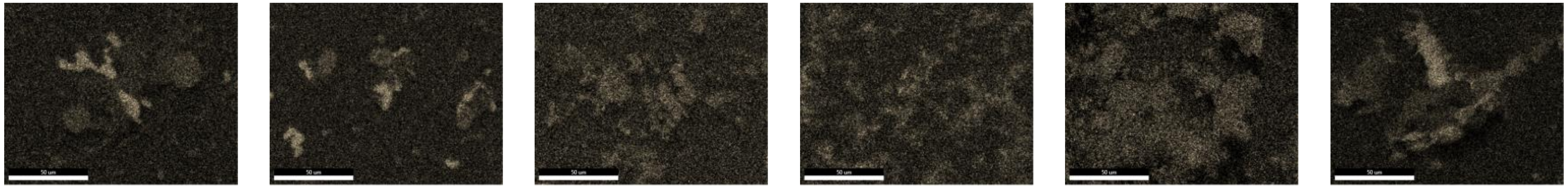

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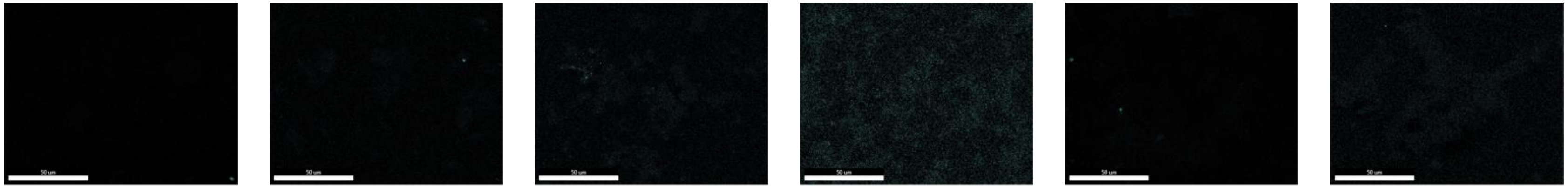

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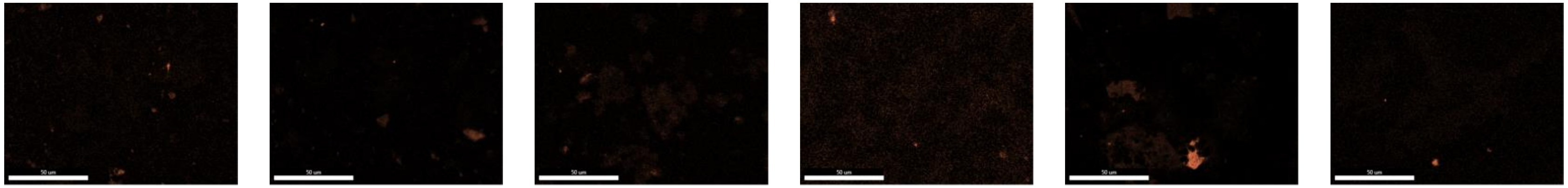

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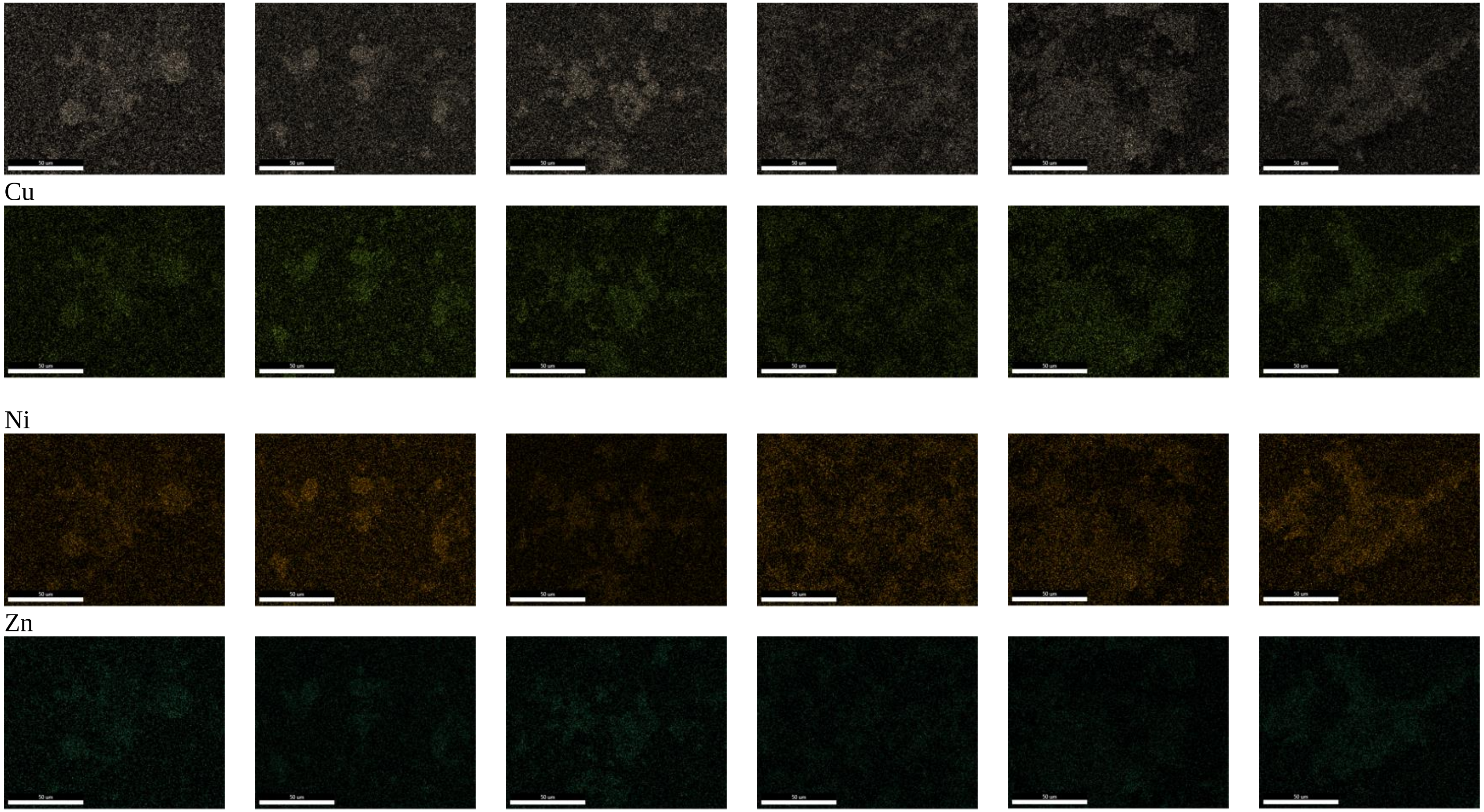

Figure 1 Elemental mapping of the tunnel wastewater samples before and after 15 minutes of sedimentation (scale bar: 50 μm)