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Analyzing the effects of land use on water quality within headwater catchments

Dissertation Thesis

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Declaration

I hereby declare that I have prepared this dissertation independently and have cited all sources of relevant information. The dissertation has not been published elsewhere.

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Ing. Linda R. Staponites

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Contents

1. Introduction

Human actions have transformed a significant proportion of the earth's landscape, impacting ecosystems worldwide. Global population growth and economic development have led to the rapid expansion of cities and suburbs, the intensification of agriculture, and large-scale deforestation. This widespread shift from undisturbed to human-dominated landscapes plays an essential role in the generation of water pollution and the alteration of hydrological processes, leading to potential cascading effects on the functioning of natural systems as well as ramifications for human health and well-being. Consequently, the quality and availability of water has become growing global concerns. As development continues at unprecedented rates, the urgency for protecting the world's water resources increases.

Providing an accurate assessment of complex processes and mechanisms that influence aquatic resources is essential for objectively informing policies and decision-making. This, in turn, can lead to more sustainable and effective strategies for management and planning. Accordingly, this thesis contributes to both the methodological and empirical literature by investigating (1) the inclusion of spatial and topographic landscape attributes for advancing empirical models of land use-water quality interactions, (2) the role of hydrological signatures for enhancing the calibration of a hydrological model, and (3) the effectiveness of land use conversions for improving water quality.

This thesis is presented in the form of three scientific publications, indexed within the Web of Knowledge database. A systematic map of the evidence base is constructed to describe the recent empirical research on the impacts of land use change on surface water quality and detail how investigations have analyzed these interactions. Significant facets of results are explored, and findings are synthesized to highlight knowledge gaps and knowledge clusters and recommend areas for future research. New perspectives into the subject matter as well as the overall importance of the research are discussed.

2. Goals of dissertation

The first scientific publication (hereafter, Article 1) sought to attain an advanced understanding on land use-water quality interactions by integrating land use data with spatial and topographic components of the landscape to determine if the incorporation of additional explanatory variables can improve predictions of water quality within headwater catchments. Novel weighting schemes (i.e., landscape composition metrics), which considered the stream proximity, slope and/or flow accumulation of each land use, were employed to explore the predictive ability of various empirical models. Although a few studies have compared the model performance of weighting schemes for land use, investigations have rarely been carried out for predictions of water quality. Thus, Article 1 investigates the following questions:

1. How do landscape attributes (i.e., slope, stream proximity and flow accumulation) influence land use predictions of water quality in small, headwater catchments?
2. Which weighting scheme has optimal performance in predicting water quality indicators?

The second scientific publication (hereafter, Article 2) sought to improve catchment-scale assessments of the water balance by investigating the role of hydrological signatures (i.e., statistics of runoff and soil moisture) in the calibration of a conceptual hydrological model. The hydrological model was calibrated using various strategies, including standard automatic and manual calibration, and the model performance was evaluated to determine the optimal strategy. Unlike calibration strategies which employ time series data, hydrological signatures can be interpolated or estimated with limited observations, and thus examining their role is essential for accurately representing hydrological processes in ungauged catchments. The objectives of Article 2 can be summarized by the following questions:

1. Do hydrological signatures improve the calibration of a conceptual hydrological model?

2. Is time series data necessary when modeling the water balance?

The third scientific publication (hereafter, Article 3) sought to provide insights on the capabilities of management interventions and expectations for potential outcomes by evaluating the effectiveness of land use conversions in mitigating nutrient loading within headwater catchments. The efficacy of catchment-scale management (i.e., the grassing of cropland) was appraised using long-term water quality data as an indicator of protected area performance. This investigation serves as one of the few documented examples of positive outcomes in a freshwater protected area and is among the few 'before and after' study designs which compares temporal changes made within the same locality. The objectives of Article 3 address the following questions:

1. How do various degrees of land use conversions influence nutrient loading?
2. What time frame is needed to observe water quality improvements in headwater catchments?

3. Systematic map of the evidence base

As the research topics included in this thesis address the performance of diverse methods (i.e., Articles 1 and 2) and land use-water quality interactions (i.e., Articles 1 and 3), an evidence synthesis was conducted to answer the primary question: Where and how have studies investigated the effects of land use change on surface water quality?

Although a multitude of studies have endeavored to elucidate the effects of land use changes on water quality, a comprehension of the relationship remains a complicated undertaking (Allan, 2004; Staponites et al., 2019). Investigating the interactions between land use and water quality requires a decision on the extent and scope of the study as well as which set of variables and measures to include. Yet, a diversity of methodologies and techniques have been applied, leaving the decision on how to construct an analysis to the discretion of scientists and practitioners. Knowledge of existing study designs, settings and methods can guide investigators on devising context-appropriate studies, helping to improve the quality of research and advanced analyses. While there is an extensive volume of scientific research, potentially useful information is spread across multiple sources, making it difficult for relevant knowledge to be examined and absorbed (Pullin et al., 2020). To address this deficiency and facilitate evidence-informed decision making, the establishment of an up-to-date evidence base is essential.

Systematic maps are an objective and transparent method used to collate, catalog, and describe the available body of evidence within a given research area (James et al., 2016). The process follows a clearly defined search procedure to increase rigor and replicability. Additionally, the screening and selection process employs specified inclusion and exclusion criteria, thus minimizing biases immanent to traditional literature reviews. Unlike a meta-analysis or systematic review, a systematic map does not attempt to calculate a mean effect across a pool of collated studies or answer a particular question. Instead, knowledge is synthesized across multiple diverse outcomes to map and explore a broad research topic (Cook et al., 2017). A presentation of the scientific evidence base enables a clear and coherent visualization of the quantity and character of existing research as well as an opportunity to disseminate key information (Randall et al., 2015).

Heeding the work of (James et al., 2016), a systematic map was constructed to describe the recent empirical research on water quality response to land use changes and detail how previous investigations have evaluated these interactions. Published scientific literature from peer-reviewed journals and books were searched using the Web of Science database and the Google Scholar search engine. To target appropriate studies, search terms were generated (see Box 1 and 2 in Appendix for search strategy), predicated on key elements for eligibility. The search included full-text articles, written in English, published between 2010 and 2021. Evidence was screened in two phases; titles and abstracts of records were initially screened for relevance, followed by a secondary screening of the full text, with discarded studies stating the reason for exclusion. Relevant studies, conforming to eligibility criteria (Table A1 in Appendix), were retained and included in a database. For this multifarious topic, documents containing measures of physical, chemical and microbiological indicators of surface water quality were considered while biological characteristics (e.g., biodiversity and bioindicators) as well as measures of geomorphic processes (e.g., soil, sedimentation and erosion) were discarded. Only studies based on empirical data were included; research on future change scenarios or projections were excluded. A combination of meta-data (i.e., descriptions) and coding variables (i.e., assigned categories) were extracted from each study, when possible, in order to catalog the available body of evidence (Table 1). The resulting dataset was summarized and compiled using descriptive statistics, enabling the identification of trends, clusters, and gaps.

Table 1. Research questions included in the systematic map and extracted meta-data and coding collated for the database.

Topic	**Research Questions**	**Coding and Meta-data**
Occurrence, volume and setting of research	When and how often does research occur? Where have studies been implemented? What types of surface waters were examined?	- Number of studies - Publication year - Climate zone - Country - Surface water

Parameters, data collection and measures	Which land use classes and water quality indicators have been investigated? How was data obtained and measured? What indices and standards have been applied?	- Land use categories - Water quality indicators - Collection method - Measures - Indices and standards
Scope	What spatial and temporal scales have been examined? How many sites were examined? How many samples or observations were taken?	- Study area size - Spatial extent - Study duration - Number of sites - Sample size
Additional variables	What additional variables or considerations have been included into the analysis?	- Spatial and seasonal considerations - Explanatory variables
Methods for analysis	How are temporal changes examined? What techniques and models have been employed?	- Analysis or model type
Outcomes	What were the notable land use changes during the study period? What were the general trends in water quality?	- Notable land use changes - Direction of change in water quality

3.1 Occurrence, volume and setting of research

The systematic search returned 2,578 potentially relevant records, of which 133 met the eligibility criteria and were included in the systematic map database (Fig. A1 in Appendix). The literature that has emerged in the last 11 years can attest to an overall growth in the field with the number of publications increasing from 4 in 2010 to 26 studies published in 2021 (Fig. 1), with 20% of articles published in 2021. However, the growth has not been consistent, with publication rates fluctuating over time. The climate zone of each study area was assigned according to Köppen–Geiger Classification zones. The largest body of research was within temperate zones (n=73), followed by continental (n=28), tropical (n=21) and arid zones (n=14). Seven studies included in the review spanned more than one climate zone (i.e., multiple zones).

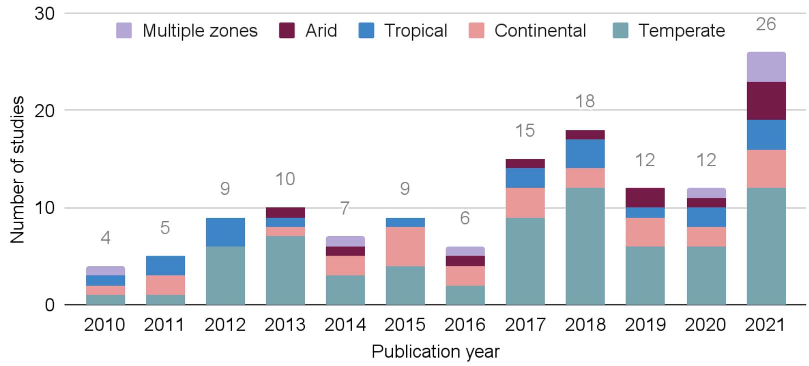

Figure 1. Distribution of relevant articles (n = 133) included in the systematic map database in regard to year of publication and climate zone of study.

Studies across 38 countries matched the scope of the review, yet research was unevenly distributed across countries, with approximately one-third of all included studies coming from China (n=44). Research was also frequently conducted in the United States (n=17, 12.8%), India (n=11, 8.3%) and South Africa (n=8, 6%), while the remaining 34 countries conducted five or less studies, with each country making up less than 4% of the research in the systematic map (Fig. 2).

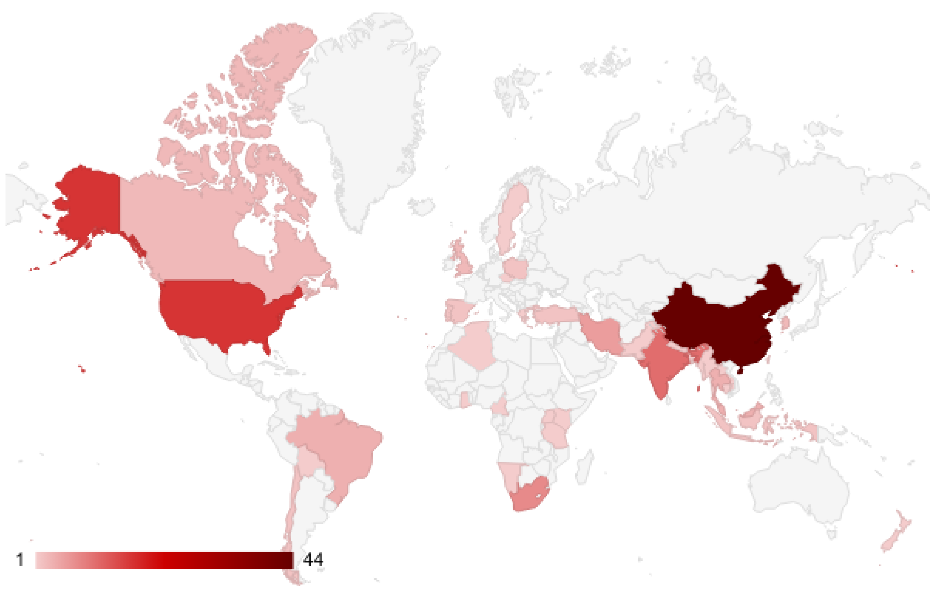

Figure 2. Geographic distribution of studies.

The most examined surface waters within research were tributaries (i.e., streams and rivers) (n=100, 72.5%), with only six identified as headwaters (Fig. 3). The remaining studies focused on the water quality of lakes (n=19. 13.8%), reservoirs (n=8, 5.8%), wetlands (n=7, 5.1%) or canals (n=2, 1.5%). Only two studies investigated the impacts of land use change on saltwater systems (i.e., coastal waters) while a few studies (n=5) investigated a combination of surface water types in their analysis.

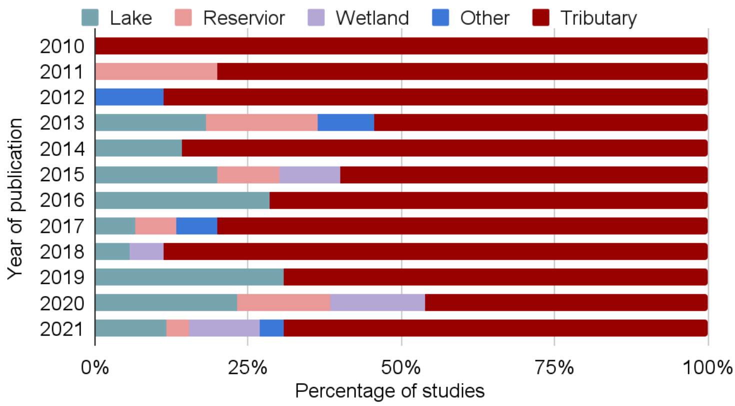

Figure 3. Distribution of surface water types within studies.

3.2 Parameters, data collection and measures

In order to collate information, land use categories identified within studies were grouped into one of nine conventional classes: agriculture, urban, forest, grassland, vegetation, water, wetlands, bare land and other. Categories were assigned according to the description given in each manuscript. Any land use that did not fit into a specified category was classified as 'Other'. A wide variety of nomenclature was employed across the evidence base to describe land use categories (Table A2 in Appendix), with slight variations of similar terminology often being used (i.e., adding 'areas', 'lands' or 'surfaces' to the end of terms or hyphenating terms). Out of the 133 studies included in the systematic map, agriculture and urban lands were the most studied land use categories (n=118 and n=116, respectively), accounting for more than 85% of research (Fig. 4a). Forest (n=103) and water (n=88) were also frequently considered, while approximately half of the studies (47%) examined grassland

and bare land (n=63). Vegetation (n=37), wetlands (n=44) and other land use types (n=45) were relatively less recurrent throughout studies. Most studies examined heterogeneous landscapes with a diversity of land uses, with 64.7% utilizing between four and six different categories (Fig. 4b). Agriculture and urban lands were frequently examined together (n=105). Only two studies included all nine of the identified land use categories. Homogeneous landscapes were less examined, with 20 studies (15%) investigating three or less categories.

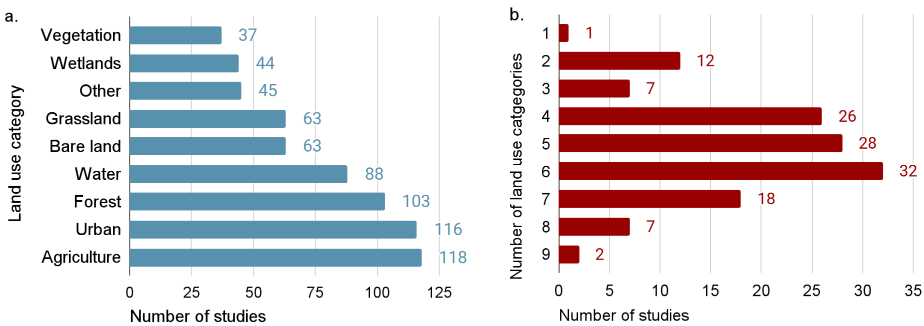

Figure 4. Number of articles reporting on each land use category (a.) and the total number of land use categories reported in each study (b).

Generally, land use categories were evaluated as the area or the percent of composition within the study area (Table 2). Only a few studies (n=3) examined land use patterns while disregarding composition. Yet, 26 studies examined the changes in landscape pattern as well as changes in land use area.

Table 2. The number of studies that applied each land use measure.

Land use Measure	Number of articles
Area	99
Pattern	3
Pattern and Area	26
Other	3
Not specified	2

Each water quality indicator examined in each study was recorded in the database. General indicator categories were created to collate measures of parameters, for example, nitrate and nitrite were classified under nitrogen. An indicator was classified under ‘additional water quality parameters’ when less than three studies examined that specific parameter. In total, 56 different physical, chemical, and microbiological indicators of surface waters were investigated across the 133 studies, with the majority of indicators classified as chemical ions (Fig. 5). The most frequently examined water quality indicators were phosphorus (n=87) and nitrogen (n=83), with almost two-thirds of included studies examining these parameters, followed by dissolved oxygen (n=58), pH (n=51), ammonia (n=49), and solids (n=48). COD (n=44), BOD (n=36), conductivity (n=41), temperature (n=30) and turbidity (n=20) were also commonly examined, while all other parameters were examined less than 20 times. Approximately half of studies (n=66) examined between two and five water quality indicators, 35.3% (n=47) examined between six and eleven indicators, while only 15 studies examined more than twelve indicators.

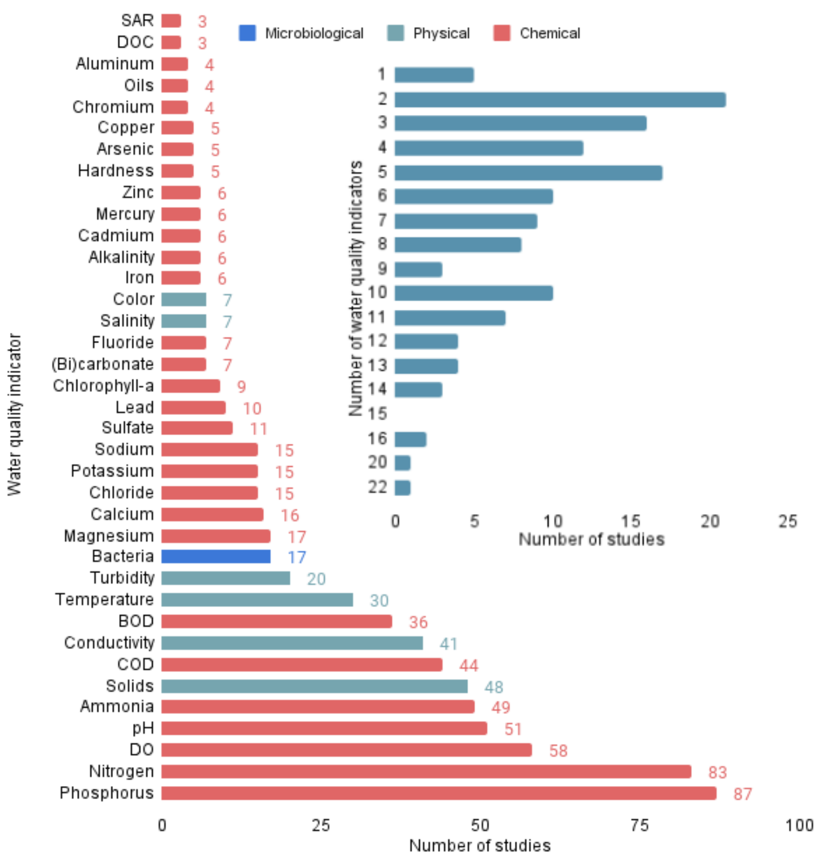

Figure 5. Number of times each water quality indicator is reported in the systematic map database.

The vast majority of research obtained water quality data from field measurements (i.e., monitoring data) (n=106, 79.7%). The remaining 27 studies calculated estimates of water quality via modeling (n=14), available monitoring data (n=9) or remote sensing data (n=3). Measures of the physical, chemical, and microbiological characteristics of surface water quality were typically described in terms of concentrations (n=117) while only a few studies were described as loads (n=14), exports (n=1), and fluxes (n=1). Nearly half of the research (n=61, 45.9%) applied indices or standards to describe the status or health of water quality, with most applying national standards or water quality indices (Table 3).

Table 3. The number of studies that applied water quality indices or standards.

Index or Standard	Number of studies
Water quality index	16
Trophic state index	4
National standards	26
Water quality grade/class	6
Pollution index	7
Management target	1
Stream habitat score	1
Water ecological index	1
Global guidelines (WHO)	4
Total	**61**

Note. Indices and standards were cataloged into broad categories. For specific indexes or standards applied, see the systematic map database.

3.3 Scope

The spatial extent was grouped into micro- (<10 km^2), meso- (10–1,000 km^2), macro- (1,000–100,000 km^2) or regional-scale (>100,000 km^2) based on the size of the investigated area. Research was predominantly carried out in macro- or meso-scale study areas (42.1% and 30.1%, respectively) (Table 4). Only ten studies (n=7.5%) examined an area smaller than 10 km^2 (i.e., micro-scale), while eight studies (n=6%) investigated an area larger than 100,000 km^2 with sites ranging from 238,348 km^2 to 1,800,000 km^2. A total of 14% of articles neglected to mention the spatial extent.

Studies have been conducted at various spatial scales, with a catchment-scale analysis being the most common (52.6%). Approximately 18% of studies examined the sub-catchment scale (n=24), however, the distinction between the catchment and sub-catchment scale was often unclear, unless multiple scales were being examined. In total, 22 studies (n=16.5%) were conducted using multiple spatial scales (e.g., a combination of buffer, sub-catchment and/or catchment). Buffer-scale studies were less common (n=8, 6%), and only a minor proportion or classified as other (n=4) or not describing the scale (n=3).

Table 4. The total number of articles performed across spatial scales (rows) according to the size of the study area (columns).

	Micro	Meso	Macro	Regional	Not specified	Total
Catchment	7	21	32	4	6	**70**
Sub-catchment	0	11	10	1	2	**24**
Buffer	0	3	3	0	2	**8**
Multiple	3	5	5	3	6	**22**
Other	0	1	3	0	2	**6**
Not specified	0	1	1	0	1	**3**
Total	**10**	**40**	**56**	**8**	**19**	

Note. Articles with multiple spatial scales were not included in the category totals. Micro = <10 km^2; Meso = 10 – 1,000 km^2; Macro = 1,000 – 100,000 km^2; Regional = >100,000 km^2.

Land use and water quality changes were frequently examined over the same or similar durations (i.e., 1 year difference with start or finish dates) (n=82, 61.7%), yet the study length for land use and water quality data differed for 47 studies (Fig. 6). A total of 16 studies started monitoring water quality trends before the land use, while 19 studies started observing water quality years after initial land uses were recorded. Moreover, 12 studies observed water quality only after land use had been surveyed. Very few case studies continued monitoring water quality for an extended period of time after the land use was recorded. A small number of studies did not specify the water quality duration (n=4), and therefore were not included in the figure.

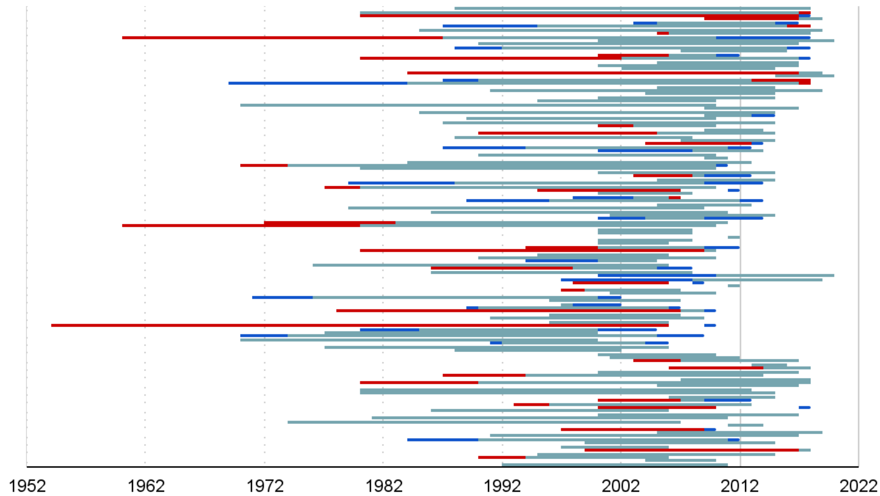

Figure 6. Gantt-Chart of the duration for studies included in the systematic map database. Each horizontal line represents a study, and the length of the line represents the duration of the study. The period of examined land use and water quality is indicated by red and blue, respectively. The green represents the period when both land use and water quality were examined.

The span of studies (time between the first and last observation) ranged from 1 to 52 years for land use and from less than 1 to 40 years for water quality (Fig. 7). Out of the 133 studies within the evidence base, over half of the research observed changes over a span of 2 to 20 years. Altogether, 19 studies (14.3%) examined land use changes longer than 30 years, while only 12 studies (9%) examined water quality over a 30-year interval. Unexpectedly, several studies (n=9, 6.8%) investigated water quality over a span of less than one year.

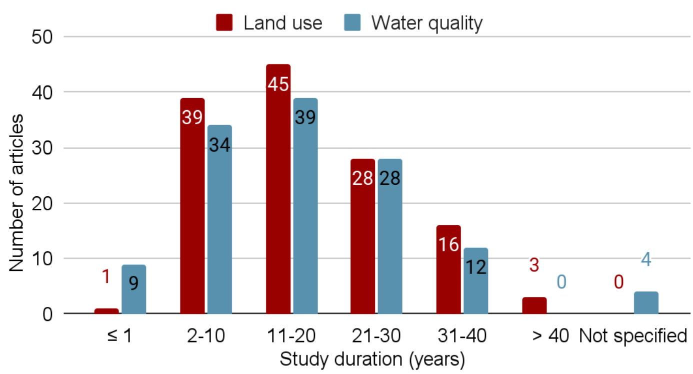

Figure 7. Span of changes in land use and water quality examined in studies.

Information on the number of sites that examined land use changes as well as the number of sites that examined water quality was recorded. Many studies identified multiple land sites in their study area (i.e., catchments, watersheds), yet would calculate the total land use change within the entire study area as opposed to changes within each site. Additionally, many studies examined one land site, but at multiple spatial scales. In both cases, the number of study sites were recorded as one. Investigations on land use changes were often limited to 12 or less sites (n=124, 93.2% %), with nearly half of studies only examining one site for land use changes (n=62, 46.6%) (Table 5). On the other hand, a wider range of sampling or collection sites were used to evaluate water quality, with many investigations examining between 2 and 18 sites (n=87, 65.4%). Details on water collection techniques for studies which employed field measurements were often lacking, with 85.8% failing to report the number of samples taken (n=91) and 44.3% not specifying the frequency of sampling (n=47). Of the 59 studies that noted the sampling frequency, rates of collection varied greatly. Samples collected monthly were the most common (n=23), followed by four times a year (n=6).

Table 5. Number of sites examined within studies included in the systematic map database.

Land use change		**Water quality**	
Statistic	**Value**	**Statistic**	**Value**
Minimum	1	Minimum	1
Maximum	55	Maximum	500
Median	2	Median	9
Standard deviation	7.18	Standard deviation	57.04
Not specified	1	Not specified	10

3.4 Additional considerations

Approximately one-third of studies (n=46) examined seasonal variations in water quality with the majority investigating variations between wet and dry seasons (n=17), two seasons (n=9) or four seasons (n=12). Four studies investigated inter-annual variations (i.e., wet and dry years), while two separate studies examined high and low flow periods, and monsoon periods, respectively. Four studies employed data from a single season instead of examining seasonal variation, while 83 studies (62.4%) did not consider seasonal effects of water quality.

Additionally, many studies examined spatial variation in land use (n=30), water quality (n=27) or both (n=30) when elucidating the relationship between land use change and water quality, while 46 studies (34.6%) did not consider any spatial aspects. The spatial distribution of land use categories was investigated via employing multiple spatial scales (n=22), examining land use pattern (n=5) or changes in land use pattern (n=22), mapping the spatial changes in land use across the study area (n=13), or weighting the distance of land use (n=3). The spatial pattern of water quality indicators within a study area was often investigated statistically, via ANOVA (n=11), cluster analysis (n=8), Global and local Moran's I (n=3), Helmert contrasts (n=1), or distance via weighting scheme (n=1). More commonly, water quality pattern was visualized spatially in maps (n=20) via simulation, interpolation, or satellite images or simply compared between the upstream and downstream continuum (n=15).

Along with land use, potential pressures on water quality have been routinely used as explanatory variables in analysis. For each study, information on additional independent variables included into the investigation were coded into the systematic map database. Due to the assortment, independent variables were grouped into one of six general categories: climate, hydrology, management, socio-economic, soil, and topography. Of the 133 studies compiled, approximately one-third of articles (n=49) included additional independent variables as possible drivers of water quality conditions while the majority of studies disregarded any impacts in addition to land use (n=84). Climatic factors (rainfall, precipitation, and air temperature) and hydrologic factors (discharge) were amongst the most prevalent variables included into the analysis (Fig. 8). Of the studies that considered factors in addition to land use change, most included one (n=14), two (n=19), or three (n=9) additional predictors of water quality, while there was less of a tendency for studies to employ more than three independent variables (n=7).

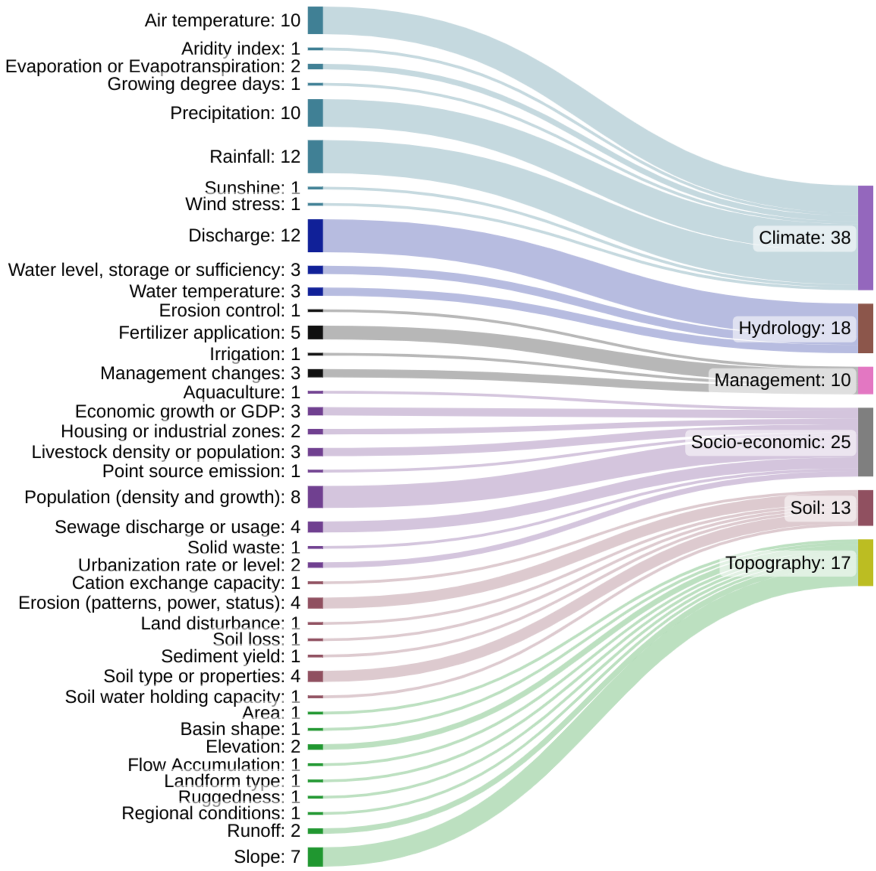

Figure 8. Sankey diagram of the frequency of independent variables included in the systematic map database.

In addition to water quality indicators, supplementary responses to land use changes were investigated in approximately one-third of studies (n=45). Response variables included in the evidence base were grouped into one of five broad categories, similar to that of independent variables: Climate, hydrology, soil, topography and other. Outcomes on hydrology and soil were most commonly examined, with many studies examining the impacts on discharge and sediment load/yield together with water quality (Fig. 9). Some variables were employed as both predictors and responses depending on the study, including air temperature, evapotranspiration, rainfall, discharge, sewage discharge, water level, soil loss and runoff. Discharge was the most investigated explanatory variable as well as the most extensively researched response variable when examining the impacts of land use change on water quality. Yet, most of the studies that examined additional explanatory variables did not examine additional response variables, with only 18 studies (13.5%) investigating both. In contrast to the independent variables, the majority of studies typically only included one additional response variable (n=32), with 13 studies investigating between two and four additional outcomes.

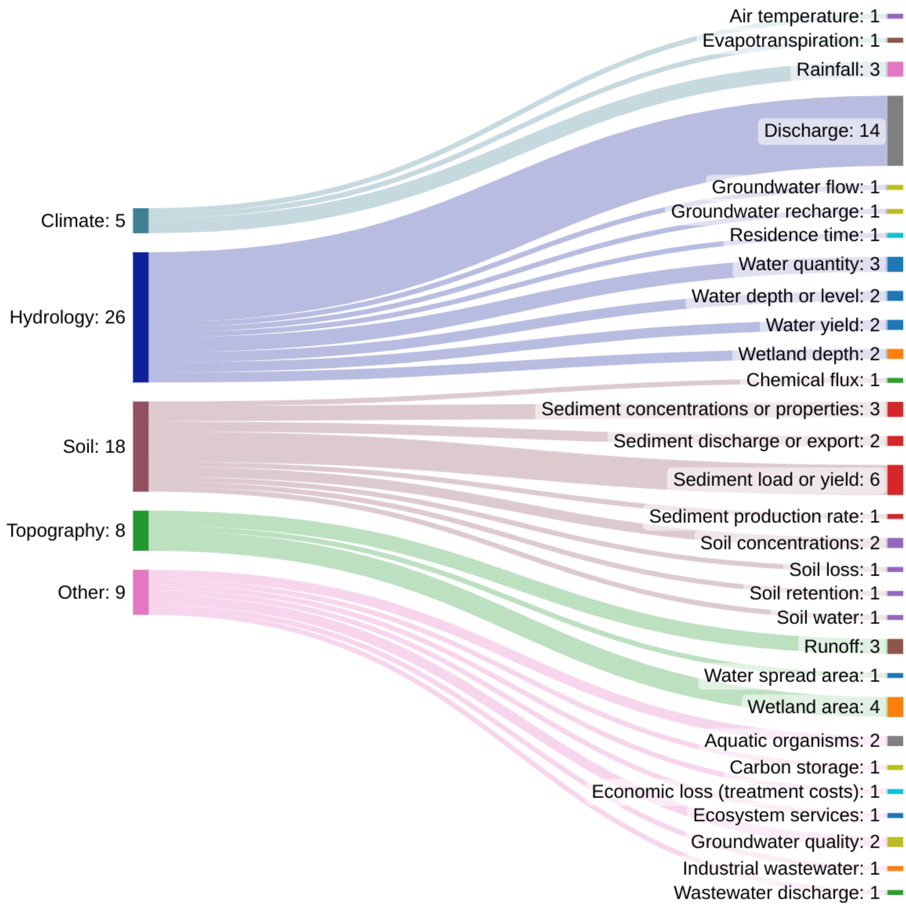

Figure 9. Sankey diagram of the frequency of response variables included in the systematic map database.

3.5 Methods for analysis

The vast majority of research articles were observational (i.e., case studies) (n= 130) comparing temporal land use changes within the same area, with only three studies employing an experimental design (i.e. paired-catchment approach) where areas with and without land use change were compared over the same period. In most investigations (74.4%), changes in land use over time were measured in terms of the total area of land that had been converted from one category to another (i.e., absolute change), while less than 10% of studies calculated the change in quantity as a percentage of the initial value (i.e. relative change) (Table 6). Approximately 15% of studies calculated the change in landscape metrics to detect trends in land use over a specific period. In addition, the rate of change and transition matrices were used to measure the absolute change over an interval, and to show the proportion of land that has changed from one category to another between the two time periods, respectively.

While all studies included in the evidence base investigated the impacts of land use change on water quality, 21.1% (n=28) did not assess changes in water quality over time, and instead described the current conditions of the water in response to land use change or used the current state to identify sources of pollution. Of the 105 studies that analyzed water quality trends over time, approximately half (49.5%) visualized the water quality trends via charts, figures, or graphs, while approximately 12.4% displayed the water quality data in tables (Table 6). Additionally, several methods were applied for statistically assessing temporal trends in water quality, including the Mann–Kendall test, ANOVA, linear regression and Seasonal Mann-Kendall trend test being commonly applied and many studies employing multiple trend detection strategies (n=10).

Table 6. Methods applied for detecting changes in land use and water quality.

Land use		**Water Quality**	
Change detection	**# of articles**	**Trend detection**	**# of articles**
Absolute change	99	Visualized	52
Change in landscape metrics	20	Shown in table	13
Relative change	13	Mann–Kendall test	11
Rate of change	11	ANOVA	9
Transition matrix	6	Linear regression	8
Growth rate	3	Seasonal Mann–Kendall test	7
Net change (change matrix)	2	Compared with reference values	4
Linear interpolation	2	Seasonal Kendall test	4

Urbanization index	2	Paired t-test	2
NDVI index	2	Multivariate Regression	2
Land use change index	1	Tukey's multiple range test	2
Land use change intensity index	1	Kruskal-Wallis rank sum test	2
Index of urban extent	1	Locally weighted regression	1

The systematic map database includes a diversity of methodologies, with various degrees of rigor applied. Since 2010, numerous efforts have been made to evaluate the impact of land use on water quality. In general, methods for analysis can be divided into one of two groups: (1) comparative, where changes in land use are compared with water quality conditions; and (2) statistical, where empirical models are employed to establish relationships between land use changes and water quality. Approximately two-thirds of studies included in the evidence base (n=87) undertook statistical modeling of land use-water quality interaction, while one-third (n=45) were comparative, with studies steadily favoring statistical analysis since 2013 (Fig. 10).

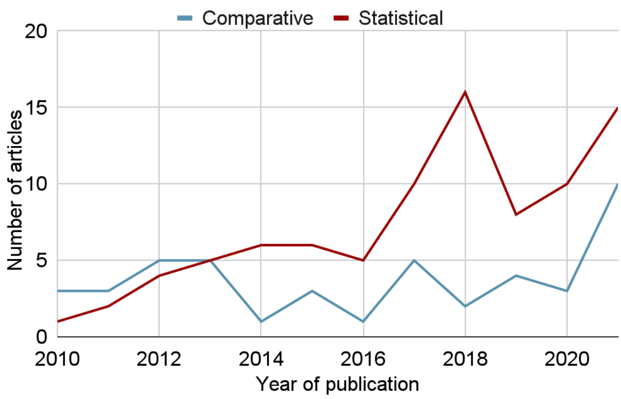

Figure 10. The distribution of the included studies in regard to the research methodologies (i.e. statistical or comparative) according to the publication year.

In order to assess the quality of research, the journal quartile was assigned according to the journal impact factor ranking via Journal Citation Reports, with Q1 being the highest ranking and Q4 being the lowest. With the exception of Q4 journals, scientific journals with higher quartiles tended to contain studies which conducted statistical analysis more often than lower quartiles, with comparative studies mostly being carried out by Q3 journals or journals without a ranking (Fig. 11). As argued by Wijesiri et al., (2018), a simple comparison may lack the ability to properly describe the complex associations between land use and water quality and can explain why statistical analysis is favored within higher quartile journals.

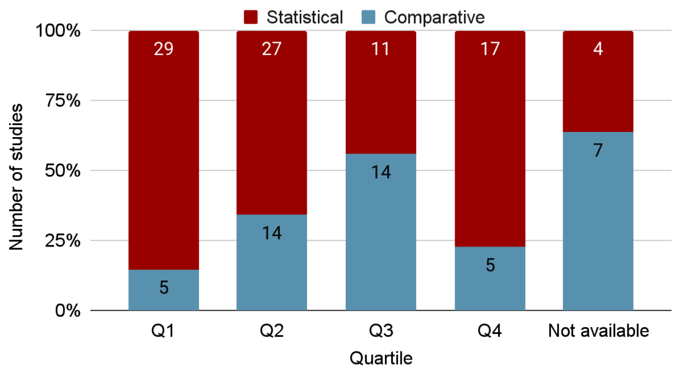

Figure 11. The distributions of the included studies in regard to the research methodologies (i.e. statistical or comparative) according to quartile.

The most commonly applied statistical approaches were conventional methods such as correlation analysis (n=48) and regression-based modeling approaches (n=50). Redundancy analysis (n=13), principal component analysis (PCA) (n=6) and ANOVA (n=6) were more seldomly applied. Over time, the applied statistical approaches have remained fairly consistent. For correlation analysis, Pearson correlation was most commonly used (n=25). Multiple linear regression (i.e., MLR) (n=32) were applied more frequently than linear regression analysis (n=18). Nonlinear regression (n=5) and spatial regressions (n=6) were seldom employed. As displayed in Figure 12, studies have evolved to include additional methods such as PCA, ANOVA and spatial regression analysis, yet methods have remained relatively consistent over time.

Of the 87 studies that applied statistical models, more than half (n=47) applied one model, while the remaining 40 studies employed multiple statistical approaches. Some statistical models included explanatory variables, in addition to land use, as predictors of water quality (n=49). Independent variables were typically included as covariates (n=21), compared with water quality (n=9), or correlated with water quality (n=7).

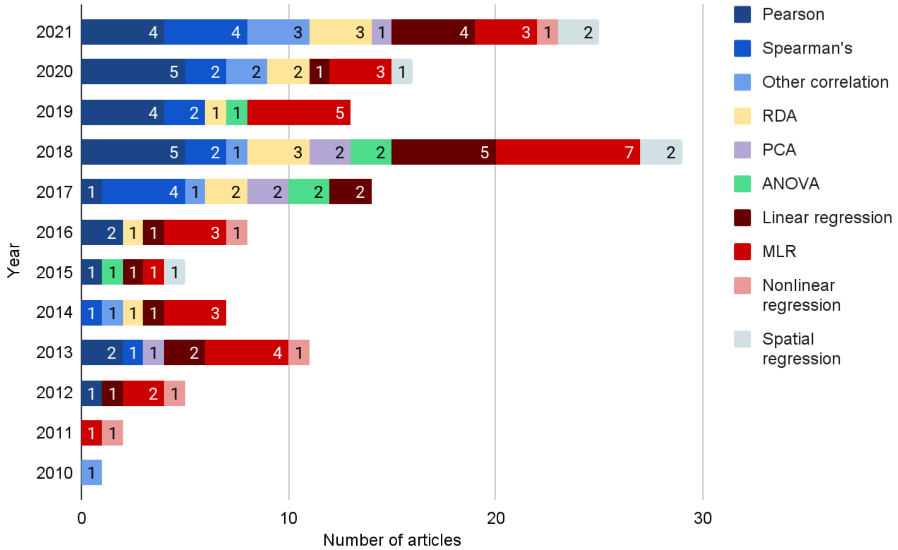

Figure 12. Applied statistical methods within the systematic map database.

3.6 Measured outcomes

The most substantial land use conversions during the study period, as noted by the authors, were recorded into the systematic map database. If more than two land use classes were noted, changes were classified as "various". Out of the 133 articles that were included in the evidence base, the bulk of studies reported on urban expansion as the most distinguished change throughout their study areas (n=53) (Fig. 13). Agricultural loss (n=27) and expansion (n=15) were also prevalent throughout investigations, yet agricultural expansion together with urban expansion was more common (n=20). Research also commonly recorded deforestation throughout their study (n=17), with few studies investigating afforestation (n=8). Notable conversions of grasslands and wetlands (i.e., both losses and gains) were often examined in combination with other land use types (n=26 and n=17. respectively), while noteworthy conversions of bare lands (n=10) and vegetation (n=8) were less uncommon. In many studies, notable land use loss was not specified (n=17) (see Table A3 in Appendix for the full list of conversions).

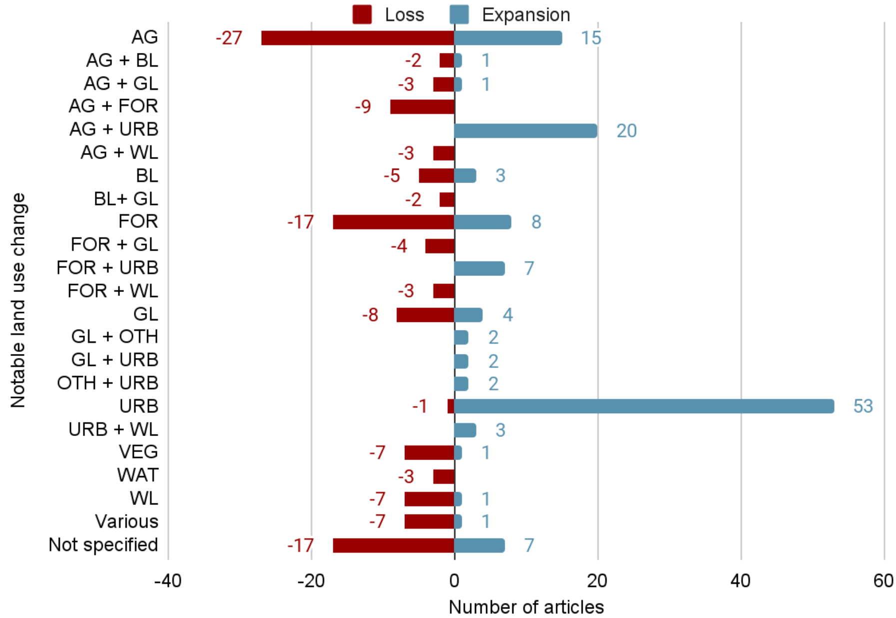

Figure 13. Number of studies examining the loss and expansion of specific land use types. Note. If only one study examined the land use change (either loss or expansion), the study was not included in the figure. AG = Agriculture; BL = Bare land; GL = Grassland; FOR = Forest; OTH = Other; URB = Urban; WAT = Water; WL = Wetland; VT = Vegetation.

The overall change in water quality indicators within each study, as noted by the authors, were classified as improvement, degradation, degradation than improvement, diverging trends or no change. Few studies of land use conversions resulted in water quality improvement (n=12, 9%), with most reporting water quality degradation as an outcome (n=46, 34.6%) and several resulting in diverging trends (n=36, 27.1%) (Fig. 14).

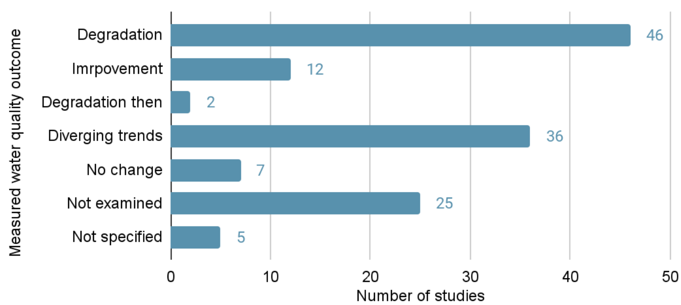

Figure 14. Number of times each water quality outcome is reported.

3.7 Summary of the evidence base

With the creation of this systematic map, a database of relevant studies was developed to provide meta-data on the existence and characteristics of empirical evidence (see Tables A4–A16 in Appendix for the complete systematic map database). In total, 133 publications provided empirical evidence of the impacts of land use change on surface water quality, consisting mainly of case studies and only two experimental designs. There has been a proliferation of publications since 2010, indicating a growing interest in the field and allowing for an identification of trends. Countries, climate zones and surface water body types were unequally represented in the evidence base, with the vast majority of research conducted in tributaries of temperate and continental climate zones of China. Most studies were carried out in large (i.e., 1,000 – 100,000 km^2), heterogeneous landscapes with a wide variety of land uses. Compositions of agriculture, urban land and forests as well as concentrations of phosphorus and nitrate were the most commonly examined parameters, with approximately half of studies applying an index or standards for water quality. Most investigations contained water quality data via field sampling, yet the vast majority did not disclose sample size or sampling frequency. Although all studies examined land use changes over time, with most calculating the absolute changes in compositions or area between two periods, approximately 20% of studies did not examine temporal trends in water quality and instead described the condition at a point in time. When examining land-water interactions, additional drivers of water quality as well as seasonal and spatial variations were frequently investigated. When analyzing the relationship, two-thirds of studies conducted statistical modeling while one-third of investigations were comparative. For the statistical analysis, correlation (Pearson’s) and regression (multiple linear regression) were most commonly applied. Urban expansion was by far the most prevalent land use change examined, while water quality response was mostly reported as degraded or diverging trends.

4. Scientific publications

4.1 Performance of landscape composition metrics for predicting water quality in headwater catchments

Staponites, L.R., Barták, V., Bílý, M., Simon O.P. Performance of landscape composition metrics for predicting water quality in headwater catchments. *Sci Rep* 9, 14405 (2019). https://doi.org/10.1038/s41598-019-50895-6

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Contribution:
LRS wrote the main manuscript, conducted land use analysis, implemented metrics, collected the water samples, and interpreted data.

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Performance of landscape composition metrics for predicting water quality in headwater catchments

Linda R. Staponites[1,2], Vojtěch Barták[1], Michal Bílý[1] & Ondřej P. Simon[1,2]

Land use is a predominant threat to the ecological integrity of streams and rivers. Understanding land use-water quality interactions is essential for the development and prioritization of management strategies and, thus, the improvement of water quality. Weighting schemes for land use have recently been employed as methods to advance the predictive power of empirical models, however, their performance has seldom been explored for various water quality parameters. In this work, multiple landscape composition metrics were applied within headwater catchments of Central Europe to investigate how weighting land use with certain combinations of spatial and topographic variables, while implementing alternate distance measures and functions, can influence predictions of water quality. The predictive ability of metrics was evaluated for eleven water quality parameters using linear regression. Results indicate that stream proximity, measured with Euclidean distance, in combination with slope or log-transformed flow accumulation were dominant factors affecting the concentrations of pH, total phosphorus, nitrite and orthophosphate phosphorus, whereas the unweighted land use composition was the most effective predictor of calcium, electrical conductivity, nitrates and total suspended solids. Therefore, both metrics are recommended when examining land use-water quality relationships in small, submontane catchments and should be applied according to individual water quality parameter.

It has been widely acknowledged that the ecological integrity of streams and rivers is intrinsically linked to the surrounding landscape[1–3]. Riverine systems are amongst the most productive and biodiverse ecosystems[4], yet extreme anthropogenic pressure has threatened the essential goods and services provided by tributaries[5]. The protection of freshwater resources and ecosystems requires an understanding of the impacts from the encompassing landscape. Although land use-water quality interactions have been extensively researched, a comprehension of such relationships remains a complex endeavor. To discern the effects of land use on water quality, initial investigations frequently employed land use composition (i.e., the proportion of each land use category) as a predictor of stream condition (e.g.[6,7]). While the composition of land use plays a crucial role on water quality, this rudimentary measure assumes that each proportion imposes an equal influence[8]. Recently, the importance of spatial scale and topography has been corroborated in the contemporary understanding of land use-water quality interactions[8,9]. Nevertheless, the intricate patterns and natural gradients of a terrestrial landscape, as well as scale-dependent mechanisms, make it difficult for empirical models to be assessed[2]. The integration of spatially-explicit landscape features and processes with land use data is crucial for providing more accurate information on how land use can impact concentrations of water quality parameters (WQP).

With the application of Geographic Information System (GIS) technologies, broadly-applicable weighting schemes have been established as methods to consider the spatial and topographic components of individual land use types on stream condition. Under the assumption that land located close to the stream generally has a larger influence on water quality than land located further away[8,10–14], distance-weighted metrics have been implemented into studies to account for the spatial proximity of land use[10,11,15–18]. In this method, a distance decay function is used, assigning weights to observations based on the hydrologic distance to the stream or sampling

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point to elucidate the inordinate impact of land situated close to the source. Additionally, flow accumulation has been incorporated into distance-weighted metrics on the basis that areas and pathways of concentrated flow have a higher tendency to generate runoff[16,19]. The concentration of overland runoff within each land use category is weighted according to the flow accumulation value determined by flow direction and preferential flow pathways from upslope areas. Such metrics are particularly suitable for examining the combined effects of land use position and hydrological processes[19]. Although studies have concluded that spatially-explicit methods can improve predictions of stream conditions and are more effective than non-spatial methods[3,11,17–19], the best weighting schemes were often determined according to the ecological response of various aquatic species assemblages. Little is known about optimal metrics for predicting the effects of land use on individual chemical parameters. Furthermore, it is unknown if the inclusion of additional variables and functions can enhance the accuracy of predictive models.

Located in Central Europe, the headwater catchments of South Bohemia, Czech Republic are a typical example of a submontane landscape, characterized by mainly forests and meadows. Headwater streams and catchments are particularly important for provisional ecosystem services (e.g., drinking water extraction) and the protection of biodiversity (e.g., nature reserves and core zones of national parks)[20]. Tributaries act as both receptors and conveyors of landscape fluxes[21], allowing upstream land use activity to influence the entire river continuum[22,23]. The development of strategic management plans within headwater catchments is, thus, imperative for improving downstream conditions. Quantifying and comparing the predictive power of empirical models using various landscape composition metrics can provide a comprehensive evaluation of the impacts of land use on water quality and better aid in the identification of landscape processes affecting this relationship[19].

In this work, various landscape composition metrics are applied and augmented to explore the predictive power of the catchment-scale landscape on the concentration of eleven WQP within headwater streams. The main objectives of this study are to (1) examine the variations in performance between landscape composition metrics, (2) investigate how the incorporation of stream proximity, slope and flow accumulation can influence the predictive ability of models, and (3) identify which landscape composition metric explains the most variation in water quality data.

Methods

Study area. The headwater streams of the Upper Vltava River Basin, located in the South-West of the Czech Republic, originate within the low-range Šumava Mountains which border Germany and Austria. Due to its oligotrophic waters, this region provides refuge for many rare aquatic species[24,25] and harbors sources of drinking water[26]. The region consists of a temperate climate with a mean annual precipitation of approximately 1400 mm and a mean annual temperature of about 4 °C[27]. The majority of the study area is included in the European system of protected areas (Natura 2000), leaving the landscape in a relatively undisturbed, semi-natural state[28].

Thirty seven headwater catchments were selected, ranging in size from 0.61 km^2 to 18.85 km^2 with stream orders $\leq$3 (Strahler method) (Fig. 1). The topography within catchments varies from hilly mountain ranges to fairly flat areas with elevations ranging from ~530 m a.s.l. to 1288 m a.s.l. and sampling points averaging ~708 m a.s.l. ($\pm$104 SD), allowing for a representative survey of the study area. Forests are the predominant land use within most catchments, comprised mainly of spruce or a mixture of spruce, pine and broadleaf forest stands[27,29], while meadows used for grazing and hay production are also prevalent. Intensive meadows can constitute as sources of eutrophication[30], however, liquid fertilization of grasslands has been decreased or discontinued within parts of this region[31,32]. As with many other border regions within the Palearctic, this sparsely populated area has experienced a gradual recession in farming due to barren soils unsuitable for agricultural intensification[33]. Over time, extensive agriculture has been replaced by meadows, with only a small extent of crop fields remaining on the foremost fertile soils[34]. In order to focus on the primary land use types within the region, only catchments with at least 77% of forested and grassed composition, and without significant point sources of pollution, were selected.

Water sampling and chemical analysis. A one-time, spatially intensive sampling approach was carried out in order to understand the relationship between land use and water quality within headwater catchments of the Upper Vltava watershed. A total of 37 water samples were taken within the low-order streams using conventional sampling protocols. Sample collection took place on 2nd May and 3rd May, 2016 under stable weather conditions. The water sampling locations were used as the catchment outlet for each catchment area in order to consider the land area that supplies water to each sample. Grab samples of electrical conductivity (EC, μS/cm), dissolved oxygen (DO, mg/L) pH and water temperature (TEM, °C) were measured in the field using a portable meter (Hach HQ40d). Laboratory analysis was conducted for the determination of nine WQP, including chemical oxygen demand by dichromate (COD, mg/L), total suspended solids (TSS mg/L), ammonium ions (NH_4^+, mg/L), nitrite nitrogen (NO_2^-N, mg/L), nitrate nitrogen (NO_3^-N, mg/L), total phosphorus (TP, mg/L), orthophosphate phosphorus (PO_43^-P, mg/L), absorbance wavelength 254 (A_{254}) and calcium (Ca, mg/L). Storage, preservation and analysis of water samples were conducted according to the standardized methods of the Czech National Standards Criterion[35]. Dissolved oxygen (DO) was omitted from analysis since the majority of streams were highly saturated with oxygen and there were minimal differences in the concentration of DO between streams. Water temperature was also disregarded in the evaluation due to the lack of seasonal influences from the one-time sampling.

Landscape composition metrics. GIS analysis via ArcMap 10.5.1 (ESRI) was used to acquire land use information. Catchment areas and streams were delineated via shapefiles provided by the Czech Digital Base of Water Management Data[36]. Detailed aerial images from 2015 were supplied by the public ArcGIS Online Map Service from the Czech Office for Surveying and Cadastre (www.cuzk.cz) and were used to determine the land use composition (i.e., the percent of each land use category) in each catchment area at a mapping scale of 1:5000, thus allowing for a precise analysis of the landscape structure. However, an aerial view via www.mapy.cz was used

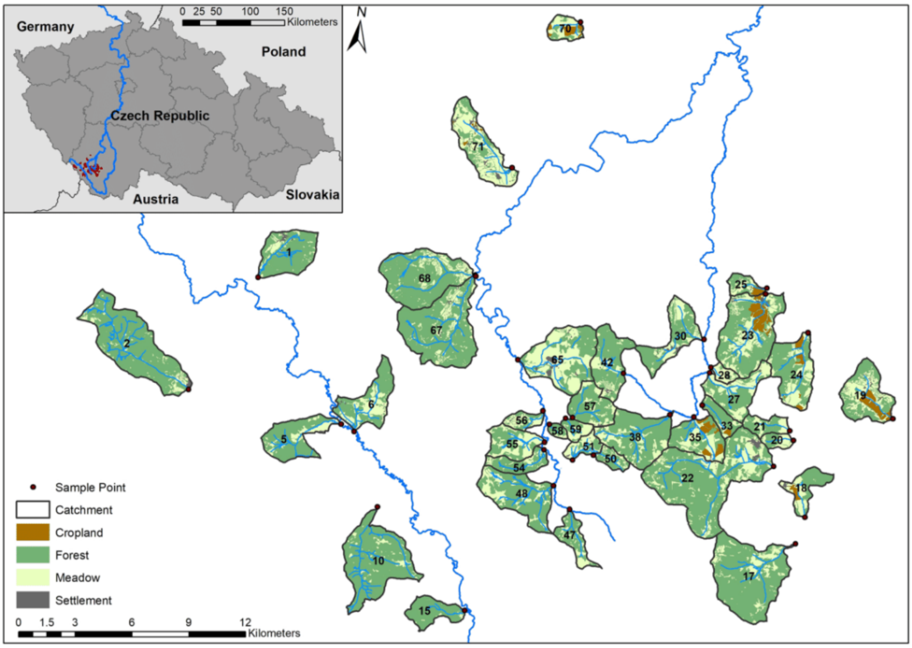

Figure 1. Selected catchments, sampling points and land use pattern with the main tributaries draining the catchments.

as a reference in case of any discrepancies. All shapefiles and layers were created using the coordinate system S-JTSK Krovak East North. Land use was classified into five categories: (1) settlements, including houses, parking lots and other infrastructure; (2) cropland, including rows of agriculture, cultivated crops and orchards; (3) meadows, including pastures, mowed areas and grass communities; (4) forests, including groups of trees and shrubs: and (5) water bodies including reservoirs, ponds and lakes. All catchments are primarily covered with forests and meadows, while small fragments of croplands, settlements and water bodies occupy less than 4% of the total study area. Incorporating the influence of land use types that are not present in every catchment creates problems with statistical analysis due to many zeros in the dataset, for that reason, croplands, settlements and water bodies were removed from analysis.

Following the approach proposed by Peterson[19] and Peterson & Pearse[11], the weighting of land use proportions was based on an arrangement of site-specific explanatory variables, including the inverse Euclidean distance of each raster cell to the stream, the inverse flow length (i.e., the inverse distance to the stream measured along the flow path identified on Digital Elevation Model) and flow accumulation. Additionally, slope was included as a supplementary explanatory variable to augment metrics. It is common practice in hydrology to use log-transformed values of flow accumulation in many applications due to its typical exponential frequency distribution (e.g., topographic wetness index), thus, a logarithmic transformation was also applied to metrics containing flow accumulation data. Using various, multiplicative combinations of these weights, thirteen landscape composition metrics were defined; each containing an inverse-distance function measured with either Euclidean distance or flow length, henceforth referred to as "Euclidean metrics" and "flow metrics", with the exception of the unweighted metric which only considered land use composition (see Table 1 for the complete list of metrics). Metrics were implemented via a Python script, utilizing the functionality of Spatial Analyst toolbox for ArcGIS 10.5 (ESRI, 2017) via ArcPy module (see Supplementary Method S1). A 5 m resolution Digital Terrain Model of the Czech Republic of the 5th generation (DMR 5G) was provided by the Czech Office for Surveying, Mapping and Cadastre and used to attain raster data for the calculation of slope, flow paths and flow accumulation.

Statistical analysis. Outliers of COD and A_{254} for sites 5 and 6 were excluded from analysis due to the possibility of riverbank stabilization efforts affecting these parameters during the time of sampling. To investigate the differences between weighting schemes, Pearson's correlation coefficient analysis was computed for all pairs of landscape composition metrics. A separate linear regression model was then fitted for each combination of WQP (response), landscape composition metric (predictor) and land use category to assess how certain metrics can influence land use predictions of chemical concentrations. The predictive power of the models was then compared using R^2 values. R statistical software (R Core Team 2018) was used for all data manipulation, computation and graphics.

Variables	Abbreviation	Description	Equation
None	Unweighted	Percentage of land use; no spatial or topographic considerations	$\%LU = \frac{\sum_{i=1}^{n} I_i(k)}{n} \times 100$
Stream proximity	Euclid	Inverse Euclidean distance from land use to tributary	$\%LU = \frac{\sum_{i=1}^{n} I_i(k)E_i}{\sum_{i=1}^{n} E_i} \times 100$
Stream proximity, Slope	Euclid-S	Inverse Euclidean distance from land use to tributary and slope degree of land use	$\%LU = \frac{\sum_{i=1}^{n} I_i(k)E_iS_i}{\sum_{i=1}^{n} E_iS_i} \times 100$
Stream proximity, Flow Accumulation	Euclid-A	Inverse Euclidean distance from land use to tributary and pathways of flow accumulation within land use	$\%LU = \frac{\sum_{i=1}^{n} I_i(k)E_iA_i}{\sum_{i=1}^{n} E_iA_i} \times 100$
Stream proximity, Flow Accumulation	Euclid-LogA	Inverse Euclidean distance from land use to tributary and logarithmically transformed pathways of flow accumulation within land use	$\%LU = \frac{\sum_{i=1}^{n} I_i(k)E_i \ln(A_i)}{\sum_{i=1}^{n} E_i \ln(A_i)} \times 100$
Stream proximity, Slope, Flow Accumulation	Euclid-SA	Inverse Euclidean distance from land use to tributary, slope degree of land use and flow accumulation within land use	$\%LU = \frac{\sum_{i=1}^{n} I_i(k)E_iS_iA_i}{\sum_{i=1}^{n} E_iS_iA_i} \times 100$
Stream proximity, Slope, Flow Accumulation	Euclid-SlogA	Inverse Euclidean distance from land use to tributary, slope degree of land use and logarithmically transformed flow accumulation within land use	$\%LU = \frac{\sum_{i=1}^{n} I_i(k)E_iS_i \ln(A_i)}{\sum_{i=1}^{n} E_iS_i \ln(A_i)} \times 100$
Stream proximity	Flow	Inverse flow length from land use to tributary	$\%LU = \frac{\sum_{i=1}^{n} I_i(k)F_i}{\sum_{i=1}^{n} F_i} \times 100$
Stream proximity, Slope	Flow-S	Inverse flow length from land use to tributary and slope degree of land use	$\%LU = \frac{\sum_{i=1}^{n} I_i(k)F_iS_i}{\sum_{i=1}^{n} F_iS_i} \times 100$
Stream proximity, Flow Accumulation	Flow-A	Inverse flow length from land use to tributary and pathways of flow accumulation within land use	$\%LU = \frac{\sum_{i=1}^{n} I_i(k)F_iA_i}{\sum_{i=1}^{n} F_iA_i} \times 100$
Stream proximity, Flow Accumulation	Flow-logA	Inverse flow length from land use to tributary and logarithmically transformed pathways of flow accumulation within land use	$\%LU = \frac{\sum_{i=1}^{n} I_i(k)F_i \ln(A_i)}{\sum_{i=1}^{n} F_i \ln(A_i)} \times 100$
Stream proximity, Slope, Flow Accumulation	Flow-SA	Inverse flow length from land use to tributary, slope degree of land use and pathways of flow accumulation within land use	$\%LU = \frac{\sum_{i=1}^{n} I_i(k)F_iS_iA_i}{\sum_{i=1}^{n} F_iS_iA_i} \times 100$
Stream proximity, Slope, Flow Accumulation	Flow-SlogA	Inverse flow length from land use to tributary, slope degree of land use and logarithmically transformed flow accumulation within land use	$\%LU = \frac{\sum_{i=1}^{n} I_i(k)F_iS_i \ln(A_i)}{\sum_{i=1}^{n} F_iS_i \ln(A_i)} \times 100$

Table 1. Variables, abbreviations and descriptions of landscape composition metrics applied to each land use category within a catchment. Notes: %LU = Percentage of land use category; n = total number of cells in the catchment; $I_i(k)$ = presence of land use k in cell i (1 or 0); E_i = inverse Euclidean distance from cell i to the stream $(\text{distance} + 1)^{-1}$; F_i = inverse flow length from cell i to the stream $(\text{distance} + 1)^{-1}$; S_i = slope gradient for cell i; A_i = flow accumulation value for cell i.

Results

Variation between landscape composition metrics.

Both land use categories experienced changes in proportions when spatial proximity and topography were incorporated into landscape composition metrics (see Supplementary Tables S2 and S3). The unweighted proportions of forests and meadows within catchments were approximately 65 ± 20 (mean ± SD) and 32 ± 17 (mean ± SD), respectively (Table 2). For both forests and meadows, the Euclidian distance metric (i.e., Euclid) led to similar mean proportions as the land use composition metric (i.e., Unweighted). Employing more complex weighting schemes, however, led to an increase in proportions of forests and a decrease in proportions of meadows, with the change varying from approximately 2 to 8%. Additionally, standard deviations of proportions experienced substantial variations, with Euclidean metrics containing untransformed flow accumulation increasing in standard deviations by approximately 10% (Table 2).

Pair-wise correlations between landscape composition metrics were 0.70 ± 0.27 (mean ± SD) for forests and 0.73 ± 0.26 (mean ± SD) for meadows (Fig. 2). Forests displayed relatively weak correlations between Euclidean and flow metrics (0.39 ± 0.06; see the light-colored rectangular section in the Forests portion of Fig. 2). The weakest correlations for meadows were observed in most pairs that included either Euclid-A or Euclid-SA (0.45 ± 0.28; see the light-colored stripes in the Meadows portion of Fig. 2), which indicates that metrics including inverse Euclidean distance in combination with flow accumulation (that is not logarithmically transformed) are the least similar to other metrics. The highest correlations were observed for pairs consisting of any flow metric when compared to the same metric enriched by log-transformed flow accumulation (0.99 ± 0.02), as well as for pairs of any Euclidean metric without slope compared to the same metric with slope (0.98 ± 0.02), indicating that the log-transformation of flow metrics as well as the addition of slope for Euclidean metrics results in limited changes of weighted proportions.

Landscape composition metric for predictions of water quality.

For parameters A_{254}, NH_4^+, and COD, no significant relationships were found between chemical concentrations and proportions of forests or meadows, regardless of which metric was applied (see Supplementary Table S4); hence, the results for these three parameters are not shown and disregarded from further analysis. Overall, the percentage of explained water quality variance ranged from 1 to 46% for forests and from 0.1 to 32% for meadows. The water quality variability principally followed the same pattern for both land use categories, albeit with lower R^2 values for meadows in all cases; consequently, only the results obtained from forests as predictors of water quality are discussed.

	Forests		Meadows	
Metric	*Mean*	*SD*	*Mean*	*SD*
Unweighted	64.82	19.6	31.6	17.4
Euclid	65.13	24.84	31.61	22.89
Euclid-S	71.55	20.97	26.11	19.43
Euclid-A	71.36	29.81	25.93	27.44
Euclid-logA	68.18	23.19	28.8	21.64
Euclid-SA	71.97	29.53	25.24	27.05
Euclid-SlogA	71.78	21.48	25.92	20.09
Flow	67.06	18.37	29.9	16.75
Flow-S	73.01	16.97	24.82	15.51
Flow-A	66.55	21.99	29.49	19.21
Flow-logA	67.47	18.78	29.56	17.05
Flow-SA	71.54	19.51	25.27	16.44
Flow-SlogA	73.16	17.5	24.71	15.89

Table 2. Mean and standard deviation for proportions of forests and meadows within catchments measured by various landscape composition metrics.

There were substantial variations in performance between the landscape composition metrics for most WQP, often leading to differences in their significance (see Fig. 3 for comparison of coefficients of determination and Supplementary Table S4 for regression slopes and their standard errors). The unweighted metric and Euclidean metrics frequently exceeded corresponding flow metrics in explained variations of water quality parameters. An exception was with Euclidean metrics employing an untransformed flow accumulation variable (i.e., Euclid-A and Euclid-SA) which created inferior predictions for parameters Ca, EC, NO_3^-N, pH and TSS. The R^2 values for models incorporating Euclidean distance in combination with slope (i.e., Euclid-S), log-transformed flow accumulation (i.e., Euclid-logA) or both slope and log-transformed flow accumulation (i.e., Euclid-SlogA) were relatively similar, typically ranging in approximately 5%, with moderately lower R^2 values for most models when including only Euclidean distance (i.e., Euclid).

Two slightly different versions of a similar pattern in variation can be identified among parameters in Fig. 2. For Ca, EC, NO_3^-N, and TSS, the best prediction was obtained by the basic, unweighted proportions, followed by Euclid-S, Euclid-logA, Euclid-SlogA, yielding approximately 10% lower R^2 values. For the remaining WQP, Euclid-S, Euclid-logA, Euclid-SlogA resulted in the highest R^2 values, whereas the performance of unweighted metric was either similar (as seen in predictions of pH) or approximately 10 to 20% lower (as seen in predictions of NO_2^-N, PO_4^{3-}P and TP).

Discussion

The effects of land use on concentrations of specific WQP were investigated at the catchment scale using landscape composition metrics, a broadly-applicable weighting scheme that considers the combined effects of individual land use categories with spatial and topographical variables. As in previous studies[10,16,17], two conventional measures used in ArcGIS for calculating distance were employed (i.e., flow length and Euclidean distance), as well as a non-spatial composition measurement (i.e., unweighted metric), to compare the predictive ability between metric types. Both King[10] and Peterson[19] found that Euclidean distance and flow length metrics were very strongly correlated with one another. On the contrary, disparity was found between relationships and performance of flow length and Euclidean distance in our study, particularly for parameters NO_2-N, pH, PO_4^{3}-P and TP. Results from the regression models revealed that metrics with a Euclidean distance measure predominately outperformed metrics containing a flow length measure. The weaker performance of flow metrics in our study was most likely due to the artificial flow paths parallel to the stream. Such parallel flow paths are a well-known feature of the Single Flow with 8 Directions (SFD8) algorithm[37], which is the most commonly used and often the only implemented algorithm in ArcGIS for the determination of outflow from a Digital Terrain Model cell. However, when flow length distance was combined with flow accumulation (i.e., Flow-A or Flow-SA), the predictive power for forests comparatively improved for certain WQP. Presumably, the low weights produced by artificially long flow paths are compensated by the higher flow accumulation downstream, since flow can accumulate to a greater extent along lengthy flow paths. Thus, caution should be taken when implementing flow length as a distance measure when flow accumulation is not being considered. Since any distance function can be employed into metrics[19], future research should explore alternative flow direction algorithms which may be more accurate in displaying near-stream flow pathways, although it is not clear how to define a flow-based distance in the presence of flow divergence. Given these findings, metrics which implemented a flow length measure were removed from further discussion.

This study follows the methodology proposed by Peterson[19] and is further augmented to examine how applying a log-transformation function for flow accumulation variables, as well as integrating a slope variable, can influence metric performance. When stream proximity, calculated with a Euclidean distance measure, was combined with untransformed flow accumulation (i.e., Euclid-A and Euclid-SA), R^2 values were often drastically altered, frequently diminishing significant predictions for certain WQP. Hence, there seems to be no justification

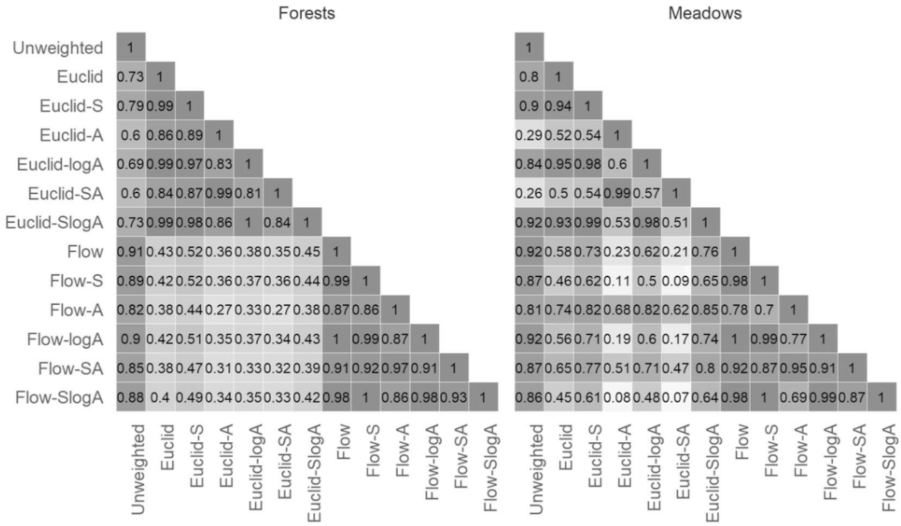

Figure 2. Pearson's correlation coefficients between pairs of landscape composition metrics for each land use category.

for including flow accumulation that is not log-transformed into landscape composition metrics when predicting stream water quality. Moreover, the differences in performance between metrics incorporating slope gradient (i.e., Euclid-S), log-transformed flow accumulation (i.e., Euclid-logA), or both slope and log-transformed flow accumulation (i.e., Euclid-SlogA) were minor. This suggests that slope and log-transformed flow accumulation produced extremely similar effects and that the inclusion of both physiographic attributes adds unnecessary complexity and is not vital for enhancing water quality predictions. However, when compared to slope gradient, flow accumulation is relatively difficult to compute, hence Euclid-S may be the more straightforward option for metric implementation.

Both the spatial proximity[10,17,19,38,39] and the topography[2,9,39–42] of land use are regarded as crucial factors influencing stream condition. However, the inclusion of stream proximity, exclusively, never resulted in optimal water quality predictions (Fig. 3). Previous studies have suggested that the predictive ability of metrics may be connected to the size of the catchment or watershed[10,14,19] and the fact that the examined catchments within our study area were small in size (average catchment area ~6 km²) may be a contributing factor to this presumed effect. Within a small spatial extent, most land use can have direct pathways of influence[2,43] and, therefore, an inverse distance measure may be negligible when examining small catchments. On the other hand, when stream proximity was combined with slope (i.e., Euclid-S), log-transformed flow accumulation (i.e., Euclid-logA) or a combination of both (i.e., Euclid-SlogA), the explained variability in water quality data often increased, confirming the importance of landform. Albeit small in surface area, the hilly, submontane terrain of this region may account for the more accurate predictions produced when slope and log-transformed flow accumulation were considered, thus, incorporating topographic variables into metrics may be pivotal for submontane regions. The influence of landscape features could be more significant when human activity is limited[2], which is the case within our sparsely populated study area. Nevertheless, these findings are circumstantial and should not be taken out of context; the influence of stream proximity and topography could further increase with larger catchment sizes[2,10]; thus, the extent to which these factors have an influence requires further investigation.

While accounting for both spatial and topographic attributes improved the predictive ability of models for parameters of pH, TP, NO_2^-N and $PO_4 3^-$P, the incorporation of stream proximity, slope and flow accumulation did not always explain the most variability in water quality data (Fig. 3). Both unweighted metrics and Euclidean metrics were optimal for predicting chemical loading, depending on which WQP was being considered. This behavior is conceivably due to the regional processes and mechanisms which govern these parameters[14] and suggests that the topography and spatial proximity of land use did not have an impact on the conveyance of Ca, EC, NO_3^-N and TSS, yet that land use composition was a dominant factor impacting these parameters. The dissimilar pattern found between these two groups of parameters can be attributed to the different geochemical cycles which can react conversely; Ca, EC, NO_3^-N and TSS are relatively stable parameters, whereas pH, TP, NO_2^-N and PO_4^{3-}P are typically reactive or unstable[44], especially in oligotrophic waters with very low concentrations which may produce highly variable ratios[45]. Hence, the factors governing land use-water quality interactions could be contingent on the reactiveness and stability of individual WQP. However, water quality can be influenced by multiple sources of contamination through dynamic pathways and at various scales and thorough information on the interactions between different nutrients and their mechanistic processes is lacking[46]. Consequently, no particular metric should be used to predict the chemical concentrations of every parameter. With the application of multiple landscape composition metrics, the relationship between land use and water quality can be examined

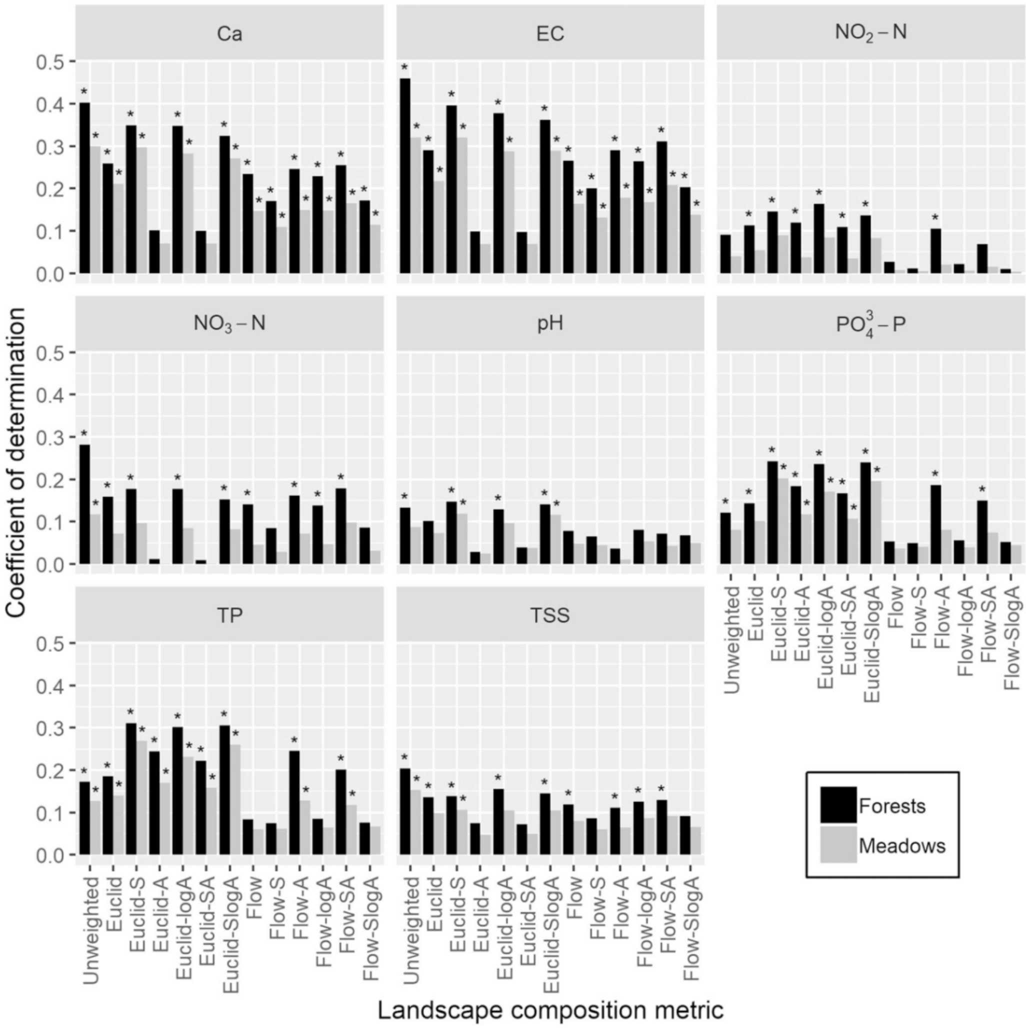

Figure 3. Coefficients of determination (R^2) for linear regressions of water quality parameters (WQP) for proportions of forests and meadows. A separate linear model was fitted for each combination of land use category, WQP, and landscape composition metric. The significant models are denoted with an asterisk.

according to the most appropriate metric which explains the highest variability in data. However, this should not lead to automatic post-hoc methodological decisions based on a limited sample size, as the outperformance of certain metrics could just be a matter of chance. One should always have a sound theoretical justification why specific metrics should be preferred over others. For instance, an inverse distance measure may be more influential in large catchments, whereas flow accumulation and slope gradient might be less significant in regions with flat terrains; hence, potential factors such as catchment size and topography should be considered when inferring metrics performance.

The protection of freshwater resources and ecosystems requires an understanding of the impacts from the surrounding land use, yet, determining the optimal spatial extent for examining land use-water quality relationships, as well as accounting for landscape attributes and processes, are currently ongoing issues facing researchers. Since each land use can impose a varying degree of influence on water quality, weighting specific land use categories according to spatial proximity and topography is an efficient way to account for the contributing, scale dependent responses and mechanisms throughout a landscape[3,13]. Still, it should not be assumed that stream proximity, slope gradient and flow accumulation are the only variables impacting land use-water quality interactions. Recently, studies have concluded that landscape patterns[39,40,47–49] and soil type[42,46,50–53] can also impact water quality; therefore, it may be beneficial for future studies to include additional variables, such as patch size of landscape elements or soil properties. Landscape composition metrics are easily reproducible approaches that have seldom been implemented and explored. The ability of weighting-schemes to integrate multiple variables creates an opportunity for further advancement of land use-water quality assessment and the potential for more accurate predictive models.

This work addresses the prevalent land use categories within the study area: forests and meadows. Inevitably, the proportions of forests and meadows were significantly correlated for all applied metrics (see Supplementary Table S5), with an overall mean correlation coefficient value ($\pm$SD) of -0.97 (±0.01), resulting in both land use categories having similar optimal metrics for each WQP. Therefore, it is unknown how other land use categories would respond to the applied metrics. King[10] found that an adequate range of land use percentage is necessary to avoid hindering the performance of certain metrics. The catchments within our study area contain 3.5–79.9% of meadows and 14.6–96.5% of forests, accounting for varying extents, while the proportions of croplands and settlements represent only small percentages within catchments, making computation problematic. Thus, their influence should be captured in another way than by percent composition.

Due to the one-time sample collection, the results represent water quality from a single point in time. However, rainfall, temperature and land use activities change depending on season, creating variations in flow rates, surface runoff and contaminant input to receiving waters[38,40,47,54,55]. Hence, seasonal effects should be incorporated whenever time series data is available.

Conclusions

Herein, landscape composition metrics were employed to discern the relative significance of stream proximity, slope and flow accumulation on predictions of water quality within headwater catchments via the incorporation of alternate spatial measures, functions and landscape variables. Overall, there were significant variations in performance between the landscape composition metrics; land use composition (i.e., unweighted metric) and stream proximity measured with Euclidean distance (i.e., Euclidean metrics) predominantly outperformed stream proximity measured with flow length (i.e., flow metrics) in predicting most land use-water quality relationships. Incorporating slope or a logarithmic transformation of flow accumulation in combination with a Euclidean distance measure of stream proximity (i.e., Euclid-S or Euclid-logA) often improved model accuracy, yet integrating both topographic variables (i.e., Euclid-SlogA) never resulted in optimal predictions. Euclid-S or Euclid-logA explained the highest variability in pH, TP, NO_2-N and PO_4^{3}-P, while the unweighted metric was most effective for predicting concentrations of Ca, EC, NO_3-N and TSS. The results suggest that the spatial position and terrain of land use can govern the conveyance of reactive or unstable water quality parameters, whereas the proportions of land use are dominant factors for predicting more stable chemical data. Thus, the application of the unweighted metric as well as the Euclid-S or Euclid-logA metric is recommended for optimal model accuracy when examining the effects of land use on water quality in small, submontane catchments. With the implementation of landscape composition metrics, management efforts can be directed according to the parameter of concern and the associated, governing processes.

Data Availability

The datasets generated during and analyzed during the current study are available in the Mendeley repository, https://doi.org/10.17632/cf5yxs28cv.2.

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Author Contributions
L.S. wrote the main manuscript and conducted land use analysis, L.S. and V.B. analyzed the results and implemented metrics, V.B. performed statistical analysis and prepared figures, M.B., O.P.S. and L.S. collected the water samples and interpreted data, O.P.S. and M.B. conceived the experiment. All authors reviewed the manuscript.

4.2 The role of hydrological signatures in calibration of conceptual hydrological model

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Contribution:
LRS participated in the investigation and formal analysis, writing, original draft preparation, reviewing and editing.

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The Role of Hydrological Signatures in Calibration of Conceptual Hydrological Model

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Abstract: Determining an optimal calibration strategy for hydrological models is essential for a robust and accurate water balance assessment, in particular, for catchments with limited observed data. In the present study, the hydrological model Bilan was used to simulate hydrological balance for 20 catchments throughout the Czech Republic during the period 1981–2016. Calibration strategies utilizing observed runoff and estimated soil moisture time series were compared with those using only long-term statistics (signatures) of runoff and soil moisture as well as a combination of signatures and time series. Calibration strategies were evaluated considering the goodness-of-fit, the bias in flow duration curve and runoff signatures and uncertainty of the Bilan model. Results indicate that the expert calibration and calibration with observed runoff time series are, in general, preferred. On the other hand, we show that, in many cases, the extension of the calibration criteria to also include runoff or soil moisture signatures is beneficial, particularly for decreasing the uncertainty in parameters of the hydrological model. Moreover, in many cases, fitting the model with hydrological signatures only provides a comparable fit to that of the calibration strategies employing runoff time series.

Keywords: hydrological model; model calibration; model validation; hydrological balance; soil moisture; ungauged catchments

1. Introduction

Hydrological models are commonly employed to calculate the hydrological balance of a catchment using various calibration strategies (i.e., diverse objective criteria including various variables, different optimization algorithms, etc.). The applied calibration strategy affects the performance of the hydrological model. The widely used manual (expert) calibration of parameters is strongly influenced by the experience of the hydrologist; it is time-consuming and strongly affects the quality of the calibrated model [1]. The automatic calibration, on the other hand, is fast and the performance of the model simulations are explicitly linked to the parameter values within the optimization criteria. The automatic calibration of hydrological models typically uses observed runoff time-series to optimize the parameters. This is, however, not possible in catchments with limited observations, especially if gauged stations are not available. In addition, due to equifinality, models of similar (good) performance may result from models with very different parameter sets and therefore not simulate the physical processes properly.

In ungauged catchments, the water balance can be estimated using different methods, e.g., extrapolation of hydrological model parameters [2], the spatial proximity [3], estimation of the spatially distributed variables from soils and other geo-spatial datasets [4], the physical similarity [5], scaling relationships [6], regression-based methods [7], the hydrological similarity [8] and employing the runoff signatures (indices characterizing hydrologic behavior, [9]). The methods utilising hydrological signatures can be further divided, according to the prediction methods, into hydrological modelling based methods [10,11], and multiple regression methods [12,13] including data-driven methods such as genetic programming [14,15] and hydrological similarity based approaches [16].

Recently, a number of studies pointed out that relying solely on calibration of hydrological models with respect to observed runoff may result in inappropriate representation of hydrological processes and highlighted the importance of expert knowledge [17,18] and/or multi-objective calibration [19].

One approach to constrain the calibration of the hydrological model is to consider hydrological signatures (typically some long-term statistics of runoff, soil moisture, snow regime). They are derived from observed or simulated time series [20] with a purpose to supplement catchment information [21], to evaluate model performance [22] or to refine calibration techniques [23]. The selection of signatures should consider their identifiability, robustness, consistency, representativeness and discriminatory power [20].

Different processes contributing to resulting hydrograph can be also accounted for by the segmentation of the flow duration curve (FDC) within calibration of the hydrological model [4,24]. For instance, it has been shown that fair balance between very high and very low flows can be achieved using five segments of the FDC (Q2–Q5, Q5–Q20, Q20–Q70, Q70–Q95, Q95) and evaluating the performance for each segment and combining it into single objective function [25].

In this paper, we explore the role of hydrological signatures within calibration of the hydrological model. Specifically, we like to answer following questions: To what extent do hydrological signatures improve calibration of conceptual hydrological model? Is calibration of conceptual hydrological model possible considering hydrological signatures only? A hydrological model Bilan is used to determine the hydrological balance for 20 gauged catchments in the Czech Republic utilizing four different calibration strategies: (1) expert calibration, (2) standard automatic calibration, (3) the standard automatic calibration considering hydrological signatures together with runoff and soil moisture time series, and (4) hydrological signatures only. The objectives of this study are to (i) evaluate the performance of different calibration strategies, (ii) assess the added value of hydrological signatures and soil moisture estimates, and (iii) determine to what extent are the time series data necessary when modelling hydrological balance.

This paper is structured as follows: Section 2 introduces the area of interest and input data. The hydrological model Bilan, four calibration strategies and model evaluation are described in Section 3. Results and discussion are presented in Sections 4 and 5 together with a detailed assessment of the calibration strategies with respect to goodness-of-fit (GOF), uncertainty of Bilan model parameters (BP), and runoff signatures (RS). The paper is concluded in Section 5.

2. Study Area and Data

The 20 considered catchments are located in the Czech Republic, where long-term mean precipitation for the 1981–2010 (climatological reference period for Czech Republic) period is 709.5 mm, mean annual temperature is 7.9 °C and mean runoff is 205.5 mm [26]. The selected catchments are shown in Figure 1, with the numbers referring to catchment IDs. The majority of the catchments is located in the northern part of the territory (235000-Ploučnice, 324000-Smědá, 006000-Labe, 306000-Stěnava, 031000-Bělá-Častolovice, 309000-Vidnávka, 313000-Bělá-Mikulovice, 266000-Opava, 354000-Moravská Sázava, the others extend into the central part (047000-Loučná, 361000-Trebůvka, 252000-Odra, 447000-Loučka) and southern part of the territory (179000-Radbuza, 153000-Skalice, 143000-Volyňka, 138000-Otava, 107000-Teplá Vltava). Only catchments with freely available data (in the time of preparation of this study) without significant anthropogenic influence were selected. For selected catchments, mean annual precipitation is 792.5 mm, mean temperature is 7.3 °C, average annual soil water storage is 997.1 mm and mean annual runoff is 318.8 mm. The catchment areas range from 348 to 932 km^2, with a mean size of 454 km^2.

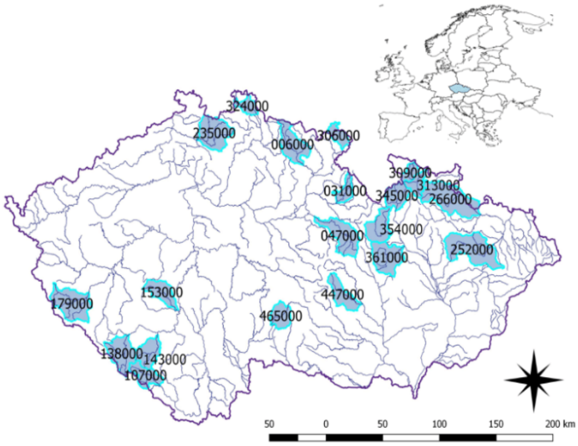

Figure 1. Evaluated catchments.

Monthly time series of temperature (°C), precipitation (mm) and observed runoff (mm) were provided for each catchment by the Czech Hydrometeorological Institute and the soil moisture estimates (mm) by the Global Change Research Institute of the Czech Academy of Sciences. The soil moisture estimates are based on the simulation of the SoilClim model—a model for water balance and the hydric and thermic soil regime assessment [27].

3. Methods

The hydrological model Bilan was used for the assessment of water balance in 20 catchments (Figure 1) considering four calibration strategies: expert calibration, standard automatic calibration, calibration considering runoff and soil moisture time series in combination with hydrological signatures, and calibration with hydrological signatures only. The resulting parameter sets were then evaluated with respect to: (i) goodness-of-fit between observed and simulated runoff (GOF, hydroGOF [28]), (ii) uncertainty of the Bilan model parameters and (BP) (iii) selected runoff and soil moisture signatures (RS). This section introduces the model, the calibrations strategies and the evaluation metrics.

3.1. Bilan Hydrological Model

The hydrological model Bilan [29,30] is a conceptual rainfall-runoff model that is used for water balance assessment in the Czech Republic. For partly or fully conceptual models, some parameters cannot be considered as physically measured (or measurable) quantities and thus have to be estimated on the basis of the available data and information [31]. The structure of the model is formed by a number of storage components and a set of their relationships based on basic principles of water balance as well as simple mathematical concepts such as linear reservoir. This structure is similar to a well-known hydrology model HBV (Hydrologiska Byråns Vattenbalansavdelning model) [32]. The water balance in model Bilan is described in three zones: on the ground, in the aeration zone, including vegetation cover, and in the groundwater [33].

The input variables are described in Table 1, in our case we used the input variable precipitation (P (mm)), air temperature (T (°C)) and optional time-series-soil water (mm)). In the model are individual components divided as input data, water balance component, and resulting parameters. The monthly type used algorithms depend on the condition of the particular month. Used mean monthly temperature as well as in the daily type the model distinguish the winter and summer conditional. In the monthly regime the total runoff (RM (mm)) is calculated as a sum of direct runoff (DR), interflow (I), and baseflow (BS) [30].

The model is shown in Figure 2 displaying input data, simulated storages and fluxes. See [34–37] for further details. The parameters of the model are identified (calibrated) using shuffled complex evolution (SCE-UA), Ref. [38] in combination with the differential evolution (DE) method [39]. The algorithm is stochastic and therefore allows for assessment of the uncertainty in the model parameters by repeated calibration. The standard calibration involves minimization of the error in simulated runoff in comparison to observed runoff represented by the value of the selected objective function (OF). However, the model also allows for widening the OF to consider also time series of other variables (typically soil moisture or baseflow estimates) or even individual hydrological signatures such as mean or variance of runoff, indicators of extremes etc.

Table 1. Input and output variables and parameters of the Bilan model.

Input Variables		**Units**
Variables	Description	
P	precipitation	(mm)
R	runoff	(mm)
T	air temperature	(°C)
H	relative air humidity	(%)
PET	potential evapotranspiration	(mm)
TS	optional time series	(mm)
Calculated variables		
Fluxes	Description	
PET	potential evapotranspiration	(mm)
ET	basin evapotranspiration	(mm)
INF	infiltration into the soil	(mm)
PERC	percolation throught the soil layer	(mm)
I	interflow	(mm)
DR	direct runoff	(mm)
BF	base flow (simulated)	(mm)
RM	total runoff (simulated)	(mm)
State variables	Description	
SS	snow water storage	(mm)
SW	soil moisture	(mm)
GS	groundwater storage	(mm)
DS	direct runoff storage	(mm)
DEFV	deficet volumes	(mm)
Model parameters		
Parameters	Description	
SPA	capacity of soil moisture storage	
DGM	temperature and snow melting factor	
DGW	water available on the land surface under winter conditions	
ALF	controls the proportion of precipitation transformed into the direct runoff	
SOC	distribution of percolation into interflow and groundwater recharge under summer cond.	
MEC	distribution of percolation into interflow and groundwater recharge under conditions of snow melting	
WIC	distribution of percolation into interflow and groundwater recharge under winter cond.	
GRD	parameter controlling outflow from groundwater storage (base flow)	

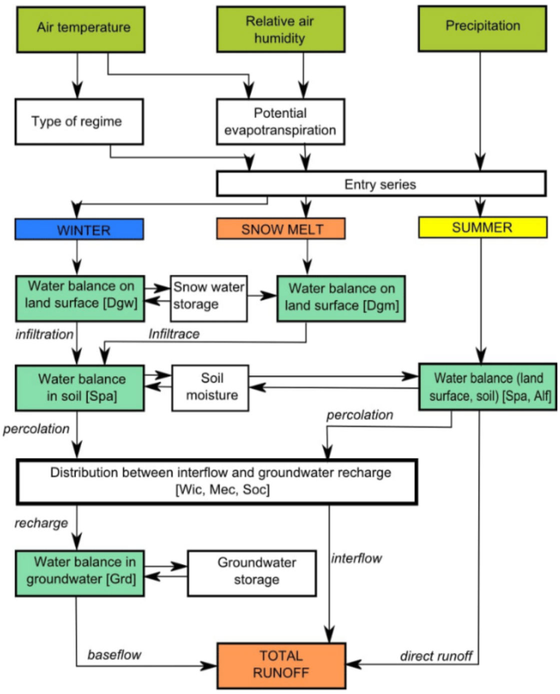

Figure 2. The Bilan hydrological model.

3.2. *Calibration Strategies*

The purpose of testing the four calibration strategies was to find such calibration setup that would minimize the bias in simulated water balance and the uncertainty in the estimated model parameters. In addition, while the first three calibration strategies (expert, standard automatic, time series with hydrological signatures) require time series of observed runoff, the fourth (calibration with hydrological signatures) can also be applied at ungauged catchments since the hydrological signatures can often be successfully interpolated from available data or estimated from general formulas.

The available time period (1981–2016) was split into calibration (1981–1998) and validation (1999–2016) period, the former being used for the identification of model parameters and the latter for the evaluation of model performance. Since the stochastic optimization algorithm implemented in the Bilan model allows for the assessment of parameter uncertainty, we fitted the model 15 times for all calibration strategies except for the expert calibration for which only the "best" parameter set was provided.

3.2.1. Expert Calibration

This strategy builds upon knowledge of the catchments and experience with hydrological modelling and is frequently applied in the case of studies for individual catchments over the Czech Republic. Typically, the expert constrains the optimization ranges of model parameters and then runs the optimization procedure. In this perspective, this calibration strategy does not always result in the best possible match between observed and simulated runoff, but at the same time, it ensures that all water balance components have reasonable values and respect physical conditions of the catchments. Therefore throughout the paper, we take these results as a reference. The parameter sets considered here were provided by experts from T. G. Masaryk Water Research Institute (developer of the Bilan model).

3.2.2. Standard Automatic Calibration

The standard automatic calibration, uses differential evolution to minimize the error between time series of observed and simulated runoff. The advantage of the automatic calibration is that it is faster than manual calibration and can be applied over large sets of catchments. It often also results in a better match between observed and simulated runoff than the manual calibration. The downside of the automatic calibration is that for some catchments the simulated water balance (and/or model parameters) may not be realistic resulting in, e.g., excessive ground water or soil water accumulation, unrealistic snow cover, etc.

3.2.3. Calibration with Hydrological Signatures

The last two calibration strategies involve hydrological signatures either in combination with runoff and/or soil moisture time series or as the only component of the objective function (OF). Model calibration was performed in 15 iterations. As the hydrological signatures, we used mean, standard deviation and interquartile range of runoff and soil moisture. The difference between the time series in the OFs was represented by mean percent bias, the match between the hydrological signatures by relative percent difference. The individual components of the OFs were summed to result in a single value. In this paper we considered 52 OFs as given in Table A1. More than a half of the OFs uses only signatures.

The OFs can be split into six groups:

1. Single-component OFs with runoff (R);
2. Single-component OFs with soil moisture (SW);
3. Two-component OFs with runoff (R2);
4. Two-component OFs with soil moisture (SW2);
5. Two-component OFs with runoff and soil moisture (RSW);
6. Three-component OFs (RSW2).

The specific combinations of variables, time series and signatures is clear from Table A1.

The aim of the introduction of hydrological signatures and/or soil moisture time series is to constrain the uncertainty in model parameters experienced with the automatic calibration and to test whether reasonable runoff simulation can be obtained without observed runoff time series.

3.3. Model Evaluation

The performance of each calibrated parameter set was evaluated with respect to the results of the expert calibration. This means that we like to evaluate to what extent we are able to obtain results close to the expert calibration but with limited information (and without expert knowledge). The parameter sets were evaluated considering:

(a) Goodness-of-fit expressed (GOF) as the root mean square error (RMSE; [40]) and Kling–Gupta efficiency (KGE; [41]) of the simulated runoff with respect to runoff simulated by the parameter set resulting from the expert calibration (further denoted as the expert simulation).

The RMSE is given by

$$RMSE = \sqrt{(\frac{1}{n})\sum_{i=1}^{n}(y_i - x_i)^2} \quad (1)$$

where y_i is expert simulation for i-th case, x_i the average of the expert simulation and N is the total number of simulated values. It was used as standard statistical metric, that gives a relatively high weight to large errors.

The KGE is calculated according to

$$KGE = 1 - \sqrt{(s[1] \times (r-1))^2 + (s[2] \times (\alpha - 1))^2 + (s[3] \times (\beta - 1))^2}, \quad (2)$$

where s is numeric weight vector of length 3 (here with all elements equal to 1), which combines the Pearson product-moment correlation coefficient (r), the ratio between the standard deviations (α) and the ratio between the mean of the expert simulation and simulation calibrated with particular OF (β).

(b) difference in the distribution of Bilan model parameters (BP) Spa (controlling soil depth) and Grd (controlling baseflow) between expert-calibrated parameters (see Section 3.2) and calibration with particular OF.

(c) relative difference in mean and the 20th (Q20) and 80th (Q80) percentile of runoff and soil moisture from the expert simulation with respect to the same signatures from the simulation calibrated with particular OF.

The relative differences are preferred here over the absolute in order to allow for comparison between catchments. To assess the performance of different calibration strategies, we subsequently ranked the results of individual strategies, according to the criteria above, for each catchment. The calibration strategies with the overall best performance were further evaluated separately as well-denoted selected characteristics.

4. Results and Discussion

This section presents a detailed assessment of the calibration strategies with respect to the flow duration curve, goodness-of-fit (RMSE, KGE), uncertainty of Bilan model parameters (Spa, Grd) and runoff signatures (Q20, Q80), according to different calibration strategies.

4.1. Runoff Difference Probability Curve

The runoff difference probability curve (Figure 3) was considered for evaluation of calibration, which shows the probability of the relative difference of the modelled runoff and the observation. The low flow are underestimated for selected (95th percentile is −49% of runoff for calibration and −37% for validation) and non-selected (95th percentile is −77% of runoff for calibration and −75% for validation) calibration strategies. The expert calibration results in runoff that matches the observed data closely. For validation, the runoff from expert calibration is positively biased for low flows (95th percentile is 8% of runoff). The selected well-performing calibration strategies are approaching the expert calibration and observed data fairly well.

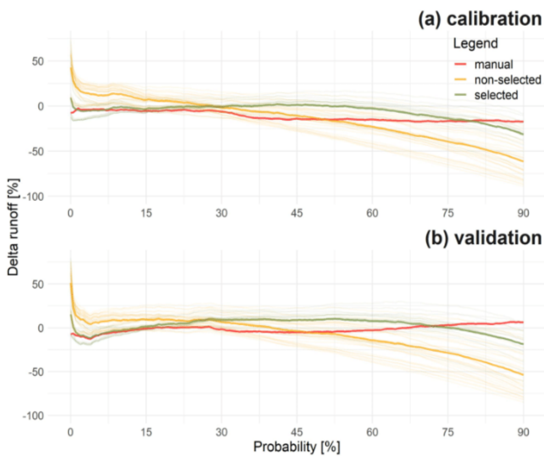

Figure 3. Runoff ((**a**)-calibration, (**b**)-validation) relative difference probability curve (red line—manual calibration settings, green line—selected calibrations strategies, orange line—non-selected calibrations strategies).

4.2. Goodness-Of-Fit

The results for different calibration strategies are compared to those of expert calibration. From the evaluation of goodness-of-fit (GOF), it is obvious that the automatic calibration provides slightly lower RMSE and improves KGE for calibration (RMSE was improved by 0.134 and the KGE by −0.097 on average) with respect to expert calibration.

For validation, the results are not much different. Obviously, introducing runoff and soil moisture signatures has negative impacts on the goodness-of-fit (GOF) metrics. This is logical since a similar metric to RMSE/KGE is used for the automatic calibration, while the calibration criterion for strategies including runoff/soil moisture signatures are more complex. Clearly, the soil moisture signatures alone are not able to provide a reasonable fit. On the other hand, the calibration strategies, including runoff or runoff and soil moisture signatures, performed reasonably for both calibration and validation. It is also obvious that strategies which consider time series data perform better than those based on signatures only. However, the signature-only strategies are also able to provide reasonable results. A quantitative comparison for all groups of objective functions (OFs), with respect to RMSE and KGE, is given in Table 2.

Table 2. Difference in RMSE (a) and KGE (b) for all groups of objective functions with respect to expert calibration. Automatic, time series + signatures and signatures only mean calibration strategies which combine runoff (R), soil moisture (SW) or runoff + soil moisture (R + SW).

GOF	Automatic		Time Series + Signatures						Signatures Only					
			R		SW		R + SW		R		SW		R + SW	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
RMSE	0.134	0.142	0.125	0.138	−0.560	−0.478	−0.257	−0.183	−0.303	−0.222	−0.537	−0.454	−0.383	−0.295
KGE	−0.097	−0.077	−0.099	−0.080	0.270	0.265	0.151	0.129	0.098	0.107	0.236	0.232	0.170	0.156

We further compared the distribution of differences in validation of RMSE and KGE between the selected (best-performing) objective functions (OFs) and the rest (Figure 4). It is obvious that the selected OFs provide consistent improvement in both RMSE and KGE, while the rest of the OFs are often worsening the results. In addition, taking into an account the time-series-based OFs only (without signatures) leads to considerably worse results.

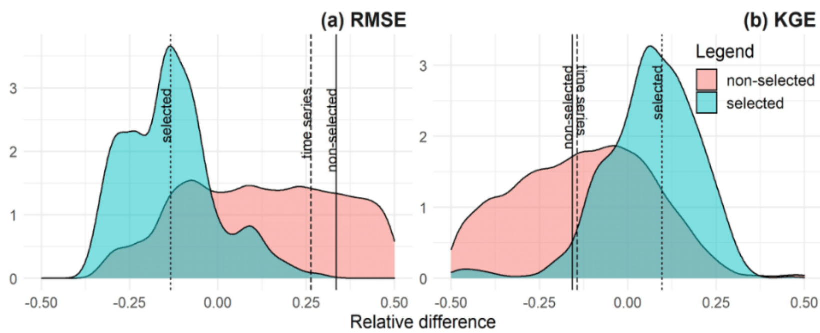

Figure 4. The density of differences in RMSE (**a**) and KGE (**b**) between expert calibration and the rest of the objective functions (OFs). The dotted line corresponds to mean of the selected best-performing OFs, the dashed line to the mean for the OFs, including time series, and the solid line to the mean of the OFs that were not selected.

4.3. Uncertainty of Bilan Model Parameters

The relative error in fitted Spa and Grd parameters for groups of objective functions (OFs) with respect to expert calibration is given in Table 3. These two parameters are important for the characterization of hydrological balance of a catchment, representing the soil water retention (Spa parameter) and ground water response (Grd parameter).

For the Spa parameter, the best results are obtained with automatic standard calibration. Very similar results are achieved with group R2. The Spa parameter is clearly improved by runoff signatures as indicated in Table 3. Including soil moisture leads to worse results (see groups SW, SW2, RSW, RSW2). The Grd parameter describing the groundwater dynamics was reliably estimated in the R2, RSW, RSW2 and A groups. In this case, the soil moisture signatures have improved the Grd parameter but only in combination with runoff.

Table 3. Relative difference of Bilan model parameters Spa and Grd between expert calibration and other calibration strategies. Automatic, time series + signatures and signatures only mean calibration strategies which combinate runoff (R), soil moisture (SW) or runoff + soil moisture (R + SW).

BP	Automatic		Time Series + Signatures						Signatures Only					
			R		SW		R + SW		R		SW		R + SW	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Spa	0.202	0.121	0.204	0.122	0.282	0.285	0.275	0.267	0.243	0.163	0.297	0.269	0.305	0.272
Grd	0.163	0.158	0.164	0.161	0.388	0.363	0.233	0.169	0.232	0.148	0.391	0.358	0.252	0.164

The density of relative errors in Bilan Spa a Grd parameters with respect to expert calibration for all calibration strategies is given in Figure 5. Again, the distribution of the errors for the selected (best-performing) objective functions (OFs) is much more consistent then for the rest of the OFs. Particularly for the Spa parameter, it is obvious that the selected OFs avoid the attraction to different parameter values which is evident for the rest of OFs (see red area on the left of Figure 5).

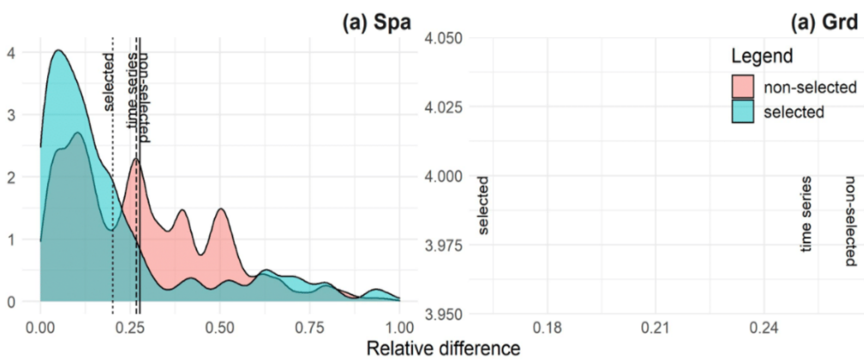

Figure 5. The density of relative errors in Spa (**a**) and Grd (**b**) based on selected best-performing OFs (green area) and the rest (red area). The dotted line correspond to the mean of the selected best-performing objective functions, the dashed line to the mean OFs, including time series, and the solid line to the mean of the OFs that were not selected.

4.4. Runoff Signatures

Lastly, we evaluated the performance of the calibration strategies with respect to low and high flows represented by the 20th (Q20) and 80th (Q80) percentile (Table 4). In the case of low flows, the performance of the model is clearly improved when runoff signatures are considered and even more so when this is done in combination with soil moisture signatures or time series. On the other hand, the standard automatic calibration ranked among the worst OFs. For the high flows in general, the differences is much less variable with automatic calibration being slightly better than the rest of the OFs.

Table 4. Relative difference in Q20 and Q80 for runoff. Automatic, time series + signatures and signatures only mean calibration strategies which combinate runoff (R), soil moisture (SW) or runoff + soil moisture (R + SW).

RS	Automatic		Time Series + Signatures						Signatures Only					
			R		SW		R + SW		R		SW		R + SW	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Q20	0.224	0.172	0.225	0.181	0.568	0.570	0.391	0.323	0.354	0.299	0.545	0.565	0.482	0.439
Q80	0.075	0.056	0.073	0.057	0.182	0.159	0.114	0.087	0.141	0.106	0.221	0.173	0.155	0.127

The difference in the behavior between Q20 and Q80 is also obvious from the density presented in Figure 6 where the best performing OFs lead to a much narrower error distribution than the rest of the OFs for Q20, while the difference is very small in the case of Q80.

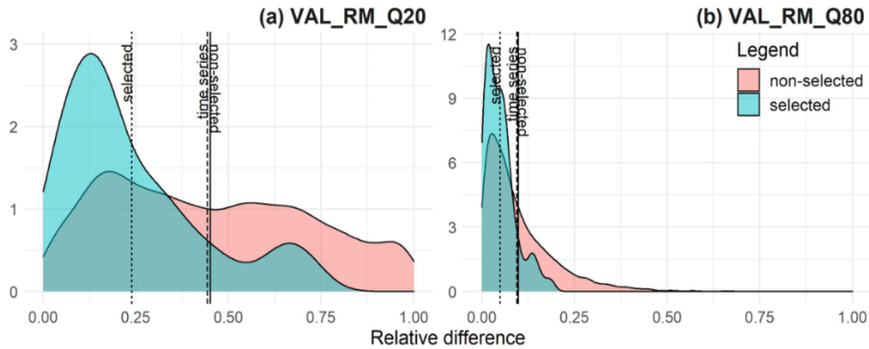

Figure 6. Density of error in runoff signatures in Q20 (**a**) and Q80 (**b**) based on selected best-performing OFs (green area) and the rest (red area). Dotted line correspond to mean of selected best-performing objective functions, dashed line to mean OFs including time series and the solid line the mean of the OFs that were not selected.

4.5. Summary of OFs' Performance

The 52 OFs considered for calibration contain runoff (R, R2), soil moisture (SW, SW2), and both runoff and soil moisture (RSW, RSW2) as a time series or hydrological signatures. The OFs were assessed with respect to goodness-of-fit (GOF), uncertainty of Bilan model parameters (BP) and bias in runoff signatures (RS). To summarize the performance of different OFs, we ranked the OFs at each catchment according to GOF, BP and RS and checked which OFs appears most frequently. The set of those OFs is presented in Table 5. There are only four OFs included in the best-performance set for all three criteria: the standard automatic calibration, R2-mean-optim and R2-iqr-optim. It is clear that time series information is crucial for hydrological simulation. However, the results also indicate that the OFs including hydrological signatures may rank among the best with respect to parameters of the hydrological model and low and high flow statistics. Our results suggest a relatively good agreement between modelled and observed runoff, however, when very low (Q80 and Q95) and very high quantiles for (Q20) are used for model diagnosis [4,25] it turns out that low flows (Q95–Q100) are significantly underestimated in most model settings.

This study was performed on 20 catchments, which means that the estimate of hydrological signatures may not be as robust as studies that include more catchments with diverse water regime allowing for better description of the behaviour of individual parameters, hydrological signatures, or selected variables [42]. Ref. [42] also mentiones, that the hydrological signatures are typically more influenced by climatic and topographic indices than by the land cover, soil properties, and geology. Although we did not consider other than hydroclimatic factors our study confirmed importance of the climatic factors especially those related to soil moisture influencing in particular low flows and groundwater-related parameter (Grd) of the Bilan model.

Similar to [17], we have shown that unconstrained calibrated model parameters are varying in wide range of implausible values and it is necessary to balance between automated model calibration with expert-knowledge and local system understanding strategy. In addition, the hydrological signatures, considerably narrow the range of parameter values and approach the expert-calibrated parameters well. Therefore they should be considered in the calibration and diagnostics of the model in particular when behavior of the extremes is of interest as was already suggested by [25].

Table 5. The best OFs according to goodness-of-fit (GOF), parameters of the hydrological model (BP) and high and low flow indices (RS). Time series, R-signatures and SW-signatures mean characteristic which combined times series or signatures of runoff (R) and of soil moisture (SW), their statistic indicators are mean, interquartile range (IQR), sd and selected settings (*).

ID	Time Series		R-Signatures			SW-Signatures			Evaluation Metrics		
	R	SW	mean	IQR	sd	mean	IQR	sd	GOF	BP	RS
automatic	*								*	*	*
R2-mean-sd			*		*					*	
R2-mean-iqr			*	*						*	*
R2-mean-optim	*		*						*	*	*
R2-sd-iqr				*	*				*	*	
R2-sd-optim	*				*				*	*	
R2-iqr-optim	*			*					*	*	*
RSW-mean-mean			*			*			*	*	
RSW-mean-iqr			*				*			*	
RSW-sd-sd					*			*		*	*
RSW-optim-optim	*	*							*		*
RSW-optim-iqr	*			*					*		*
RSW-iqr-iqr				*			*				*
RSW2-sd-sd-optim		*			*			*		*	
RSW2-optim-optim-sd	*	*						*	*		*
RSW2-optim-optim-mean	*	*				*			*		*
RSW2-optim-optim-iqr	*	*					*		*		*
RSW2-optim-mean-sd	*					*		*	*		*
RSW2-optim-iqr-sd	*						*	*	*		*
FDC-all	*								*	*	*
FDC-300-330-355-364	*								*	*	*

5. Concluding Remarks

In the present paper, we assessed the performance of a conceptual runoff model (Bilan) calibrated using hydrological signatures based on long term runoff and soil moisture characteristics. The results of these strategies are compared to those of the standard automatic and expert calibration. The performance of tested combinations of runoff and soil moisture time series and signatures is evaluated with respect to goodness-of-fit (GOF) between simulated and observed runoff, uncertainty of the estimated Bilan model parameters (BP) and runoff signatures (RS) representing low and high flows.

The main findings can be summarized as follows:

- The standard automatic calibration performs best for most of the evaluation criteria, except for low flows;
- The objective functions (OFs) utilizing time series are always performing better than those based on signatures only;
- It is however clear that the good performance of automatically calibrated models can be counterbalanced by poor representation of hydrological processes, important hydrological signatures and overall increasing uncertainty of model parameters. Therefore, evaluation metrics

accounting for biases in hydrological processes representation and objective functions combining the bias in runoff time series with that of other runoff characteristics should be considered;
- In the cases where the runoff time series are not available, it is possible to get sufficient fit even using signatures representing runoff mean and variability;
- The role of the runoff and soil moisture signatures is significant, in particular for low flows and parameters of the hydrological model.

The study was performed in specific conditions of the Czech Republic with a single hydrological model and further research is needed to confirm the findings also in different hydroclimatic and physical conditions and hydrological models.

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Abbreviations

The following abbreviations are used in this manuscript:

GOF	Goodness-of-fit between observed and simulated runoff
RMSE	Root mean square error
KGE	Kling–Gupta efficiency
BP	Uncertainty of the estimated Bilan model parameters
RS	Selected runoff and soil moisture signatures
Q20	Percentile of runoff and soil moisture
Q80	Percentile of runoff and soil moisture
P	Precipitation (mm)
R	Runoff (mm)
RH	Relative air humidity (%)
PET	Potential evapotranspiration (mm)
RM	Simulated runoff (mm)
DR	Direct runoff (mm)
DS	Runoff storage (mm)
BS	Baseflow (mm)
GS	Groundwater storage (mm)
I	Interflow (mm)
Spa	Capacity of soil moisture storage
Dgm	Temperature and snow melting factor
Dgw	Water available on the land surface under winter conditions
Alf	Direct runoff parameters
Soc, Mec, Wic	Divide percolation into interflow and groundwater recharge under summer, Snow melt and winter conditions
Grd	Parameter controlling the outflow from groundwater storage
SCE-UA	Shuffled complex evolution
DE	Differential evolution method
OF	Objective function
R	Single-component OFs with runoff

SW	Single-component OFs with soil moisture
R2	Two-component OFs with runoff
SW2	Two-component OFs with soil moisture
RSW	Two-component OFs with runoff and soil moisture
RSW2	Three-component OFs with runoff and soil moisture

Appendix A

Table A1. Optimal OFs are denoted in bold. The time series column contains time series as runoff (R) and soil moisture (SW). The column's hydrological signature of (R) and (SW) is combined with statistical indicators as mean, IQR, sd and selected settings (*).

ID	Time Series		R-Signatures			SW-Signatures		
	R	SW	mean	IQR	sd	mean	IQR	sd
Automatic	*							
R-mean			*					
R-iqr				*				
R-sd					*			
SW-mean						*		
SW-iqr							*	
SW-sd								*
SW-optim		*						
R2-mean-sd			*		*			
R2-mean-iqr			*	*				
R2-mean-optim	*		*					
R2-sd-iqr				*	*			
R2-sd-optim	*				*			
R2-iqr-optim	*			*				
SW2-mean-iqr						*	*	
SW2-mean-sd						*		*
SW2-mean-optim		*				*		
SW2-sd-iqr							*	*
SW2-sd-optim		*						*
SW2-iqr-optim		*					*	
RSW-mean-mean			*			*		
RSW-mean-sd			*					*
RSW-mean-optim		*	*					
RSW-mean-iqr			*				*	
RSW-sd-sd					*			*
RSW-sd-optim		*			*			
RSW-sd-iqr					*		*	
RSW-optim-optim	*	*						
RSW-optim-iqr	*						*	
RSW-iqr-iqr				*			*	
RSW2-mean-mean-sd			*			*		*
RSW2- mean-mean-optim		*	*			*		
RSW2-mean-mean-iqr			*			*	*	
RSW2-sd-sd-mean					*	*		*
RSW2-sd-sd-optim		*			*			*
RSW2-sd-sd-iqr					*		*	*
RSW2-optim-optim-sd	*	*						*
RSW2-optim-optim-mean	*	*				*		
RSW2-optim-optim-iqr	*	*					*	
RSW2-iqr-iqr-mean				*		*	*	
RSW2-iqr-iqr-sd				*			*	*
RSW2-iqr-iqr-optim		*		*			*	
RSW2-mean-sd-optim		*	*					*
RSW2-sd-mean-optim		*	*		*			
RSW2-optim-mean-sd	*					*		*
RSW2-iqr-sd-optim		*		*				*
RSW2-sd-iqr-optim		*			*		*	
RSW2-optim-iqr-sd	*						*	*
RSW2-iqr-mean-optim		*		*		*		
RSW2-mean-iqr-optim		*	*				*	
FDC-all	*							
FDC-180	*							
FDC-300-330-355-364	*							

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4.3 Management effectiveness in a freshwater protected area: Long-term water quality response to catchment-scale land use changes

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Original Articles

Management effectiveness in a freshwater protected area: Long-term water quality response to catchment-scale land use changes

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ABSTRACT

As freshwater environments become increasingly threatened, the need for efficient and effective protection grows more urgent. Yet quantitative evidence of management effectiveness within freshwater protected areas is limited, inhibiting our ability to infer the practicality and efficacy of practices. Herein, we employ linear mixed-effects models and time series models to evaluate the connection between catchment-scale management actions and surface water quality within a freshwater protected area, over the past three decades. Within the study area, all croplands were restored to traditional grasslands resulting in a landscape dominated by meadows and forests. The extent of land use change and time frame needed for water quality improvements were investigated and management effectiveness appraised. Results indicate that the complete grassing of croplands was approximately three times more effective at reducing concentrations of nitrate than electrical conductivity and calcium. Significant improvements in water quality occurred within nine years of management implementation, with mean annual nitrate concentrations decreasing from 5.5 to 1.9 mg/L following the grassing of all croplands covering 3.1% of the study area, whereas gradual improvements continued over the next 20 years, ultimately resulting in nitrate concentrations below 1.0 mg/L. The results of this study provide valuable insights on how land use conversions in small headwater catchments can influence stream water quality and helps to establish expectations for outcomes when planning conservation strategies.

1. Introduction

Fresh water is an essential resource needed to support humanity, yet freshwaters are among the most imperiled ecosystems on Earth (Dudgeon et al., 2006; Saunders et al., 2002). Anthropogenic activities, such as intensive agriculture, are a direct threat to freshwater systems (Revenga et al., 2005), driving habitat degradation and water pollution worldwide (Dudgeon, 2019). Consequently, nearly 80% of the global population is vulnerable to high levels of water security threats (Vörösmarty et al., 2010). As anthropogenic pressures intensify, the necessity for effective and efficient conservation strategies becomes increasingly urgent.

Protected areas are a cornerstone for the conservation and use of natural resources, yet the sheer existence of a protected area does not warrant its protection (Roux et al., 2008). Maximizing capabilities requires the monitoring of management effectiveness to identify and address prevailing problems (Hockings, 2000). Nevertheless, the capabilities of existing protected areas to reduce threats and conserve freshwater ecosystems remains relatively unexamined compared to that of terrestrial and marine systems (Abell et al., 2017; Hermoso et al., 2016). According to a systematic review by Acreman et al. (2019), case studies providing quantitative evidence of protected area effectiveness for freshwaters include only 38 reports of positive outcomes and merely 15 which compare the same locality before and after designation, with constraints on monitoring and study design often inhibiting an adequate evaluation of success. This paucity of evidence essentially hinders a deeper understanding of the efficacy of management interventions for improving protected area performance (Coad et al., 2015; Geldmann et al., 2018). Consequently, decision-making remains largely predicated on traditional practices (Pullin et al., 2004) and personal norms (Pradhananga and Davenport, 2019), rather than empirical evidence. Objectively informing practitioners and planners on evidence-based conservation is crucial for underpinning actions (Pullin and Knight, 2009; Sutherland et al., 2004) and, ultimately, raising management standards within protected areas (Leverington et al., 2010).

Site-level investigations of management actions and outcomes are

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necessary for understanding the effectiveness of individual practices (Anthony and Shestackova, 2015; Coad et al., 2015) and the extent to which goals and objectives of protected areas are being achieved (Hockings, 2000; Lu et al., 2012). Although site-level research is often perceived as too parochial (Esler et al., 2010), interventions predicated on site specific knowledge have been used to guide management actions. For example, a global analysis by Geldmann et al. (2013) found that the majority of practices suggested for the conservation of threatened species were based on site-level management, while a review from Melland et al. (2018) highlighted how adapting measures established from site specific research has enabled a practical application of findings. Examining the effectiveness of individual interventions in producing specific outcomes can help establish expectations from subsequent management (Schilling and Spooner, 2006) and advance the capacity for planning and implementing sound responses (Williams et al., 2020).

Inaugurated in 1989, the Blanice River nature reserve was designated to protect the upper river network of the Blanice River against anthropogenic eutrophication and restore habitat conditions for sensitive freshwater species (Hruška, 1991a; Simon et al., 2015). Between 1991 and 1992, management in the form of land use transitions altered the study area; all croplands were restored to traditional grasslands, resulting in a semi-natural landscape dominated by meadows and forests. Water quality monitoring over a period of 33 years, along with defined limits, enables an opportunity to appraise the efficacy of management in an existing freshwater protected area. In this work, we compare observations of land use composition and surface water quality, before and after management implementation, to deduce the relative effectiveness of practices in mitigating nutrient loading and examine temporal trends in nitrate concentrations to assess the response time needed for observing improvements.

2. Methods

2.1. Study area

The Blanice River nature reserve encompasses the headwaters of the Upper Blanice River with an area of approximately 63 km^2 (Fig. 1a). Originating from the southwestern border-region of the Czech Republic, the primary channel of the river system flows north into Germany (Fig. 1b). Due to its position in Central Europe, this submontane region has a continental climate with cold and heavy precipitation, consisting mostly of snow in the winter. The mean annual temperature is approximately 4° C and mean annual precipitation is about 1090 mm (Svoboda et al., 2010). This cultural landscape is characterized by rolling hills, composed primarily of forests and meadows. The tributaries have unaltered watercourses with natural stream banks and contain no dams or weirs.

Prior to management, croplands intensively used for fodder production were a primary source of water quality impairment (Simon et al., 2011). Cropland covered a small fraction of the nature reserve (approximately 3.1%), yet land practices including fertilization, tillage, tile drainage and pesticide application contributed to a significant increase in nitrogen. Incentivized by state subsidies, an excess of fertilizer and lime were applied to compensate for the poor skeletal soils within these submontane altitudes (800–850 m a.s.l.).

The study area was declared a Nature Reserve in 1989 (classified as IUCN category IV protected areas) and a management plan was instituted to protect the natural habitats of freshwater species which require low levels of nutrients to survive (Hruška, 1991b, 1991a). Active management interventions included the eradication of mineral fertilization, liming and pesticide application in 1990 followed by the complete grassing of all croplands between 1991 and 1992 (Table 1). Additional

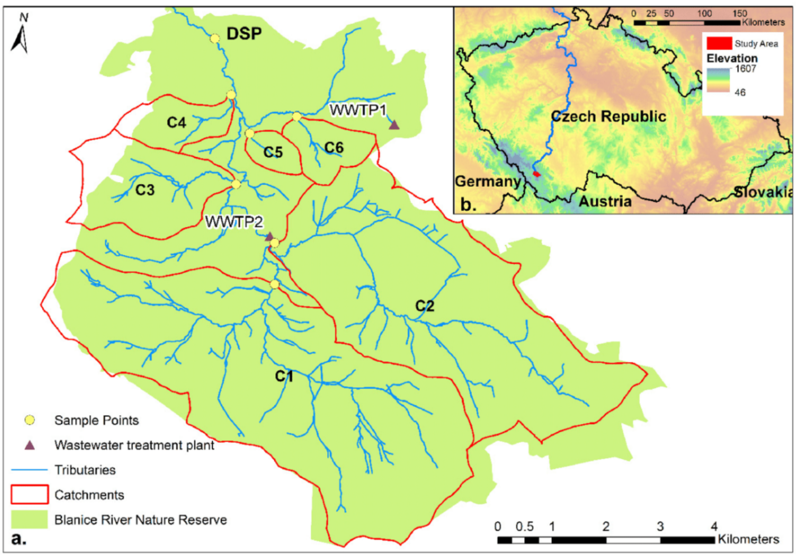

Fig. 1. **a** Water quality sampling locations of selected headwater catchments (C1-C6) and the downstream sampling point (DSP) of the Blanice River. **1b.** Location of study area.

Table 1
Characteristics of selected sites, categories for evaluation and management actions.

Site ID	Stream Order	Area drained (km^2)	Catchment Category	Before Management (1989)	Management (1990)	Management (1991–1992)
C1	4	20.59	Low-Cropland	0% cropland	Ceasing of all intensive mineral fertilization, liming and pesticide application	Conversion of all croplands to extensive meadows and pastures via grassing
C2	3	16.34	Low-Cropland	2.9% cropland		
C3	2	3.90	Moderate-Cropland	6.9% cropland		
C4	2	1.51	Moderate-Cropland	5.6% cropland		
C5	1	0.61	High-Cropland	18% cropland		
C6	2	1.30	High-Cropland	49.9% cropland		
DSP	4	57.88	Entire Nature Reserve	3.1% cropland		

Note: Stream order is according to Strahler (1957).

efforts took place after 1992 with no significant effects on water quality (see Supplementary Table 1 for a complete list of conservation measures), and therefore were not included in the analysis.

The study area is sparsely populated, accommodating ~ 80 residents within the protected area. In order to focus on the impacts of land use conversions, six catchments without point sources of pollution were selected for investigation (i.e., C1-C6). Two small wastewater treatment plants (WWTP1 and WWTP2 in Fig. 1a) which treat domestic sewage from a small number of houses (Supplementary Table 2) are situated within the nature reserve, outside of the examined catchment areas. Longitudinal measurements taken below the outfall of WWTP1 (Supplementary Fig. 1) as well as above and below the outfall of WWTP2 (Supplementary Fig. 2), suggests that these systems had little to no impact on downstream water quality. Additionally, the long-range transport of atmospheric pollutants over Central Europe between 1980 and 1990 did not alter the chemical composition of surface waters in the Blanice River nature reserve (Hruška and Majer, 1996) with trends in nitrogen deposition remaining primarily unchanged thereafter (Erisman et al., 2015; Oulehle et al., 2008).

3. Data collection

Long-term monitoring data of surface water quality, extending from 1989 to 2016, was available for the six sampling points along the headwaters of the Blanice River (i.e., the outlet of catchments C1-C6). Sampling occurrence during this period was recurrent, yet irregular (see Supplementary Table 3 for annual sampling intervals). Some sites were not monitored during certain years and none of the sites were monitored between 1993 and 2000; thus, water quality data were separated into two periods of record: before (i.e., 1989–1992) and after (i.e., 2000–2016) management. Due to data availability and the nature reserve's mandated standards for surface water quality, four water quality parameters were selected for evaluation: electrical conductivity (EC, μS/cm), calcium (Ca, mg/L), nitrate (NO_3^-, mg/L) and pH. These chosen parameters are important indicators of the mineralization of agricultural soils, the eutrophication of surface waters and long-term atmospheric acidification. Water samples were collected using conventional sampling protocols and analyzed according to the standardized methods of the Czech National Standards Criterion.

Continual monitoring of NO_3^- was available for one downstream sampling point (DSP) on the Blanice River that drains the entire study area. Sample collection for DSP began in 1986 and continued until 2019, occurring minimally twice a year, yet largely on a monthly basis (see dataset in data repository). To account for inter-annual variations, all water quality data were divided into winter (i.e., October–April) and summer (i.e., May-September) seasons, periods that correspond to high and low periods of nitrogen saturation, respectively (Lamberti and Hauer, 2017; Zhang et al., 2008).

Standards for surface water quality were legally mandated by the National Natural Monuments decree (Supplementary Table 4), explicitly defining objectives for desired outcomes. The decree was extended in 2008 (Supplementary Table 5), with stricter limits on admissible concentrations for water quality parameters and used as an indicator of management effectiveness.

3.1. Analysis

Land use information was acquired using ArcMap 10.6.1 software. All shapefiles and layers were created using the coordinate system S-JTSK Krovak East North. The approximate area of the nature reserve was defined according to reference maps. Catchment areas and streams were delineated via shapefiles provided by the Czech Digital Base of Water Management Data (https://www.dibavod.cz/), using the water sampling locations as the outflow for each catchment area. The composition of land use within each catchment was quantified for two periods: 1989 (i.e., before management) and 2017 (i.e., after management). Black and white aerial photographs from 1988, acquired from the Military Geographical and Hydro meteorological Office, were georeferenced using clearly distinguishable reference-target points. A geometric transformation was made using the 1st order polynomial, allowing images to be reshaped and correctly positioned. Otho-photographs from 2017 were supplied by the Czech Office for Surveying, Mapping and Cadastre (https://www.cuzk.cz). Vectorization of land use classes was based on the visual interpretation of the aforementioned data sources, at a mapping scale of 1:5000, allowing for a detailed observation of the landscape. Land use was categorized into four classes: (1) cropland, including all arable land and cultivated crops; (2) meadows, including pastures, mowed areas and natural grasslands; (3) forests, including groups of trees and shrubs; and (4) settlements, including houses, farmhouses and roads. The proportion of each land use class within each catchment area was calculated to obtain the percent value. The net change in percentages of land use classes (i.e., the difference between time periods) was calculated for each catchment to assess land use dynamics between pre- and post-management states. In this work, cropland is the main focus, as it is an influential land use class that reflects the potential of nutrient runoff (Supplementary Fig. 3); therefore, catchments were grouped into three categories according to their initial extent of cropland (see Table 1). These categories were created to represent various degrees of management and ascribe water quality change to an approximate range of land use conversions. Furthermore, catchments were categorized based on their size (i.e., area drained) and location within the watershed (see Fig. 1a.), reflecting similar stream orders and soil conditions.

R statistical software (R Core Team 2021) was used for statistical analysis. Visual examination of the normal probability plot of residuals (Normal Q-Q) demonstrated that NO_3^-, Ca and EC were not normally distributed; therefore, logarithmic transformations (base-10) were conducted on these water quality variables, prior to analysis, to meet the assumptions of normality. For each water quality parameter as response, a separate linear mixed-effect model (Pinheiro and Bates, 2006) was fitted, with period (before and after management), season (winter and summer) and catchment category (low-cropland, moderate-cropland and high-cropland) as categorical fixed-effect predictors. Because there were repeated measurements in the same site, and such measurements were probably not independent, the site ID was included as a random-intercept effect. To assess whether the effect of period varied in different seasons and catchment categories, all possible interactions among the fixed-effect predictors were included. The significance of individual predictors and interactions were assessed by comparing the full model with the model excluding the given term using Wald chi-squared tests. A final model, including only significant predictors, was then fitted while adhering to the principle of marginality (i.e., the main terms or lower-order interactions were kept whenever the higher-order interactions were significant). The final evaluation of the effects of the significant predictors were based on visual assessment of the effect plots, in which we plotted model predictions for all combinations of significant predictors levels, together with Wald confidence intervals conditioned on the estimates of random effect variances (see Fig. 2).

To assess a temporal trend in the NO_3^- concentrations, a time series analysis was performed on the DSP measurements. First, the measurements were plotted against time, with the seasons distinguished, and a local polynomial regression was used to assess a possible non-linear trend. To examine possible finer intra-annual differences in the temporal trend, the data were also plotted in a 3D plot against both year and month. For further time series analysis, the data were aggregated by computing monthly means. After this aggregation, there were 37 out of 405 (9%) missing observations, ten of them occurring in 2003 (for all months except for January and February) and the rest being spread across the years. Since the methods further applied for the time series analysis cannot handle missing observations, the missing observations were replaced by interpolated values. For this interpolation, a quadratic polynomial regression was used with year, month, and their interaction as predictors (function loess in R; see the Supplementary Fig. 4 for the visualization of the regression surface). Further analysis was done using this imputed dataset. To assess possible seasonality and trend, the time series was decomposed to trend, seasonal, and random components using a multiplicative model (function *decompose* in base R). The multiplicative model was selected because the variation in NO_3^- concentrations clearly increased with increasing trend (see the Supplementary Fig. 4 and 5). The autocorrelation was then assessed by plotting the autocorrelation function of the estimated random component. The presence of a possible trend was assessed by the seasonal Mann-Kendall test, and a possible change point in the time series was assessed using the Pettitt test (the R package trend; Pohlert, 2020).

4. Results

4.1. Land use transitions

Between 1988 and 2017, cropland was reduced to 0% amongst sites, ranging from a 2.9% decrease in low-cropland catchments to a 49.9% decrease in high-cropland catchments (Table 2). The disappearance of

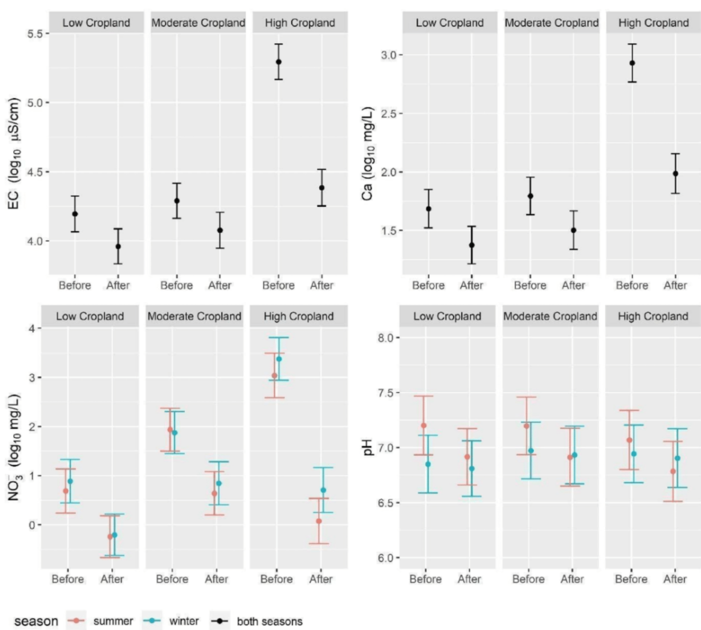

Fig. 2. Linear mixed-effects models for water quality parameters according to management period (i.e., before, 1989–1992 and after, 2000–2016), catchment category (i.e., low-cropland, moderate-cropland and high-cropland) and season (i.e., winter, summer or both seasons). The points represent the model predictions. The error bars are 95% Wald confidence intervals, conditional on the estimates of random effect variance. The values are expressed in orders of magnitude (i.e., on a log scale) for all parameters, except for pH.

Table 2
Net changes in the composition (%) of land use classes before (1989) and after (2017) management.

		Cropland			Meadows			Forests		
Site ID	Category	1989	2017	Change	1989	2017	Change	1989	2017	Change
C1	Low-Cropland	0	0	0	24.4	18.2	−6.2	74.8	80.9	6.1
C2	Low-Cropland	2.9	0	−2.9	33.1	29.5	−3.6	62.9	69.4	6.5
C3	Moderate-Cropland	6.9	0	−6.9	47	41.5	−5.5	45.4	57.8	12.4
C4	Moderate-Cropland	5.6	0	−5.6	54.4	49.6	−4.8	38.9	48.9	10
C5	High-Cropland	18	0	−18	9.8	25.4	15.6	72	74.4	2.4
C6	High-Cropland	49.9	0	−49.9	5.4	53.5	48.1	43	44.9	1.9

cropland was predominantly compensated by a marked expansion of meadows in high-cropland catchments whereas low- and moderate-cropland catchments experienced declines in both croplands and meadows, paralleled by an increase in forests, resulting in bidirectional transitions for meadows between sites. Forested composition increased across all catchments between periods, albeit marginally, with the largest increases of 10 and 12.4% within moderate-cropland catchments. Settlements covered<2% of each catchment area, with only one catchment experiencing an increase of<1% (Supplementary Table 6); hence, settlements are omitted from results. In total, cropland covering 3.1% of the 58 km^2 study area was eliminated between 1988 and 2017.

4.2. Variations in stream water quality

According to the linear mixed-effect models, concentrations of water quality varied significantly between management periods ($p < 0.001$), with net reductions in concentrations across all parameters except for winter values of pH (Fig. 2; Table 3, Supplementary Table 7). The highest magnitude of response was displayed in models of NO_3^-, whereas temporal changes in concentrations for models of EC and Ca were approximately three times smaller, with decreases corresponding between EC and Ca. The values of pH remained the most stable between management periods, with relatively neutral values ranging from 6.5 to 7.5. Explained water quality variance for models of NO_3^-, Ca and EC ranged from 77 to 82% (see Supplementary Table 8 for conditional R^2 values), whereas the explained variance for models of pH were considerably weaker, with approximately 18%.

There were statistically significant differences between catchment categories, as well as between management periods and catchment categories, for concentrations of EC, Ca and NO_3^- ($p < 0.001$). High-cropland catchments, predominantly exhibiting the highest concentrations, reduced EC and Ca by an order of magnitude and NO_3^- by three orders of magnitude between management periods. Low-cropland catchments possessed the lowest concentrations, yet experienced declines analogous to moderate-cropland catchments with EC and Ca decreasing approximately 0.2 orders of magnitude and NO3 decreasing by an order of magnitude. Changes in seasons had statistically significant effects on concentrations NO_3^- and pH ($p < 0.001$), with parameters exhibiting diverse responses. Seasonal effects varied between catchment categories ($p < 0.001$ for NO_3^- and $p < 0.05$ for pH) and management periods ($p < 0.001$ for pH).

Table 3
Analysis of deviance table of final models for each water quality parameter (WQP).

WQP	Variable	Df	Chi sq	p-value
NO_3^-	Period	1	1160.5750	***
	Category	2	27.1367	***
	Season	1	27.1367	***
	Period: Category	2	274.1582	***
	Period: Season	1	1.4607	
	Category: Season	2	16.3108	***
	Period: Category: Season	2	6.5740	*
EC	Period	1	755.76	***
	Category	2	100.24	***
	Period: Category	2	433.29	***
Ca	Period	1	516.891	***
	Category	2	92.878	***
	Period: Category	2	188.195	***
pH	Period	1	16.6735	***
	Category	2	0.1931	
	Season	1	14.2061	***
	Period: Season	1	12.4097	***
	Category: Season	2	6.9221	*

Note: *** level of significance $p < 0.001$; ** level of significance $p < 0.01$; * level of significance $p < 0.05$.

4.3. Temporal trends in nitrate

Concentrations of NO_3^- exhibited discernible temporal trends at the study area outlet (i.e., DSP) where cropland covering 3.1% of the study area was eliminated; there was a slight increase from 1986, with annual concentrations culminating in 1991 averaging 5.5 ± 2.0 mg/L (mean ± SD), followed by a decrease until 2019 (Fig. 3; Supplementary Table 9). Corresponding patterns were observed between seasons, with slightly higher concentrations and more drastic declines in winter than in summer. The 3D plot of NO_3^- concentrations against year and month did not reveal any finer intra-annual patterns (Supplementary Fig. 4). The most substantial reductions in nitrate transpired between 1991 and 2000 with mean annual nitrate concentrations decreasing from 5.5 to 1.9 mg/L, whereas declines remained gradual for the remainder of the monitoring period, with concentrations averaging 0.9 ± 0.2 mg/L (mean ± SD) by 2019. The same general trend was confirmed by the time series decomposition (Supplementary Fig. 5) and was found significant in all months by the seasonal Mann-Kendall test (max p = 0.0001, τ ranging from −0.48 to −0.69). The use of the test was justified by only very little residual autocorrelation after the series decomposition (Supplementary Fig. 6). The Pettitt test further revealed a highly significant ($p < 10^{-16}$) change point in May 2000 (Supplementary Fig. 7), suggesting abrupt changes in mean NO_3^- concentrations before and after that time. Since 2001, median annual concentrations of NO_3^- have remained within the designated limits of the 2008 National Natural Monument Decree (i.e., below 1.8 mg/L; see Fig. 3 and Supplementary Table 9).

5. Discussion

The management applied within the Blanice River nature reserve was straightforward; all cropland was converted to meadows. Water quality concentrations were examined before and after management implementation, making this investigation one of the few published ‘before and after’ studies which compares the changes made within the same freshwater protected area (Acreman et al., 2019). Measurable improvements in surface water quality were observed after management was implemented, demonstrating a close connection between land use alterations and stream condition. Nevertheless, the initial extent of cropland predominantly corresponded to post-management concentrations, tentatively suggesting that the complete impacts of land use alterations have not yet transpired. According to outcomes, the elimination of cropland was approximately three times more effective at

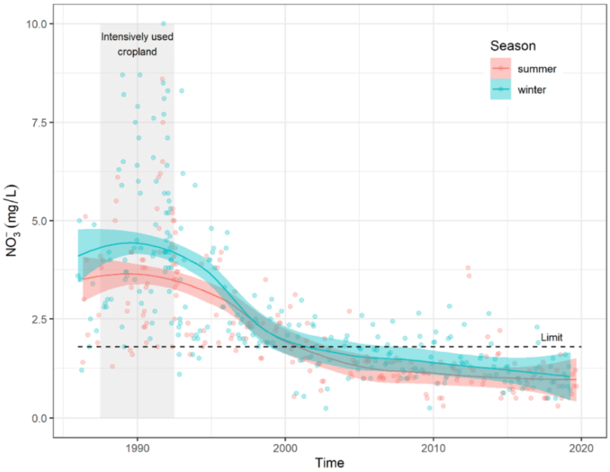

Fig. 3. Annual nitrate (NO_3^-) concentrations for the downstream sampling point (DSP) during each season. The trend lines are created by fitting a local quadratic polynomial regression (function *loess* in R with default settings). The confidence bounds represent 95% Wald intervals. The shaded grey area represents the period of intensively used cropland and the dashed line represents the upper limit for permissible NO_3^- concentrations of surface waters according to the 2008 National Natural Monument Decree.

reducing concentrations of NO_3^- than EC and Ca. Agricultural land is considered a primary source of nutrient enrichment, particularly for nitrate (Carpenter et al., 1998; Hill, 1978), therefore it is unsurprising that concentrations of NO_3^- exhibited the largest decrease after cropland was eradicated. Albeit statistically significant, reductions in values of pH were relatively negligible between management periods with exceedingly low model accuracy inconsistent with the other modelled parameters.

The assignment of catchment categories allowed for the examination of how varying degrees of management may influence nutrient loading. Reductions of concentrations within low-cropland catchments, where land use with 0 and 2.9% coverage of croplands was converted into meadows, were comparable to depletions within moderate-cropland catchments, where land use with 5.6 and 6.9% coverage of croplands was converted to meadows, whereas improvements exhibited a threefold increase within high-cropland catchments in which 18 and 49.9% of the total coverage of croplands was transferred. However, the magnitude of response differed between parameters; within low- and moderate-cropland catchments, concentrations of nitrate decreased by an order of magnitude, whereas concentrations of EC and Ca exhibited seemingly trivial reductions, suggesting that transferring the land use of catchments with between 0 and 6.9% coverage of croplands into meadows may be extensively impractical for reducing EC and Ca concentrations, yet useful for mitigating stream NO_3^- concentrations. When croplands covering 18 and 49.9% of catchments were grassed, all measured concentrations were successfully reduced by orders of magnitudes; however, large-scale changes can be costly and ostensibly implausible given growing demands for food production (Mclellan et al., 2015). Thus, the cessation of cropland covering a relatively small proportion of the catchment may be a viable solution for nitrate removal in locations with certain conditions. For example, remote and mountainous regions of Europe with poor soil quality and decreasing rural populations, such as areas within Spain (Khorchani et al., 2020) and the Balkan Peninsula (Zakkak et al., 2018), have already experienced agricultural land abandonment (Navarro and Pereira, 2012; Ceausu et al., 2015) and hence may be suitable for removing croplands. Nevertheless, additional research on the possible effects of grassing cropland for water quality improvement is lacking and would benefit from examining a larger array of cropland extents and catchments.

Concentrations of NO_3^- exhibited significant, yet modest, variability between seasons, which differed between catchment categories. While the magnitude of change was comparable for both seasons, concentrations were generally higher during winter. Runoff typically increases during the winter seasons due to greater rainfall and snowmelt, likely accounting for the greater contaminant inputs. While inter-annual measurements can be beneficial for detecting modest changes amid seasonal variations (Bechmann et al., 2008), data from the winter season may be better suited for assessing NO_3^- limits in temperate climates when year-round data is unavailable.

The DSP, located downstream from the six examined catchments, was the only site monitored consistently throughout this 33-year investigation, providing ongoing observations on water quality trends for the entire study area. Prior to management, NO_3^- was progressively increasing. Concentration dynamics shifted in 1991, with net declines of NO_3^- and the grassing of cropland commencing simultaneously, indicating an immediate water quality response to management actions. This was presumably due to the spatial extent of the study area; within small catchments, most land use is located close to the stream, enabling a swift and direct influence on water quality (Allan, 2004; Staponites et al., 2019), reaffirming that spatial scale should be considered when setting expectations on recovery time (Meals et al., 2010; Schilling and Spooner, 2006). Although the water quality response was prompt, recovery was slow; accelerated improvements continued until 2000, with concentrations gradually decreasing for the remainder of the monitoring period, demonstrating that the elimination of cropland, covering 3.1% of the study area, had a response time of approximately nine years, yet it can take more than 30 years for the complete impacts on water quality to manifest. Similarly, in a review of agricultural land management changes in *meso*-scale catchments, Melland et al., (2018) found that positive effects on water quality can occur 4–20 years after the implementation of measures. Elucidating the response time of management efforts is important for supporting actions that do not yield rapid solutions (Meals et al., 2010), yet, if the delayed transport of nutrients is longer than the monitoring period, an accurate evaluation of management effectiveness is not possible. Contaminants move at varying speeds and are subject to hydrological and biogeochemical time lags (Melland et al., 2018; Vero et al., 2017); long-term water quality monitoring is, therefore, necessary for identifying critical transitions in water quality condition and accurately discerning the progress of land use alterations.

Clearly defining intended outcomes is an important requirement for evaluating management effectiveness (Hockings, 1998). With quantitative water quality monitoring and defined water quality standards, if and when the desired results are achieved can be easily identified, giving stakeholders evidence of management performance in the form of numbers. Arguments for freshwater protection are more likely to be supported over arguments for biodiversity protection (Abell et al., 2007); fresh water is vital for both the provision of ecosystem services and human welfare; hence water quality assessments can have relevance beyond biodiversity conservation (Hermoso et al., 2016). However, as exhibited in the review by Acreman et al. (2019), employing water quality as an indicator for freshwater protected area effectiveness is rare. In the case of the Blanice River nature reserve, the original decree established in 1989 was the first attempt of imposing surface water quality limits within a Protected Landscape Area of the Czech Republic (Hruška, 1991a). Admissible concentrations of water quality parameters were stringent, analogous to high-quality drinking water. Due to intermittent measurements of nutrients, water quality assessments of progress for each site were not possible. Nevertheless, an appraisal of the DSP confirms that median annual concentrations of NO_3^- have maintained compliance with newly prescribed limits since 2001, indicating that the upper network of the Blanice River has been sufficiently cleaned, and moreover, that water quality has been restored to a robust state. Improving the quality of heavily polluted streams, as documented by studies from the same region (e.g., Fučík et al., 2014; Knott et al., 2019), is not as difficult as restoring low concentrations of nutrients, which has been accomplished in this freshwater protected area. Using systematic water quality standards as conservation targets enables an empirical evaluation of the resilience and vigour of aquatic conditions as well as the effectiveness of actions, suitably serving as evidence-based conservation.

In addition to proper management (Dearden et al., 2005), the success of freshwater protected areas is largely dependent on an effective spatial design (Abell et al., 2007; Hermoso et al., 2016); nevertheless, protected areas are seldom established explicitly for safeguarding freshwater resources (Harrison et al., 2016). Inaugurated in 1989, the Blanice River nature reserve was one of the first terrestrially defined protected areas designated specifically for freshwater protection (Saunders et al., 2002). The boundaries of the nature reserve roughly correspond to catchment boundaries (Hruška, 1991b, 1985), protecting the majority of the upstream terrestrial landscape. This modern design was implemented long before relevant concepts of whole-catchment management were published and was possible due to the low population density. While recent studies have confirmed that the management and protection of terrestrial ecosystems can support freshwater conservation (Acreman et al., 2019), many of the world's freshwater protected areas lack a proper spatial design needed for protection (Abell et al., 2007). For example, Hermoso et al. (2015) found that the largest network of protected areas, i.e. Natura 2000, does not possess suitable coverage to effectively protect freshwater ecosystems. Riverine networks are inherently connected to the encompassing environment (Allan et al., 1997; Hynes, 1975), making fluvial ecosystems particularly vulnerable to exogenous threats (Dudgeon, 2019). Although maintaining river connectivity is essential for regulating ecological functions and processes (Grill et al., 2019), implementing strict restrictions within an entire upstream catchment area is often not possible outside of pristine areas with little human use (Abell et al., 2007). As development expands, the opportunity to protect entire catchment areas lessens (Thieme et al., 2016); thus catchment-scale protection should be prioritized within areas that remain undeveloped or undisturbed (Abell et al., 2007; Geist and Hawkins, 2016).

This site-level investigation details long-term management of a nature reserve for the protection of stream water quality, helping to fill the research gap on the effectiveness of freshwater protected areas. Evidence of management effectiveness, progress and outcomes can be used to guide future actions via providing insights on the intensity of efforts and time frame needed for improvements, however contextualizing findings is key for ensuring applicability in practice (Sunderland et al., 2009). The explanation for the decreasing nitrate concentrations within the Blanice River nature reserve focused on land use conversions, however, reductions in NO_3^- at the study area outlet may have been assisted by additional factors, such as the establishment and upgrade of two small wastewater treatment systems (see Fig. 1a). The statistical models demonstrate that the NO_3^- reductions from the six catchments without treatment systems corresponded with reductions at the study area outlet (i.e., DSP), hence, major improvements in water quality cannot be attributed to the wastewater treatment systems. In addition, these systems treat domestic sewage from a small number of houses (see Supplementary Table 1 and 2) and available water quality data suggests that there were no significant impacts on downstream water quality (see Supplementary Figs. 1 and 2). Nevertheless, wastewater treatment systems can potentially serve as a source of pollution as well as a measure for pollution reduction. Moreover, the small spatial extent of the headwater catchments and relatively semi-natural state of the study area presumably influenced protected area performance; hence these factors should be considered when anticipating water quality response from land use conversions. As threats to fresh waters intensify (Dudgeon, 2019), additional investigations of management and responses are crucial for demonstrating realistic expectations and capabilities as well as facilitating decision-making.

This work addresses land use conversions within six catchments, devoid of point sources of pollution. The size of the drainage area differed among catchments; thus, composition was employed as a metric for land use. The chosen technique was predicated on the research by Staponites et al. (2019) which examined catchments within the study area and found the proportion of land use to be a better predictor of NO_3^-, EC and Ca than the slope or spatial arrangement of land use. While composition was the most effective metric in these small, headwater catchments, the slope and location (Lei et al., 2021; Yu et al., 2016) as well as spatial pattern (Bu et al., 2014; Nafi et al., 2021) of land use have been shown to be dominant factors influencing water quality within larger catchments. Accordingly, the selected water quality parameter and its governing processes should be considered when designing future investigations (Staponites et al., 2019).

6. Conclusions

Herein, we evaluate water quality response to catchment-scale land use changes within an existing freshwater protected area where all croplands were restored to traditional grasslands to determine the relative performance of management practices and the response time needed to observe improvements. Overall, the grassing of all croplands was approximately three times more effective at reducing concentrations of NO_3^- than EC and Ca, and had little influence on pH values, which remained neutral over time. The results suggest that the complete grassing of croplands over a relatively small scale can be a practical strategy for mitigating large percentages of NO_3^- loading to headwater streams, whereas notable reductions in EC and Ca concentrations may require more extensive conversions. Substantial water quality benefits took approximately nine years to manifest, with mean annual nitrate decreasing from 5.5 to 1.9 mg/L following the grassing of cropland covering 3.1% of the study area. Although management elicited an immediate response, concentrations continued to marginally decline over the next 20 years ultimately resulting in stream nitrate concentrations below 1.0 mg/L by 2019, highlighting the enduring impacts of changing land use and the importance of long-term monitoring programs in detecting delayed improvements. Employing water quality standards as an indicator for protected area efficacy enabled an empirical appraisal of management effectiveness. Consequently, this case study serves as one of the few documented examples with quantitative evidence of positive outcomes inside a freshwater protected area, corroborating that success can be achieved with proper design and management. Evidence of management responses can enhance our understanding of the practicality and effectiveness of practices as well as provide insights and expectations on potential outcomes, thus enabling a basis for decision-making when planning conservation strategies.

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CRediT authorship contribution statement

Linda R. Staponites: Writing – original draft, Project administration. **Ondřej P. Simon:** Conceptualization, Investigation, Funding acquisition, Writing – review & editing. **Vojtěch Barták:** Methodology, Software, Visualization, Writing – review & editing. **Michal Bílý:** 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.

Data availability

The datasets generated and analyzed during the current study are available in the Mendeley repository, 10.17632/s9b9pjysnh.3.

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Appendix A. Supplementary data

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5. Discussion

5.1 Analyzing the impacts of land use on water quality in headwater catchments: The influence of landscape attributes

The terrestrial landscape is inherently linked to the ecological integrity of receiving waters (Allan, 2004; Gergel, 2005; Hynes, 1975). Understanding how land use can influence water quality conditions is therefore crucial for developing efficient and effective management strategies and protecting aquatic resources. Although the impacts of land use on water quality have been corroborated, a comprehension of interactions remains rudimentary. Water quality is governed by an amalgamation of anthropogenic and environmental factors, with influences changing over space and time (Allan, 2004; Baker et al., 2007; Mouri et al., 2011; Rodrigues et al., 2018), making diffuse water pollution difficult to assess. Consequently, researchers often encounter challenges in deciding on the optimal spatial extent for analysis and accounting for landscape attributes (Staponites et al., 2019). Article 1 attempts to address this issue by establishing novel weighting schemes (i.e., landscape composition metrics) to account for the combined effects of land use with spatial and topographical landscape characteristics. Landscape composition metrics operate under the assumption that each land use within a catchment area does not produce an equal influence on water quality (Giri & Qiu, 2016). Using GIS analysis, land use proportions are assigned weights based on site-specific observations. In the approach proposed by Peterson et al. (2011) and Peterson & Pearse (2017), a distance-weighting function is applied to account for the disproportionate influence of land located closer to the stream, while a flow-weighted function is used to consider the hydrological activity within each land use (Fig. 15). Although weighting land use according to its spatial position and hydrological effects has been carried out by previous studies (e.g., King et al. 2004; Peterson et al., 2011; Sheldon et al., 2012), Article 1 further supplements weighting schemes to integrate the impacts of landform via additionally weighting land use according to its slope gradient.

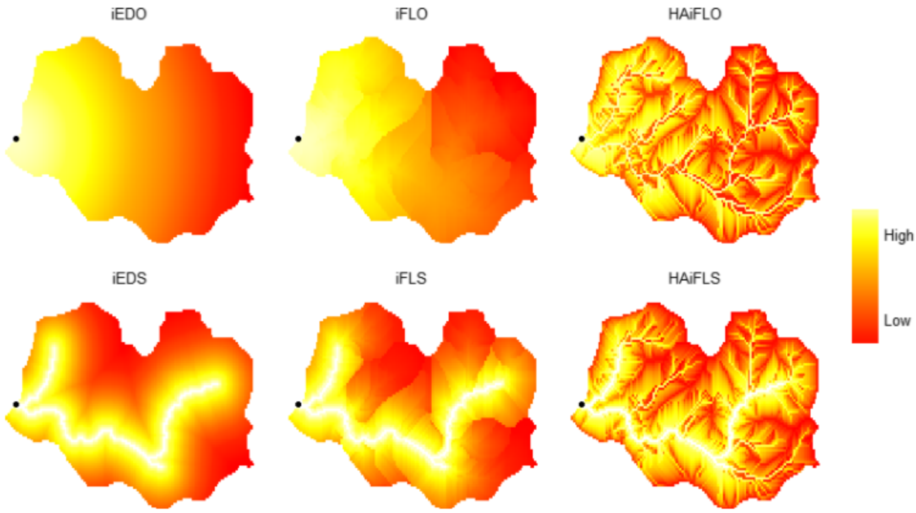

Figure 15. Schematic representation of the different weighting schemes applied within a watershed. Each land use is weighted according to the inverse distance to the outlet or to the stream, measured with Euclidean distance (iEDO and iEDS) or flow length (iFLOand iFLS), respectively, or according to the flow accumulation (HA-iFLO and HA-iFLS). Source: Peterson and Pearse (2017)

In Article 1, landscape composition metrics were applied to investigate how specific landscape variables (i.e., slope, stream proximity and flow accumulation) can impact land use-water quality interactions. This was accomplished via comparing the predictive power of empirical models that included various combinations of spatial and topographic attributes to determine which model resulted in optimal water quality predictions. Although some studies have suggested that accounting for landscape characteristics can make models and their results more reliable (e.g., Delkash et al., 2018; Peterson et al., 2011), Article 1 found that including landscape variables does not always improve model predictions. The study concluded that the influence of landscape attributes depends on the indicator being examined: namely, stream proximity, slope and flow accumulation can govern the conveyance of pH, TP, NO2-N and PO43-P, yet had no influence on Ca, EC, NO3-N and TSS. It is common to find a coequal or mixed influence of both natural and anthropogenic variables on stream condition (Allan, 2004), ergo the fact that spatial and hydrological components of land use did not influence the transport of some parameters was unexpected and may be attributed to the local setting. The study was conducted within headwater catchments with an average area of ~6 km². In small catchments, most land is located relatively close to the stream enabling a direct pathway of influence, indicating that the spatial location of land use only plays a small role in the transport of nutrients under these circumstances. Nevertheless, the proximity of land use to the stream could have more of an influence on water quality within larger catchments. Previous studies have also suggested that the impact of landscape variables on land use-water quality interactions may be connected to the size of the catchment (King et al. 2004, Peterson et al., 2011; Strayer et al., 2003). Additionally, the study area represents a standard submontane landscape, characterized by mostly forests and meadows and hilly terrain, hence the landform may have less of an influence within flatter terrains or more densely populated areas or conversely, more of an influence in mountainous regions. Accordingly, both the size and the topography of the study area should be considered when determining which landscape attributes to include into the analysis.

Overall, Article 1 provides insights on the pathways and mechanisms through which land use can impact stream water quality, and the necessity of landscape attributes when examining the relationship, thus advancing the ability to accurately model interactions. However, it is incorrect to assume that stream proximity, slope gradient, and flow accumulation are the only factors impacting land use-water quality interactions. For example, both soil type and landscape pattern can impact water quality (Ding et al., 2016; Varanka et al., 2015), and neglecting their influence could misrepresent interactions, leading to an inaccurate assessment. The ability of landscape composition metrics to easily integrate multiple variables presents plenty of opportunities for future research to investigate the predictive power of models and ultimately define appropriate methods for particular environments (Peterson et al., 2011; Staponites et al., 2019). In particular, the current weighting schemes can be further supplemented to identify the impact from additional factors, such as the spatial pattern or configuration of landscape elements which have been corroborated as influential for governing the quality of receiving waters (Cheng et al., 2018; Lei et al., 2021) and repeatedly employed as a measure of land use (e.g., Dai et al., 2017; Peng & Li, 2021; Xiong et al., 2018).

Despite the presumption that the results from Article 1 are contextual, findings suggest general recommendations for devising future study designs of the impacts of land use on water quality of small catchments with similar regional characteristics: Methods for analysis should be applied according to the individual parameter of concern. Specifically, incorporating stream proximity, together with slope or flow accumulation, is recommended when examining the effects of land use on reactive or unstable water quality parameters, whereas land use composition only is recommended when examining impacts on stable indicators. Geochemical cycles play a significant role in shaping the quality and movement of water through the landscape; hence it is important to consider the reactiveness or stability of individual water quality parameters in the analysis. The results from Article 1 were used to inform the analysis of Article 3, which examined the catchments within the same study area. Composition was chosen as a measure for land use, whereas it was found to be the most effective predictor of stable indicators which were the subject of investigation in Article 3. This, in turn, demonstrates how the governing processes of the selected water quality parameters should be considered when planning forthcoming investigations.

It is also important to consider the limitations of this study. Due to the absence of data, the results of this investigation were based on a discrete, one-time sampling and therefore measurements are subject to uncertainty. Water quality can vary over space and time, hence samples taken from a single instance may not be representative of the actual water quality conditions. Of the 11 water quality parameters examined, half were unstable or reactive, suggesting that they may need to be monitored more frequently than stable parameters to ensure an accurate assessment of water quality. Moreover, seasonal effects from rainfall and snowmelt can impact runoff levels, and consequently, contaminant inputs (Ai et al., 2015; Yu et al., 2015), thus, time series data should be utilized when available to get a more precise portrayal of water quality condition.

Although previously conducted studies have concluded that landscape composition metrics are an effective tool to improve predictions of stream condition (King 2004; Peterson et al., 2011; Sheldon et al., 2012; Strayer et al., 2003; Van Sickle & Burch Johnson, 2008; Walsh & Webb, 2014), research predominantly examined the ecological response of various aquatic species. Knowledge of the mechanistic processes of nutrients moving through the landscape is still limited, therefore weighting schemes for water quality should be further implemented and explored to help identify, control, and regulate sources of land-based pollution and strategically target management. Landscape composition metrics can be easily applied in any region to continue to increase our understanding of land use-water quality interactions under different contexts.

5.2 Comparing calibration strategies to advance hydrological models: The role of time series data and hydrological signatures

Changes in land use play an important role in the functioning of the water cycle by altering the natural hydrology of an area, which can lead to changes in runoff, streamflow (i.e., discharge) and water levels. An accurate assessment of the water balance is therefore necessary for supporting and developing effective water management strategies to ensure the sustainable use of aquatic resources, particularly in regions where water availability is limited. Hydrological models have frequently applied various calibration strategies when computing the water balance of a catchment, yet the employed strategy can significantly impact the performance of the model (Melišová et al., 2020). A well-calibrated model can provide greater confidence in the model’s predictions and reduce the risk or errors, biases, and uncertainty, hence a robust representation of water balance components requires an optimal calibration strategy. Although most methods of model calibration employ time series data when estimating the water balance (e.g., automatic and manual calibration), conducting field measurements or gauging water bodies can be costly and labor-intensive, hence observational data is often unavailable presenting challenges when modeling hydrological processes in ungauged catchments. A calibration with hydrological signatures (i.e., runoff and soil moisture) is based on long-term statistics (e.g., interpolated from available data or estimated from general formulas) and thus can be implemented in catchments with limited observed data. Yet it is unknown if a conceptual hydrological model can be calibrated using hydrological signatures only, or if hydrological signatures can improve the calibration of a hydrological model. Consequently, Article 2 investigates the role of hydrological signatures in the calibration of a conceptual hydrological model.

Exploring the capabilities of models allows for a better understanding of how the inclusion of certain variables and functions can influence processes, thus enabling the opportunity to determine which strategy is optimal. Both Articles 1 and 2 aim to enhance assessments via comparing the performance of various, diverse models. In Article 1, the performance of various landscape composition metrics was compared to identify which model explained the most variability in water quality data, helping determine the features, processes, and spatial scales with the strongest influence on receiving waters. Conversely, Article 2 compares the performance of different calibration strategies to determine the necessity of time series data and if hydrological signatures can add value to the hydrological model. The results from Article 2 found that calibrating the model with strategies that employ time series data outperformed strategies based only on hydrological signatures, thus highlighting the importance of observed data when calibrating the hydrological model. Nevertheless, the study found that when time series data is not available, using signatures representing the mean or variance of runoff could provide a comparable fit. This strategy should therefore be considered when calibrating hydrological models in ungauged catchments.

Interestingly, the results from Article 2 indicate that including the hydrological signatures of runoff or soil moisture in addition to time series data was found to be beneficial for decreasing the uncertainty in model parameters, particularly for low flow conditions, and therefore should be considered in future calibrations. However, calibrating hydrological models involves adjusting model parameters to achieve the best fit between simulated and observed hydrological variables and it is important to be aware of the limitations. The validity and accuracy of a model is dependent on several factors, including the quality of the input data, parameters, and the assumptions applied. Article 2 found that the performance of calibration strategies can be negated by a poor representation of hydrological processes, biases in hydrological signatures and uncertainty of model parameters. Therefore, future evaluations should account for such limitations when determining the accuracy of model predictions, especially when applying the model for decision-making when unambiguous information is crucial. Still, identifying an optimal calibration strategy can help to minimize the bias in simulations as well as the uncertainty in the estimated model parameters and is thus important for improving overall reliability and usefulness of the modeling process. Exploring how models have been calibrated can help researchers to determine the most appropriate strategy for their given dataset.

Although Article 2 provides insights on the performance of various calibration strategies the study was performed on a single hydrological model (i.e. Bilan) and additional research is needed to further investigate if this is also the case with other hydrological models. Similarly to Article 1, the research from Article 2 was carried out in catchments of the Czech Republic under specific hydroclimatic and physical conditions and additional studies are necessary for verifying findings across diverse regions.

5.3 The consequences and temporal persistence of land use conversions in headwater catchments: Expectations for water quality response

As human-induced pressures continue to threaten freshwater environments, effective management practices are increasingly imperative. Site-level investigations of management effectiveness play a crucial role in providing information on the utility of interventions, as well as response times needed for improvements. Yet, according to a systematic review by Acreman et al. (2020), evidence of the effectiveness of freshwater protected areas, particularly reports of positive outcomes, are generally lacking. This paucity of evidence suggests that there is a poor understanding of the conditions needed for a protected area to achieve its objectives (Geldmann et al., 2013). Article 3 attempts to fill this gap by providing quantitative evidence of management success in a freshwater protected area via employing long-term stream water quality data, monitored over a 33-year period, as an indicator of protected area performance. Limits for each water quality parameter were defined by the national standards for surface water quality, allowing for clear conservation targets which is vital when evaluating management effectiveness (Hockings, 1998). Accordingly, Article 3 was able to identify when water quality was restored to the desired state, thus functioning as one of the few cases of evidence-based conservation success in a freshwater protected area and illustrating that the enforcement of water quality standards can be an efficient means to quantify the degree to which goals and objectives are being met.

While GIS and remote sensing technologies have enabled readily available land use data, adding to an increasing volume of literature on landscape patterns and processes (Turner et al. 2001), the availability of continuous water quality data over long periods is often limited, hindering empirical investigations of long-term water quality response. Consequently, approximately 20% of research included in the systematic map database did not assess the temporal changes in water quality, and instead examined only the resultant water quality conditions. Such assessments typically lack the scope needed to deduce the impacts from land use change. In Article 3, continual monitoring data of surface water quality was available enabling the long-term assessment of trends. Substantial improvements in water quality occurred approximately nine years after the land use was altered, thus emphasizing the importance of long-term data in showing the full extent of recovery. Water quality response to land use changes can experience time lags and legacies from previous occurrences which may persist for a significant duration, hence long periods of time are typically required to identify trends and account for these factors (Meals et al., 2010; Melland et al., 2018; Spooner et al., 1987). By accounting for the impeded response of land use alterations, managers and policy makers can make more informed decisions on the long-term efficacy of efforts. Nevertheless, additional empirical appraisals into the response time of specific efforts would be beneficial for providing further information on the temporal persistence of land use changes and the timeframes needed for the full impacts to be evident.

Article 3 was carried out within a study area of approximately 58 km^2 and findings agree with the review from Melland et al. (2018) which determined that it could take from 4 to 20 years for positive water quality effects to occur within catchments sized 1–100 km^2 and concluded that water quality response time will generally increase with the size of the catchment. This signifies that longer monitoring may be necessary for detecting delayed improvements of surface water in larger catchments. Although the spatial extent of research within the systematic map database ranged from micro- to regional-scales, larger study sites did not have longer monitoring duration (Fig. 16). The most common duration over which land use and water quality was observed was 2-20 years, with very few studies lasting longer than 30 years, suggesting that many investigations, especially those within larger spatial extents, may not have captured the complete impacts from land use changes. Moreover, Article 3 is among the few 'before and after' study designs which compares temporal changes made within the same protected area, suggesting that implementation of a long-term monitoring program should begin prior to land use change and continue long after, when possible. As demonstrated in the systematic map database, only ten studies examined water quality before or after land use changes, with most investigations examining land use and water quality over the same temporal scale.

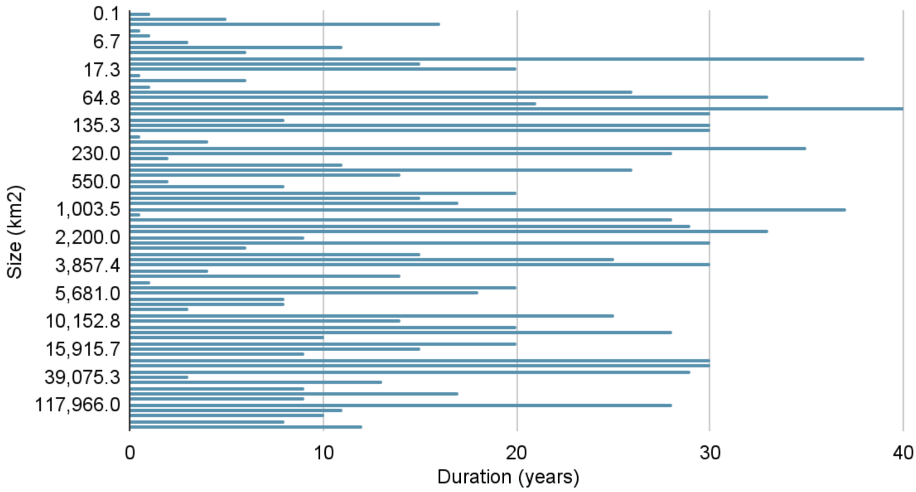

Figure 16. A comparison of the size of study sites and duration of water quality monitoring. Studies that included multiple sites were averaged. Studies that did not specify the size of individual sites were not included.

Although the impacts from land use changes may be long-lasting, the lag between treatment and response can vary depending on the intensity of land use changes, with studies finding smaller changes need longer periods to detect changes (e.g., Bechmann et al., 2008; Melland et al., 2018). In Article 3, a relatively small percentage of the study area was converted from cropland to meadows (approximately 3.1%) and while the response time until restoration was slow, measurable improvements in water quality conditions were detected immediately. As with Article 1, the results from Article 3 were presumably due to the small spatial extent of the study area which can enable land use to have a direct influence on water quality. However, similar small-scale land use changes may not produce such rapid results if carried out in larger catchments, hence spatial scale should be a principal consideration when setting expectations for the rate and length of recovery. In addition to a sufficient monitoring period, an adequate sampling frequency is crucial for enabling a rigorous assessment of the lag between treatment and response, and thus should additionally be considered when designing a monitoring program (Meals et al., 2010). Additionally, frequent monitoring (i.e., daily or weekly) can help to enable a distinction between point and nonpoint sources as well as the influence of short-term weather events (e.g., rainfall or drought) (Buss & Achten, 2022).

Basing decisions on experience rather than evidence is an increasing concern in environmental sciences (James et al., 2016). Individuals are easily skewed by implicit biases, therefore providing decision-makers with access to evidence is essential for ensuring that decisions are based on the best available information, rather than on personal beliefs or interests (Cook et al., 2017; James et al., 2016). Quantitative evidence of the capabilities of individual interventions for mitigating pollution helps to achieve evidence-based management by offering a deeper understanding of the intensity of efforts needed to produce a desired outcome and ultimately how to plan effectively and sustainably. In Article 3, land use data and water quality concentrations were compared before and after management implementation to infer how eliminating agriculture from the study area influences nutrient loading within headwater catchments. Similarly to Article 1, the response varied depending on the examined parameter, reinforcing the importance of directing efforts towards the indicator of concern. The study found that the complete conversion of croplands to meadows is roughly three times as effective in reducing NO3-N concentrations compared to EC and Ca, yet had a minimal impact on pH values, thus providing insights on the practicality of efforts. In order to examine how various intensities of management can impact nutrient loading, catchment categories were assigned according to the percentage of land use conversions. The results suggest that small-scale agricultural elimination may be viable for mitigating NO3−N loading, yet ineffective for reducing concentrations of EC and Ca which may require more extensive conversions for notable reductions. Although past research can offer insights on potential outcomes, investigations cannot fully address all scenarios where a particular practice may or may not be effective. The specific impacts of a land use change will likely depend on the size and characteristics of the study area as well as the sensitivity of the examined response indicator, and thus should be considered when establishing prospects for potential responses under similar circumstances. As such, many empirical studies may have restricted applicability or generalizability (Julian et al. 2017). In this regard, Article 3 contains some limitations; only six catchments with various extents of agricultural elimination were examined. Investigating additional catchments with a larger range of transformations would be beneficial for broadening applicability, reaffirming findings, and contributing to an understanding of the intensity of change needed to effectively reduce concentrations of specific indicators.

5.4 Empirical evidence for guiding future investigations: Insights from the systematic map database

With an increasing body of scientific research, parsing out what has been done is a prerequisite for consolidating knowledge. A detailed overview of the evidence base is an essential starting point for storing all the patterns of published work, identifying emerging trends, investigating potential areas of concern, and formulating subsequent research questions (Wolffe et al., 2019). Improving on these patterns and trends by highlighting commonalities can help to obtain an improved understanding of an evidence base as a whole. A systematic mapping methodology has been increasingly applied in environmental sciences to address broad, multifarious questions that are lacking quantitative data (James et al., 2016). The systematic approach helps to minimize biases and distill an objective understanding of a topic by gathering information from diverse sources. Such a resource enables scientists, practitioners, and decision makers alike to explore the extensive collection of literature by locating and obtaining all pertinent data related to a specific subject matter (Pullin et al., 2020). Moreover, an overview of the available database can expose knowledge gaps that warrants further research and reveal knowledge clusters that can be addressed within a systematic review (James et al., 2016).

A robust apprehension of approaches to investigate the impacts of land use change on water quality was lacking in the scientific literature, thus prompting the need for an evidence synthesis. Consequently, this is the first attempt to systematically map this topic, helping to demonstrate available techniques, recent developments and the frequency and distribution of methods. According to the database, investigations are considerably heterogeneous in terms of research context. Investigations have been executed in different climates, at multiple spatial and temporal scales, using diverse parameters and incorporating numerous catchment characteristics, all which can impact the relationships between land use and water quality (Mello et al., 2020; Uriarte et al., 2011). Moreover, the overall structure of study designs generally vary in terms of population, data collection methods, data analysis and evaluation techniques. Due to this lack of uniformity, comparing the outcomes between all studies is not practical. Nevertheless, a database of investigations provides functionality in its format by enabling a search and selection of data subsets that can be relevant for different scenarios (Wolffe et al., 2019). For example, identifying studies within similar settings or that utilize similar parameters can enable a comparison of results or provide examples of potential outcomes. Whereas the impacts of land use changes on water quality are likely site-specific (Baker et al., 2007), contextualizing findings is key for ensuring applicability. Readily available examples of how previous investigations have been carried out can facilitate researchers when planning and conducting evaluations and aid in the development of advanced assessments.

The relationship between land use and water quality is not isolated and static, but constantly changing with lags, legacies effects, and nonlinear responses (Allan, 2004; Julian et al., 2017). Moreover, the stochastic components of diffuse pollution make behavior and outcomes difficult to predict (O'Donoghue et al., 2021). As such, difficulties exist when designing investigations and modeling the relationship between land use changes and water quality conditions and the systematic map database can help shed light on the complexities involved with an analysis.

Despite recent advances in geospatial techniques, the issues of spatial scale remain ongoing. Approximately two-thirds of studies within the evidence base conducted a spatial analysis, with ~17% employing multiple spatial scales to determine an optimal spatial extent, while one-third examined the spatial distribution of land use and one-third investigated the spatial pattern of water quality. Very few studies incorporated spatial regressions (e.g., geographically weighted regression, or locally weighted regression) to account for the unequal influence that can arise for the spatial position or pattern of individual land use types. Implementing more studies to explore and showcase the predictive power of spatial models would be beneficial.

The complexities of natural systems present fundamental challenges when determining causality (Cook et al., 2017; Melland et al., 2018). For instance, land use variables may be correlated with other more influential environmental factors. Correlation approaches were commonly applied within research, yet a covariation between natural and anthropogenic factors can hinder the ability to determine the respective impacts on water quality (Allan, 2004), creating difficulties for correlation analysis. Hence, including a variety of variables into an analysis can help identify confounding effects (O'Donoghue et al. 2021). Multiple regression analysis allows for the simultaneous consideration of multiple predictors in a single model and several techniques can be used to address the presence of multicollinearity, such as adding interaction terms to the model or applying. Principal Component Analysis (PCA) or Partial Least Squares Regression (PLS) can be used to reduce the dimensionality of the data, and thus account for the covariation between independent variables and determine their respective impacts on water quality. As the field of research continues to evolve, new methods and technologies are being developed and applied to better understand the intricate and dynamic impacts from land use conversions. Providing a rigorous delineation is of the utmost importance, whereas an imprecise evaluation can misrepresent mechanisms and ultimately misinform decision-making.

Land-water relationships are complex and can depend on a number of interacting landscape characteristics and anthropogenic factors (Allan et al. 1997). While a simplistic representation of processes can enable foundational assumptions to be made, investigating land use as the only source of water pollution can reduce the complexity of the problem, resulting in an overestimation of impacts (Allan, 2004). Selecting relevant explanatory variables is essential for correctly modeling the relationship (Giri & Qiu, 2016). Yet with so much individual variation between study sites and a wide range of possible variables to consider, deciding which factors to include presents major challenges. Models are based on a set number of variables and selecting which explanatory variables to include into the equation means choosing which contributing factors are fundamental for describing this complex relationship. As illustrated in the systematic map, climate, hydrology, management, soil, topography and socio-economic factors were the major attributes included when examining the effects of land use change on water quality. Natural factors, such as rain, discharge, and slope, may be fundamental in cases where human impact is small or relatively consistent throughout the study region (Allan, 2004), while anthropogenic factors, such as population density or sewerage will likely play a larger role in more densely populated areas. Moreover, the influence of each factor may change under various spatial and temporal scales. For instance, changes in climate and soil characteristics can vary regionally, yet are unlikely to change drastically within a small study area, whereas topography and hydrology can vary within small-scales, impacting land use-water quality interactions as exhibited by Article 1. Climatic and socio-economic factors may not influence land use-water quality relationships over the short-term yet may become more important over longer timescales. Accordingly, the scale of the study area and the time frame of the investigation as well as the amount of human influence can all provide clues on which explanatory variables may be relevant for an analysis.

Of the studies that considered predictors in addition to land use change, very few incorporated more than one or two explanatory variables into the analysis. An analysis that does not take into account all the possible factors that affect the systems being studied, including those that may not be immediately apparent, can misrepresent interactions. On the other hand, the inclusion of redundant elements may add unnecessary complexity in the analysis. Achieving a systems understanding of the pressures and drivers on water quality, in addition to land use change, has received increasing attention within the scientific literature (e.g. Burke et al., 2018; Peng & Li, 2021; Shi et al., 2016; Wu et al., 2021), yet this emerging topic requires additional research to explore the significance of various factors and to provide more insights on which explanatory variables may be appropriate under which contexts.

Opportunities for future research

Although there is a scientific consensus that land use change can impact surface water quality, empirical evidence is relatively lacking with 133 studies over the past 12 years. The limited evidence base provides many opportunities for further inquiry or analysis. There are several knowledge gaps which may be worthy of future consideration, including the impacts of land use change on coastal systems and wetlands as well as studies within micro-scale catchments with homogenous landscapes. Impacts from the conversion of grasslands, wetlands, bare lands and vegetation are scarce as well as studies within arid and temperate climates around the world. Subsequent research could explore examples of land use change for water quality improvement whereas reports of positive outcomes were limited. Further systematic reviews that address cause-and-effect questions for research conducted under similar contexts (e.g., with corresponding study area sizes, spatial scales, climates and parameters) could be potentially useful for drawing some absolutes about the impact of land use change on water quality. For example, research could compare results of urban expansion on phosphorus and nitrogen, whereas these were the most frequently studied parameters.

Framework for future research

Our knowledge about the functioning of the environment is continually evolving. Detailing various methods of analysis and techniques to analyze land use-water quality interactions can connect practitioners with scientific research, helping to provide a framework when devising future investigations. Consequently, findings from the systematic map database, can lead to some general recommendations for future empirical research:

- *Study sites:* When examining land use changes, it is important to consider the number of sites. Nearly half of the studies included in the systematic map examined only one site for land use changes. Investigating additional sites with various degrees of land use alterations has the potential to expand applicability and reaffirm findings.
- *Data transparency:* The quality of data used to generate results is a determining factor in the reliability of research. The number of samples taken, and the frequency of sampling were often not specified. To ensure the reliability of observations, it is crucial to be transparent about the data by disclosing any uncertainties (e.g., data gaps or analytical variability) as well as the specifics on the sample size, sampling frequency, number of sites monitored, and sampling duration.

- *Disclosing specifics:* Details on the spatial scale of analysis, water quality duration, the number of sites examined, and the size of the study sites were occasionally lacking across investigations and therefore should be disclosed when describing the study design.
- *Water quality indicators:* Approximately 27% of studies resulted in diverging trends for water quality parameters, suggesting individual indicators can respond in different ways to a land use change. Therefore, examining only one or two indicators may misrepresent overall outcomes. Investigating the response of a range of water quality parameters can potentially achieve a more accurate portrayal of the impacts of land use changes.
- *Water quality indices and standards:* Approximately half of studies applied an index or standards to assess water quality. Employing limits or standards for water quality can clearly communicate information on water quality conditions, and therefore may be beneficial.
- *Identifying relevant explanatory variables:* Properly controlling for confounding variables can help ensure that the observed relationship between the independent and dependent variables is not due to the influence of other factors. Approximately one-third of studies included additional independent variables as possible drivers of water quality conditions, including attributes of climate, hydrology, management, soil, topography and socio-economic factors. Such components may be worthy of consideration, depending on the size and characteristics of the examined area.
- *Method of analysis:* Statistical modeling was preferred in high quartile journals and more prevalent than a comparison of land use changes and water quality, with approximately two-thirds of studies undertaking a statistical analysis. A comparative analysis may lack the ability to accurately depict the intricate relationship between land use and water quality and should be a consideration when devising an investigation.

6. Conclusions

The protection of water resources and ecosystems requires an accurate assessment and comprehensive understanding of the impacts from the encompassing landscape. Accordingly, the published studies within this thesis helps to advance the accuracy of methods and techniques used in research (Articles 1 and 2) and provide empirical evidence to support decision-making (Articles 3 and Systematic Map). Firstly, this thesis explores the implementation of novel weighting schemes (i.e., landscape composition metrics) to account for the scale-dependent mechanisms and natural processes of the terrestrial landscape when analyzing the impacts of land use on water quality. By integrating land use data with spatial and topographic components of the landscape, Article 1 sheds light on the significance of landscape attributes when examining the relationship within submontane headwaters, thereby enhancing the capability to model interactions with greater accuracy. The results showed that incorporating landscape variables into empirical models did not always improve the accuracy of water quality predictions. Moreover, the impact of landscape characteristics on model performance varied depending on the type of indicator under consideration, suggesting that the inclusion of landscape features should be tailored to the specific parameters of interest when devising investigations. According to the findings, factors such as stream proximity, slope, and flow accumulation may have a significant impact on the conveyance of reactive or unstable water quality parameters within small, headwater catchments, yet may not influence stable chemical data. Nevertheless, knowledge of pathways and mechanisms through which land use can impact water quality remains limited. Consequently, it is important to further explore, implement and augment current weighting schemes to enhance our comprehension of the interactions between land use and water quality and ultimately establish suitable techniques for specific settings.

Secondly, this thesis explores the role of hydrological signatures, as well as the necessity of time series data, in the calibration of a conceptual hydrological model. Through investigating the performance of various calibration approaches and identifying an optimal strategy, Article 2 helps to ensure a reliable and robust model of hydrological processes. The findings indicate that calibrating hydrological models using time series data resulted in better performance compared to using strategies based solely on hydrological signatures, thus emphasizing the significance of incorporating observed data during the calibration process. However, in cases where time series data is not accessible, utilizing signatures that represent the average or variance of runoff could yield a similar outcome, and thus can be particularly useful when examining hydrological processes in catchments with sparse observed data. The analysis verified that incorporating hydrological signatures of runoff and soil moisture, together with time series data, can aid in reducing the uncertainty in model parameters, especially during low flow conditions. Further research that corroborates these results across various regions and explores the applicability of findings with additional hydrological models would be beneficial.

Finally, this thesis evaluates long-term water quality response to catchment-scale land use changes to provide evidence of management effectiveness in a freshwater protected area. By examining the consequences and temporal persistence of land use changes and the susceptibility of specific water quality indicators, Article 2 reveals realistic expectations for potential outcomes while providing insights on the efficacy of management interventions and response times needed for improvements. The findings suggest that converting croplands to grassland on a relatively small scale can be an effective strategy for mitigating a significant amount of nitrate loading to headwater streams, while reducing conductivity and calcium may require more extensive changes. Substantial improvements in water quality occurred approximately nine years after management implementation, emphasizing the persistent effects of altered land use and the importance of long-term data for detecting delayed improvements. Overall, the findings can help inform decision-making when planning strategies under similar contexts. Nevertheless, examining additional catchments that include a larger range of land use alterations could increase applicability and validate results.

As human development continues to transform the earth's surfaces, the conservation and management of water resources becomes increasingly crucial. Ensuring the protection of water resources will depend on a better understanding of land-water interactions as well as an accurate portrayal of processes. Such information will be key for developing appropriate policies, facilitating effective management decisions, and advancing assessments.

7. Appendix

Box 1. Search string of terms and Boolean operators used for an advanced search of the Web of Science database.

TS = (“surface water$” OR “receiving water$” OR lake$ OR pond$ OR river$ OR stream$ OR tributar* OR headwater$ OR spring$ OR creek$ OR channel$ OR canal$ OR rivulet$ OR brook$ OR watercourse$ OR waterway$ OR bog$ OR lagoon$ OR pool$ OR reservoir$ OR loch$ OR wetland$ OR estuar* OR delta$ OR bay$ OR “marsh*” OR swamp$ OR fen$ OR “coastal water$” OR sea$ OR ocean$ OR waterbod* OR basin$ OR catchment$ OR watershed$) NOT TS= (groundwater OR subsurface$ OR subsoil) AND TS = (“land use$” OR “land cover$”) NOT TS = (projection$ OR forecast$ OR scenario$) AND TS = (“water quality” OR “water chemistry”) NOT TS = (assemblage$ OR population$ OR communit* OR genetic$ OR fish* OR macroinvert* OR bee$ OR biomass OR organism$ OR phytoplankton OR atmospher* OR particulat*)

Note: The search was conducted on January 20, 2022 with the language limited to English and the publication date between January 1, 2010 and December 31, 2021. The search included all Web of Science core collection citation indexes.

Box 2. Search string of terms used for an advanced search of the Google Scholar search engine.

with **all** of the words: ~land use AND ~water quality

Note: The search was conducted on February 3, 2022 with the time span from 2010 to 2021. The search was conducted so the words occur only in the title of the article. The search results do not include citations. Only evidence published in English was retained. The search was sorted by relevance and only the first 500 search results were obtained.

Table A1. The following eligibility criteria was applied for screening results.

Key elements	**Inclusion criteria**	**Exclusion criteria**
Population	Surface waters, globally.	Subsurface waters (i.e., groundwater).
Exposure	Observed changes in various extents, compositions or configurations of terrestrial land use/land cover.	Projections or forecasts of future land use scenarios. Changes in farming practices (e.g., crop growth, cultivation, production or harvesting)
Comparator	Changes within the same area over time or compared with a reference area without changes (e.g. paired-catchment approach)	A multisite comparison of different land use types at a single point in time (e.g. cross-sectional studies).
Outcome	Measures of physical, chemical and microbiological indicators of surface water quality based on empirical data.	Measures of biological indicators, water quantity, sediment yields, soil properties or erosion rates.
Study Design	Case studies, observational studies and experimental research	Review or perspective articles.

Note. Only research published in scientific journals or books were retained, conference papers or proceedings, dissertations, theses, and reports were discarded.

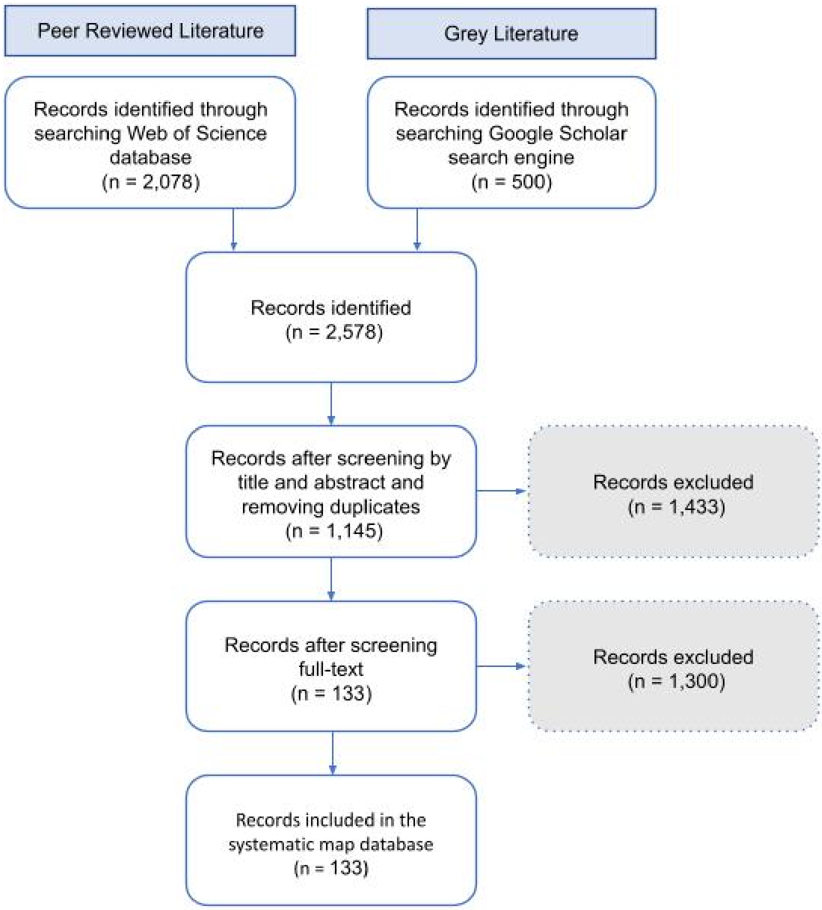

Figure A1. Flow diagram of the numbers of records included or excluded at each stage of the screening and selection process.

Table A2. Nomenclature of land use types employed across the 133 studies in the systematic map database. Each term was classified into one of nine conventional land use categories according to the description in the study.

Land use category	**Included terms**
Agriculture	Agricultural, Agricultural areas, Agricultural land(s), Agricultural land/cropland, Agricultural land/Grassland, Agriculture, Agriculture land, Arable land, Arable cropping, Citrus, Crop(s), Crop and pasture lands, Cropland, Crop land, Cropping land, Cultivated, Cultivated crops, Cultivated field, Cultivated land, Cultivation, Dry farmland, Dry field, Dryland, Fallow land, Farming, Farmland, Farm land, Farms/crops, Fieldcrop, Garden, Garden land, Garden plot, Ginseng, Greenhouses, Horticulture, Irrigated arable land, Irrigated centre pivots, Irrigated cultivation, Irrigated orchards, Irrigated vegetables, Non irrigated arable land, Orchard(s), Other agriculture, Paddy, Paddy field, Plantation(s), Rainfed cropland, Rice, Rice fields, Row crops, Smallholdings, Sugarcane Vegetation, Upland(s), Water cultivation/garden
Urban	Artificial surfaces, Artificial surfaces intensive, Artificial surfaces extensive, Built-up, Built-up area(s), Built-up area/rural complex, Bare land / Settlements, Brick fields area, Built-up/settlements area, Builtup land, Built-upland, City lands, Commercial, Constructed, Constructed land, Construction land, High urban, Developed, Impervious surface, Impervious surface area(s), Industrial, Industrial facilities, Industrial zone, Land covered by Industry, Low urban, Medium urban, Peri-urban, Residential, Residential area, Residential land, Residential-industry land, Residential settlement, Road, Settlement area, Settlement(s), Suburban, Urban, Urban and barren lands, Urban and built-up, Urban area(s), Urban blocks, Urban build-up, Urban built-up land, Urban/built-up, Urban and developed area, Urban land, Urban infrastructure, Urbanization
Forest	Artificial forest, Closed savannah, Dense moist forest, Evergreen broadleaved forest, Fair forest, Flooded forest, Forest(s), Forest cover, Forest formation, Forest land, Forestland(s), Forest plantation(s), Forested land, Forest and scrub area, Forests and semi-natural areas, Forest/grassland/high vegetation, Forest/wetland, Forestry, Forestry and grass cover, Forestry and Plantations, Native forest, Natural forest, Non-plantation forest, Old-growth forests, Open forest, Open pine forest, Original forest, Plantation forest, Rubber plantations, Secondary forest(s), Stunted forest, Thick pine forest, Upland forest,

	Woodland, Woodland/Open bush, Wooded rangeland, Woody Plants, Young secondary forest
Grassland	Fair range, Good rangeland, Grass, Grass land, Grassland(s), Grassland/degraded land, Grass/Pasture, Green space, Improved grassland, Irrigated pastures, Meadow, Medium rangeland, Native grassland, Opened savannah, Pasture, Poor range, Poor rangeland, Range land, Rangeland, Savanna, Savanna formation, Shrub/grassland, Steppic grasslands and bare land
Vegetation	Goukamma Dune Thicket, Green space, Herbaceous cover, Low shrubland, Mountain/vegetation, Natural, Natural vegetation, Perennial, Rough grazing, Scrub, Scrubland, Shrub, Shrublands, Shrubland Fynbos, Shrub-land, Shrub land, Shrubs and grassland, Thicket/Dense bush, Vegetation, Vegetation cover, Vegetative surface, Woody/herbaceous
Water	Clear water, Fresh Water, Hydrography, Inland water, Lakes, Open water, Ponds, Rivers, Water(s), Water area, Water bodies, Water-bodies, Water bodies/swamps, Water body, Watercourse
Wetlands	Aquatic macrophytes, Aquatic vegetation, Mangrove, Mangrove area, Mangrove swamp, Marsh, Marshy, Marshland vegetation. Marshy land, Peatland, Salt marsh, Swamp, Water wetlands, Wetland(s), Wetland landscape, Wetland & saltern, Wetlands and water bodies
Bare land	Bare, Bare areas, Bare none vegetated, Bare soil, Bare soil/rocks, Barren, Barren land, Barrenland, Bare ground, Bare land, Bareland, Barren land, Barren soil and snow covers, Bare field, Bare land(s), Bare rocky land, Bare surface area, Cleared land, Deforested land, Desertified land, Disturbed/bare Exposed hill, Exposed land, Open area, Open space, Rocky outcrop, Undeveloped land, Unused land, Unutilizable land, Unutilized land, Un-utilized land, Wasteland
Other	Burnt area, Dams, Degraded, Degraded Outeniqua Plateau Fynbos, Desert, Disturbed land and open space/recreation, Drained wetland, Dryland, Dunes, Exposed rock, Floating garden, Flows sands, Green house, Ground cover, Hay, Hoor, Infiltration zones, Landslide, Mine, Mining, Mining area, Miscellaneous, Natural floodplain, Natural Knysna Afromontane, Natural Outeniqua Plateau Fynbos, Non-forest natural formation, Non-Urban, Other(s), Other land, Other land uses, Other land-uses, Other types, Rich, Reed beds, Riverine vegetation, Rock, Rocky, Rural, Saline and alkaline land, Salinized land, Sand, Sea, Semi-natural, Snow/glaciers, Snow/ice, Trans and uti, Unconsolidated shore, Un-surveyed land, Yuan land

Note. Plantations were considered agriculture unless specified as forest plantations.

Table A3. Frequency of studies recording notable land use expansions or losses for specific land use categories during the study period.

Notable Land use Change	Expansion	Loss
Agriculture	15	-27
Agriculture + Bare land	1	-2
Agriculture + Grassland	1	-3
Agriculture + Forest	0	-9
Agriculture + Other	0	-1
Agriculture + Urban	20	0
Agriculture + Water	0	-1
Agriculture + Wetland	0	-3
Bare land	3	-5
Bare land + Forest	0	-1
Bare land + Grassland	0	-2
Bare land + Vegetation	0	-1
Bare land + Water	0	-1
Forest	8	-17
Forest + Grassland	0	-4
Forest + Urban	7	0
Forest + Vegetation	0	-1
Forest + Wetland	0	-3
Grassland	4	-8
Grassland + Other	2	0
Grassland + Urban	2	0
Grassland + Vegetation	0	-1
Other	1	0
Other + Urban	2	0
Urban	53	-1
Urban + Vegetation	1	0
Urban + Wetland	3	0
Vegetation	1	-7
Vegetation + Wetland	0	-1
Water	0	-3
Wetland	1	-7
Various	1	-7

Not specified	7	-17

Note. If more than two land use classes were noted for expansion or loss, changes were classified as "various".

Table A4. Publication details of studies included in the systematic map database.

	Publication details				
ID	Year	Author(s)	Article title	Publishing source	DOI
20	2021	Senbore, S; Oke, SA	Urban development impact on climate variability and surface water quality in part of Mangaung metropolis of South Africa	DEVELOPMENT SOUTHERN AFRICA	10.1080/0376835X.2021.1993794
29	2021	Dar, SA; Bhat, SU; Rashid, I	Landscape Transformations, Morphometry, and Trophic Status of Anchar Wetland in Kashmir Himalaya: Implications for Urban Wetland Management	WATER AIR AND SOIL POLLUTION	10.1007/s11270-021-05416-5
32	2021	Dar, SA; Rashid, I; Bhat, SU	Linking land system changes (1980-2017) with the trophic status of an urban wetland: Implications for wetland management	ENVIRONMENTAL MONITORING AND ASSESSMENT	10.1007/s10661-021-09476-2
46	2021	Lei, KG; Wu, YF; Li, F; Yang, JY; Xiang, MT; Li, Y; Li, Y	Relating Land Use/Cover and Landscape Pattern to the Water Quality under the Simulation of SWAT in a Reservoir Basin, Southeast China	SUSTAINABILITY	10.3390/su131911067
54	2021	Chen, ZK; An, CJ; Tan, Q; Tian, XL; Li, GC; Zhou, Y	Spatiotemporal analysis of land use pattern and stream water quality in southern Alberta, Canada	JOURNAL OF CONTAMINANT HYDROLOGY	10.1016/j.jconhyd.2021.103852
55	2021	Fernandes, ACP; Martins, LMD; Pacheco, FAL; Fernandes, LFS	The consequences for stream water quality of long-term changes in landscape patterns: Implications for land use management and policies	LAND USE POLICY	10.1016/j.landusepol.2021.105679
82	2021	Lee, J; Chung, J; Woo, S; Lee, Y; Jung, C; Park, D; Kim, S	Evaluation of Land-Use Changes Impact on Watershed Health Using Probabilistic Approaches	WATER	10.3390/w13172348
96	2021	Wu, J; Zeng, SD; Yang, LH; Ren, YX; Xia, J	Spatiotemporal Characteristics of the Water Quality and Its Multiscale Relationship with Land Use in the Yangtze River Basin	REMOTE SENSING	10.3390/rs13163309
97	2021	Klante, C; Larson, M; Persson, KM	Brownification in Lake Bolmen, Sweden, and its relationship to natural and	JOURNAL OF HYDROLOGY-REGIONAL	10.1016/j.ejrh.2021.100863

			human-induced changes	STUDIES	
114	2021	Zhang, MX; Rong, GZ; Han, A; Riao, D; Liu, XP; Zhang, JQ; Tong, ZJ	Spatial-Temporal Change of Land Use and Its Impact on Water Quality of East-Liao River Basin from 2000 to 2020	WATER	10.3390/w13141955
132	2021	Yan, JF; Wang, MH; Su, FZ; Xiao, RM; Wang, T	Analysis of the change in the ecological environment based on remote sensing in typical coastal zones of the Indian Ocean from 1990 to 2017	ARABIAN JOURNAL OF GEOSCIENCES	10.1007/s12517-021-07484-7
139	2021	Delia, KA; Haney, CR; Dyer, JL; Paul, VG	Spatial Analysis of a Chesapeake Bay Sub-Watershed: How Land Use and Precipitation Patterns Impact Water Quality in the James River	WATER	10.3390/w13111592
149	2021	Piyapong, C; Chamroensaksri, N; Aroonsrimorakot, S; Eyosawat, L; Khankhum, S; Rattana, S; Sunthamala, N; Warapetcharayut, P; Paradis, E	A predictive model of the impact of urbanization on bacterial loads in watersheds	JOURNAL OF CLEANER PRODUCTION	10.1016/j.jclepro.2021.126704
162	2021	Liu, JF; Xu, JJ; Zhang, X; Liang, ZM; Rao, K	Nonlinearity and threshold effects of landscape pattern on water quality in a rapidly urbanized headwater watershed in China	ECOLOGICAL INDICATORS	10.1016/j.ecolind.2021.107389
177	2021	Dar, SA; Rashid, I; Bhat, SU	Land system transformations govern the trophic status of an urban wetland ecosystem: Perspectives from remote sensing and water quality analysis	LAND DEGRADATION & DEVELOPMENT	10.1002/ldr.3924
209	2021	Peng, SY; Li, SH	Scale relationship between landscape pattern and water quality in different pollution source areas: A case study of the Fuxian Lake watershed, China	ECOLOGICAL INDICATORS	10.1016/j.ecolind.2020.107136
216	2021	Fraga, MD; da Silva, DD; Reis, GB; Guedes, HAS; Elesbon, AAA	Temporal and spatial trend analysis of surface water quality in the Doce River basin, Minas Gerais, Brazil	ENVIRONMENT DEVELOPMENT AND SUSTAINABILITY	10.1007/s10668-020-01160-8
218	2021	Saedpanah, M; Reisi, M; Nadoushan, MA	The Effect of Land Use Changes on Water Quality (Case Study: Zayandeh-Rud Basin, Isfahan, Iran)	POLLUTION	10.22059/POLL.2021.324387.1100
227	2021	Bukunmi-Omidiran, T; Sridhar, BBM	Evaluation of spatial and temporal water and soil quality in the Buffalo and Brays Bayou watersheds of	REMOTE SENSING APPLICATIONS -SOCIETY AND	10.1016/j.rsase.2020.100455

			Houston, Texas	ENVIRONMENT	
232	2021	Molekoa, MD; Avtar, R; Kumar, P; Minh, HVT; Dasgupta, R; Johnson, BA; Sahu, N; Verma, RL; Yunus, AP	Spatio-Temporal Analysis of Surface Water Quality in Mokopane Area, Limpopo, South Africa	WATER	10.3390/w13020220
309	2020	Szatten, D; Habel, M	Effects of Land Cover Changes on Sediment and Nutrient Balance in the Catchment with Cascade-Dammed Waters	REMOTE SENSING	10.3390/rs12203414
320	2020	Sridhar, BBM; Johnson, J; Mosuro, A	Impact of Land Cover Changes on the Soil and Water Quality of Greens Bayou Watershed	WATER AIR AND SOIL POLLUTION	10.1007/s11270-020-04890-7
323	2020	Wei, W; Gao, YN; Huang, JC; Gao, JF	Exploring the effect of basin land degradation on lake and reservoir water quality in China	JOURNAL OF CLEANER PRODUCTION	10.1016/j.jclepro.2020.122249
381	2021	Soltani-Gerdefaramarzi, S; Gheisouri, M; Saberi, A; Yarami, N	The effect of land use change on surface water quality under the wet and dry years in a semi-arid catchment (case study: the Godarkhosh catchment)	ENVIRONMENT DEVELOPMENT AND SUSTAINABILITY	10.1007/s10668-020-00820-z
408	2020	Zong, M; Hu, YM; Liu, M; Li, CL; Wang, C; Ping, XY	Effects of Landscape Pattern Change on Water Yield and Nonpoint Source Pollution in the Hun-Taizi River Watershed, China	INTERNATIONAL JOURNAL OF ENVIRONMENTAL RESEARCH AND PUBLIC HEALTH	10.3390/ijerph17093060
427	2020	Li, JH; Bai, Y; Alatalo, JM	Impacts of rural tourism-driven land use change on ecosystems services provision in Erhai Lake Basin, China	ECOSYSTEM SERVICES	10.1016/j.ecoser.2020.101081
564	2019	Yadav, S; Babel, MS; Shrestha, S; Deb, P	Land use impact on the water quality of large tropical river: Mun River Basin, Thailand	ENVIRONMENTAL MONITORING AND ASSESSMENT	10.1007/s10661-019-7779-3
587	2019	DeBues, MJ; Eimers, MC; Watmough, SA; Mohamed, MN; Mueller, J	Stream nutrient and agricultural land-use trends from 1971 to 2010 in Lake Ontario tributaries	JOURNAL OF GREAT LAKES RESEARCH	10.1016/j.jglr.2019.05.002
616	2019	Hu, XQ; Wang, HQ; Zhu, Y; Xie, G; Shi, HJ	Landscape Characteristics Affecting Spatial Patterns of Water Quality Variation in a Highly Disturbed Region	INTERNATIONAL JOURNAL OF ENVIRONMENTAL RESEARCH AND PUBLIC HEALTH	10.3390/ijerph16122149
685	2019	Carstens, D; Amer, R	Spatio-temporal analysis of urban changes and surface water quality	JOURNAL OF HYDROLOGY	10.1016/j.jhydrol.2018.12.033

690	2019	Xu, GC; Li, P; Lu, KX; Zhan, TT; Zhang, JX; Ren, ZP; Wang, XK; Yu, KX; Shi, P; Cheng, YT	Seasonal changes in water quality and its main influencing factors in the Dan River basin	CATENA	10.1016/j.catena.2018.10.014
694	2019	Xiong, C; Hoyer, MV	Influence of land use and rainfall variability on nutrient concentrations in Florida Lakes	LAKE AND RESERVOIR MANAGEMENT	10.1080/10402381.2018.1511659
710	2019	Mahmoodi, M; Honarmand, M; Naseri, F; Mohammadi, S	LINKING LAND USE CHANGES TO VARIATION IN SURFACE WATER QUALITY: EVIDENCE FROM 36 CATCHMENTS IN IRAN	APPLIED ECOLOGY AND ENVIRONMENTAL RESEARCH	10.15666/aeer/1704_81518169
743	2018	Zhang, WS; Chen, DQ; Li, HP	Spatio-temporal dynamics of water quality and their linkages with the watershed landscape in highly disturbed headwater watersheds in China	ENVIRONMENTAL SCIENCE AND POLLUTION RESEARCH	10.1007/s11356-018-3310-6
759	2018	Li, K; Chi, GQ; Wang, L; Xie, YJ; Wang, XR; Fan, ZQ	Identifying the critical riparian buffer zone with the strongest linkage between landscape characteristics and surface water quality	ECOLOGICAL INDICATORS	10.1016/j.ecolind.2018.05.030
766	2018	Zhang, X; Zheng, Q; Zhou, L; Wei, JW	Nonpoint Pollution Source-Sink Landscape Pattern Change Analysis in a Coastal River Basin in Southeast China	INTERNATIONAL JOURNAL OF ENVIRONMENTAL RESEARCH AND PUBLIC HEALTH	10.3390/ijerph15102115
809	2018	Xie, YJ; Yu, XJ; Ng, NC; Li, K; Fang, L	Exploring the dynamic correlation of landscape composition and habitat fragmentation with surface water quality in the Shenzhen river and deep bay cross-border watershed, China	ECOLOGICAL INDICATORS	10.1016/j.ecolind.2017.11.051
812	2018	Li, HX; Wang, CZ; Huang, X; Hug, A	Spatial Assessment of Water Quality with Urbanization in 2007-2015, Shanghai, China	REMOTE SENSING	10.3390/rs10071024
824	2018	Asare, F; Palamuleni, LG; Ruhiiga, T	Land Use Change Assessment and Water Quality of Ephemeral Ponds for Irrigation in the North West Province, South Africa	INTERNATIONAL JOURNAL OF ENVIRONMENTAL RESEARCH AND PUBLIC HEALTH	10.3390/ijerph15061175
826	2018	Namugize, JN; Jewitt, G; Graham, M	Effects of land use and land cover changes on water quality in the uMngeni river catchment, South Africa	PHYSICS AND CHEMISTRY OF THE EARTH	10.1016/j.pce.2018.03.013
841	2018	Burke, MWV; Shahabi, M; Xu, YQ; Zheng, HC;	Identifying the Driving Factors of Water Quality in a Sub-Watershed of the	INTERNATIONAL JOURNAL OF ENVIRONMENT	10.3390/ijerph15051041

		Zhang, XD; VanLooy, J	Republican River Basin, Kansas USA	AL RESEARCH AND PUBLIC HEALTH	
842	2018	Liu, ZH; Yang, HY	The Impacts of Spatiotemporal Landscape Changes on Water Quality in Shenzhen, China	INTERNATIONAL JOURNAL OF ENVIRONMENTAL RESEARCH AND PUBLIC HEALTH	10.3390/ijerph15051038
843	2018	Kim, K; Kim, B; Eum, J; Seo, B; Shope, CL; Peiffer, S	Impacts of Land Use Change and Summer Monsoon on Nutrients and Sediment Exports from an Agricultural Catchment	WATER	10.3390/w10050544
847	2018	Abdulkareem, JH; Sulaiman, WNA; Pradhan, B; Jamil, NR	Long-Term Hydrologic Impact Assessment of Non-point Source Pollution Measured Through Land Use/Land Cover (LULC) Changes in a Tropical Complex Catchment	EARTH SYSTEMS AND ENVIRONMENT	10.1007/s41748-018-0042-1
887	2018	McCarthy, MJ; Muller-Karger, FE; Otis, DB; Mendez-Lazaro, P	Impacts of 40 years of land cover change on water quality in Tampa Bay, Florida	COGENT GEOSCIENCE	10.1080/23312041.2017.1422956
889	2018	Kopacz, M; Kowalczyk, A; Smoron, S; Rychtarczyk, M	The influence of structural and functional changes on N-P-K input of agricultural origin and surface water quality in the upper Dunajec River basin in the years 1980-2010	GEOLOGY GEOPHYSICS AND ENVIRONMENT	10.7494/geol.2018.44.3.295
896	2018	Xiong, JF; Lin, C; Min, M; Ma, RH; Wu, ZP; Jia, JJ	SPATIO-TEMPORAL PATTERN EVOLUTION OF NON-POINT SOURCE PHOSPHORUS LOADS IN CHAOHU LAKE BASIN (ANHUI PROVINCE, CHINA) UNDER DIFFERENT LAND USE PATTERNS	APPLIED ECOLOGY AND ENVIRONMENTAL RESEARCH	10.15666/aeer/1605_62196238
903	2018	Chotpantarat, S; Boonkaewwan, S	Impacts of land-use changes on watershed discharge and water quality in a large intensive agricultural area in Thailand	HYDROLOGICAL SCIENCES JOURNAL	10.1080/02626667.2018.1506128
983	2017	Zhang, YN; Huang, X; Yin, W; Zhu, D	Multitemporal Landsat Image Based Water Quality Analyses of Danjiangkou Reservoir	PHOTOGRAMMETRIC ENGINEERING AND REMOTE SENSING	10.14358/PERS.83.9.643
984	2017	Bhandari, S; Sridhar, BBM; Wilson, BL	Effect of Land Cover Changes on the Sediment and Water Quality Characteristics of Brays Bayou Watershed	WATER AIR AND SOIL POLLUTION	10.1007/s11270-017-3538-7
1029	2017	Wan, YS; Wan, L; Li, YC; Doering, P	Decadal and seasonal trends of nutrient concentration and export from highly managed coastal catchments	WATER RESEARCH	10.1016/j.watres.2017.02.068

1034	2017	Brill, G; Anderson, P; O'Farrell, P	Methodological and empirical considerations when assessing freshwater ecosystem service provision in a developing city context: Making the best of what we have	ECOLOGICAL INDICATORS	10.1016/j.ecolind.2017.01.006
1042	2017	Taniwaki, RH; Cassiano, CC; Filoso, S; Ferraz, SFD; de Camargo, PB; Martinelli, LA	Impacts of converting low-intensity pastureland to high-intensity bioenergy cropland on the water quality of tropical streams in Brazil	SCIENCE OF THE TOTAL ENVIRONMENT	10.1016/j.scitotenv.2016.12.150
1050	2017	Shi, P; Zhang, Y; Li, ZB; Li, P; Xu, GC	Influence of land use and land cover patterns on seasonal water quality at multi-spatial scales	CATENA	10.1016/j.catena.2016.12.017
1063	2017	Rios-Villamizar, EA; Piedade, MTF; Junk, WJ; Waichman, AV	Surface water quality and deforestation of the Purus river basin, Brazilian Amazon	INTERNATIONAL AQUATIC RESEARCH	10.1007/s40071-016-0150-1
1066	2017	Julian, JP; de Beurs, KM; Owsley, B; Davies-Colley, RJ; Ausseil, AGE	River water quality changes in New Zealand over 26 years: response to land use intensity	HYDROLOGY AND EARTH SYSTEM SCIENCES	10.5194/hess-21-1149-2017
1074	2017	Dai, XY; Zhou, YQ; Ma, WC; Zhou, LG	Influence of spatial variation in land-use patterns and topography on water quality of the rivers inflowing to Fuxian Lake, a large deep lake in the plateau of southwestern China	ECOLOGICAL ENGINEERING	10.1016/j.ecoleng.2016.11.011
1080	2017	Huang, HB; Ouyang, W; Wu, HT; Liu, HB; Andrea, C	Long-term diffuse phosphorus pollution dynamics under the combined influence of land use and soil property variations	SCIENCE OF THE TOTAL ENVIRONMENT	10.1016/j.scitotenv.2016.11.198
1085	2017	Fuentes, R; Leon-Munoz, J; Echeverria, C	Spatially explicit modelling of the impacts of land-use and land-cover change on nutrient inputs to an oligotrophic lake	INTERNATIONAL JOURNAL OF REMOTE SENSING	10.1080/01431161.2017.1339928
1115	2017	Hua, AK	Land Use Land Cover Changes in Detection of Water Quality: A Study Based on Remote Sensing and Multivariate Statistics	JOURNAL OF ENVIRONMENTAL AND PUBLIC HEALTH	10.1155/2017/7515130
1145	2016	Shi, W; Xia, J; Zhang, X	Influences of anthropogenic activities and topography on water quality in the highly regulated Huai River basin, China	ENVIRONMENTAL SCIENCE AND POLLUTION RESEARCH	10.1007/s11356-016-7368-8
1151	2016	Stefanidis, K; Kostara, A; Papastergiadou, E	Implications of Human Activities, Land Use Changes and Climate Variability in Mediterranean Lakes of Greece	WATER	10.3390/w8110483
1240	2016	Putro, B; Kjeldsen, TR; Hutchins, MG;	An empirical investigation of climate and land-use effects	SCIENCE OF THE TOTAL	10.1016/j.scitotenv.2015.1

		Miller, J	on water quantity and quality in two urbanising catchments in the southern United Kingdom	ENVIRONMENT	2.132
1287	2016	Li, YF; Li, Y; Wu, W	Threshold and resilience management of coupled urbanization and water environmental system in the rapidly changing coastal region	ENVIRONMENTAL POLLUTION	10.1016/j.envpol.2015.08.042
1297	2015	Li, Y; Li, YF; Qureshi, S; Kappas, M; Hubacek, K	On the relationship between landscape ecological patterns and water quality across gradient zones of rapid urbanization in coastal China	ECOLOGICAL MODELLING	10.1016/j.ecolmodel.2015.01.028
1307	2015	Muller, FLL; Chang, KC; Lee, CL; Chapman, SJ	Effects of temperature, rainfall and conifer felling practices on the surface water chemistry of northern peatlands	BIOGEOCHEMISTRY	10.1007/s10533-015-0162-8
1324	2015	Zhao, WJ; Zhu, XD; Sun, X; Shu, YQ; Li, YF	Water quality changes in response to urban expansion: spatially varying relations and determinants	ENVIRONMENTAL SCIENCE AND POLLUTION RESEARCH	10.1007/s11356-015-4795-x
1339	2015	Meneses, BM; Reis, R; Vale, MJ; Saraiva, R	Land use and land cover changes in Zezere watershed (Portugal) - Water quality implications	SCIENCE OF THE TOTAL ENVIRONMENT	10.1016/j.scitotenv.2015.04.092
1372	2015	du Plessis, A; Harmse, T; Ahmed, F	Predicting water quality associated with land cover change in the Grootdraai Dam catchment, South Africa	WATER INTERNATIONAL	10.1080/02508060.2015.1067752
1418	2015	Na, XD; Zang, SY; Zhang, NN; Cui, J	Impact of land use and land cover dynamics on Zhalong wetland reserve ecosystem, Heilongjiang Province, China	INTERNATIONAL JOURNAL OF ENVIRONMENTAL SCIENCE AND TECHNOLOGY	10.1007/s13762-013-0398-6
1438	2015	Su, ZH; Lin, C; Ma, RH; Luo, JH; Liang, QO	EFFECT OF LAND USE CHANGE ON LAKE WATER QUALITY IN DIFFERENT BUFFER ZONES	APPLIED ECOLOGY AND ENVIRONMENTAL RESEARCH	10.15666/aeer/1303_639653
1443	2015	Dumbrovsky, M; Sobotkova, V; Sarapatka, B; Vachalova, R; Pavelkova Chmelova, R; Vachal, J	Long-Term Improvement in Surface Water Quality after Land Consolidation in a Drinking Water Reservoir Catchment	SOIL AND WATER RESEARCH	10.17221/108/2013-SWR
1479	2014	Zhai, XY; Xia, J; Zhang, YY	Water quality variation in the highly disturbed Huai River Basin, China from 1994 to 2005 by multi-statistical analyses	SCIENCE OF THE TOTAL ENVIRONMENT	10.1016/j.scitotenv.2014.06.101
1490	2014	Ouyang, W; Song, KY; Wang, XL;	Non-point source pollution dynamics under long-term	ECOLOGICAL INDICATORS	10.1016/j.ecolind.2014.05.

		Hao, FH	agricultural development and relationship with landscape dynamics		025
1512	2014	Zhang, Z; Chen, Y; Wang, P; Shuai, JB; Tao, FL; Shi, PJ	River discharge, land use change, and surface water quality in the Xiangjiang River, China	HYDROLOGICAL PROCESSES	10.1002/hyp.9938
1573	2014	Courville, BC; Jensen, JLR; Dixon, RW; Fonstad, MA	A Landsat-based evaluation of lake water clarity in Maine lakes	PHYSICAL GEOGRAPHY	10.1080/02723646.2014.909716
1576	2014	Yang, HC; Wang, GQ; Yang, Y; Xue, BL; Wu, BB	Assessment of the Impacts of Land Use Changes on Nonpoint Source Pollution Inputs Upstream of the Three Gorges Reservoir	SCIENTIFIC WORLD JOURNAL	10.1155/2014/526240
1603	2013	Bateni, F; Fakheran, S; Soffianian, A	Assessment of land cover changes & water quality changes in the Zayandehroud River Basin between 1997-2008	ENVIRONMENTAL MONITORING AND ASSESSMENT	10.1007/s10661-013-3348-3
1618	2013	Leon-Munoz, J; Echeverria, C; Marce, R; Riss, W; Sherman, B; Iriarte, JL	The combined impact of land use change and aquaculture on sediment and water quality in oligotrophic Lake Rupanco (North Patagonia, Chile, 40.8 degrees S)	JOURNAL OF ENVIRONMENTAL MANAGEMENT	10.1016/j.jenvman.2013.05.008
1656	2013	Memon, S; Paule, MC; Park, SJ; Lee, BY; Kang, S; Umer, R; Lee, CH	Monitoring of land use change impact on stormwater runoff and pollutant loading estimation in Yongin watershed Korea	DESALINATION AND WATER TREATMENT	10.1080/19443994.2013.781105
1685	2013	Elci, S; Selcuk, P	Effects of basin activities and land use on water quality trends in Tahtali Basin, Turkey	ENVIRONMENTAL EARTH SCIENCES	10.1007/s12665-012-1852-3
1691	2013	Chu, HJ; Liu, CY; Wang, CK	Identifying the Relationships between Water Quality and Land Cover Changes in the Tseng-Wen Reservoir Watershed of Taiwan	INTERNATIONAL JOURNAL OF ENVIRONMENTAL RESEARCH AND PUBLIC HEALTH	10.3390/ijerph10020478
1717	2013	Shupe, S	Statistical and Spatial Analysis of Land Cover Impact on Selected Metro Vancouver, British Columbia Watersheds	ENVIRONMENTAL MANAGEMENT	10.1007/s00267-012-9955-x
1718	2013	Huang, JL; Li, QS; Pontius, RG; Klemas, V; Hong, HS	Detecting the Dynamic Linkage between Landscape Characteristics and Water Quality in a Subtropical Coastal Watershed, Southeast China	ENVIRONMENTAL MANAGEMENT	10.1007/s00267-011-9793-2
1732	2013	Taboada-Castro, MM; Rodriguez-Blanco, ML; Taboada-Castro,	Assessing the Influence of Catchment Land-Use Patterns on the Nutrients and Major Ions Chemistry of Drainage Water	COMMUNICATIONS IN SOIL SCIENCE AND PLANT ANALYSIS	10.1080/00103624.2013.742337

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1754	2012	Zhou, T; Wu, JG; Peng, SL	Assessing the effects of landscape pattern on river water quality at multiple scales: A case study of the Dongjiang River watershed, China	ECOLOGICAL INDICATORS	10.1016/j.ecolind.2012.03.013
1763	2012	Zuazo, VHD; Martinez, JRF; Tejero, IG; Pleguezuelo, CRR; Raya, AM; Tavira, SC	Runoff and sediment yield from a small watershed in southeastern Spain (Lanjaron): implications for water quality	HYDROLOGICAL SCIENCES JOURNAL	10.1080/02626667.2012.726994
1784	2012	Rymbai, PN; Dey, S; Jha, LK	The impact of topographical characteristics and land use change on the quality of Umbaniun micro-watershed water resources, Meghalaya	INGENIERIA E INVESTIGACION	Not available
1789	2012	Huang, JL; Klemas, V	Using Remote Sensing of Land Cover Change in Coastal Watersheds to Predict Downstream Water Quality	JOURNAL OF COASTAL RESEARCH	10.2112/JCOASTRES-D-11-00176.1
1795	2012	Hadibarata, T; Abdullah, F; Yusoff, ARM; Ismail, R; Azman, S; Adnan, N	Correlation Study between Land Use, Water Quality, and Heavy Metals (Cd, Pb, and Zn) Content in Water and Green Lipped Mussels Perna viridis (Linnaeus.) at the Johor Strait	WATER AIR AND SOIL POLLUTION	10.1007/s11270-012-1095-7
1802	2012	Madrinan, MJM; Al-Hamdan, MZ; Rickman, DL; Ye, J	Relationship Between Watershed Land-Cover/Land-Use Change and Water Turbidity Status of Tampa Bay Major Tributaries, Florida, USA	WATER AIR AND SOIL POLLUTION	10.1007/s11270-011-1007-2
1824	2012	Lorz, C; Abbt-Braun, G; Bakker, F; Borges, P; Bornick, H; Fortes, L; Frimmel, FH; Gaffron, A; Hebben, N; Hofer, R; Makeschin, F; Neder, K; Roig, LH; Steiniger, B; Strauch, M; Walde, D; Weiss, H; Worch, E; Wummel, J	Challenges of an integrated water resource management for the Distrito Federal, Western Central Brazil: climate, land-use and water resources	ENVIRONMENTAL EARTH SCIENCES	10.1007/s12665-011-1219-1
1889	2011	Tang, LH; Yang, DW; Hu, HP; Gao, B	Detecting the effect of land-use change on streamflow, sediment and nutrient losses by distributed hydrological simulation	JOURNAL OF HYDROLOGY	10.1016/j.jhydrol.2011.08.015
1895	2011	Uriarte, M; Yackulic, CB; Lim, Y; Arce-Nazario, JA	Influence of land use on water quality in a tropical landscape: a multi-scale analysis	LANDSCAPE ECOLOGY	10.1007/s10980-011-9642-y

1948	2011	Tu, J	Spatial and temporal relationships between water quality and land use in northern Georgia, USA	JOURNAL OF INTEGRATIVE ENVIRONMENTAL SCIENCES	10.1080/1943815X.2011.577076
1964	2011	Liu, YM; Li, LJ; Liang, LQ; Li, JY	Study on the Non-point Source Pollution in the Upper and Middle Reaches of the Taoer River Basin	CHINESE JOURNAL OF POPULATION RESOURCES AND ENVIRONMENT	10.1080/10042857.2011.10685018
1998	2010	Gitau, MW; Chaubey, I; Gbur, E; Pennington, JH; Gorham, B	Impacts of land-use change and best management practice implementation in a Conservation Effects Assessment Project watershed: Northwest Arkansas	JOURNAL OF SOIL AND WATER CONSERVATION	10.2489/jswc.65.6.353
2012	2010	Ouyang, W; Skidmore, AK; Toxopeus, AG; Hao, FH	Long-term vegetation landscape pattern with non-point source nutrient pollution in upper stream of Yellow River basin	JOURNAL OF HYDROLOGY	10.1016/j.jhydrol.2010.06.020
2038	2010	Mahmoudi, B; Bakhtiari, F; Hamidifar, M; Kar, AD	Effects of Land use Change and Erosion on Physical and Chemical Properties of Water(Karkhe watershed)	INTERNATIONAL JOURNAL OF ENVIRONMENTAL RESEARCH	10.22059/IJER.2010.13
2091	2016	Chen, X., Zhou, W., Pickett, S. T., Li, W., & Han, L.	Spatial-Temporal Variations of Water Quality and Its Relationship to Land Use and Land Cover in Beijing, China	International Journal of Environmental Research and Public Health	10.3390/ijerph13050449
2098	2018	Shukla, A.K., Ojha, C.S.P., Mijic, A., Buytaert, W., Pathak, S., Garg, R.D. and Shukla, S.	Population growth, land use and land cover transformations, and water quality nexus in the Upper Ganga River basin	Hydrology and Earth System Sciences	10.5194/hess-22-4745-2018
2105	2020	Tahiru, A.A., Doke, D.A. and Baatuuwie, B.N.	Effect of land use and land cover changes on water quality in the Nawuni Catchment of the White Volta Basin, Northern Region, Ghana	Applied Water Science	10.1007/s13201-020-01272-6
2109	2020	Luo, Z., Shao, Q., Zuo, Q. and Cui, Y.,	Impact of land use and urbanization on river water quality and ecology in a dam dominated basin	Journal of Hydrology	10.1016/j.jhydrol.2020.124655
2129	2020	Singh, S., Bhardwaj, A. and Verma, V.K.	Remote sensing and GIS based analysis of temporal land use/land cover and water quality changes in Harike wetland ecosystem, Punjab, India	Journal of environmental management	10.1016/j.jenvman.2020.110355Get
2132	2020	Chen, D., Elhadj, A., Xu, H., Xu, X. and Qiao, Z.,	A study on the relationship between land use change and water quality of the Mitidja watershed in Algeria based on	Sustainability	10.3390/su12093510

			GIS and RS		
2134	2011	Twesigye, C.K., Onywere, S.M., Getenga, Z.M., Mwakalila, S.S. and Nakiranda, J.K.,	The impact of land use activities on vegetation cover and water quality in the Lake Victoria watershed	The Open Environmental Engineering Journal	Not available
2152	2020	Ewane, E.B.	Assessing land use and landscape factors as determinants of water quality trends in Nyong River basin, Cameroon	Environmental Monitoring and Assessment	10.1007/s10661-020-08448-2
2162	2021	Rimba, A.B., Mohan, G., Chapagain, S.K., Arumansawang, A., Payus, C., Fukushi, K., Osawa, T. and Avtar, R.	Impact of population growth and land use and land cover (LULC) changes on water quality in tourism-dependent economies using a geographically weighted regression approach	Environmental Science and Pollution Research	10.1007/s11356-020-12285-8
2164	2020	Rather, I.A. and Dar, A.Q.,	Assessing the impact of land use and land cover dynamics on water quality of Dal Lake, NW Himalaya, India	Applied Water Science	10.1007/s13201-020-01300-5
2172	2019	Li, S., Peng, S., Jin, B., Zhou, J. and Li, Y.	Multi-scale relationship between land use/land cover types and water quality in different pollution source areas in Fuxian Lake Basin	PeerJ	10.7717/peerj.7283
2203	2017	Petersen, C.R., Jovanovic, N.Z., Le Maitre, D.C. and Grenfell, M.C.,	Effects of land use change on streamflow and stream water quality of a coastal catchment	Water SA	10.4314/wsa.v43i1.16
2211	2019	Gong, X., Bian, J., Wang, Y., Jia, Z. and Wan, H.,	Evaluating and predicting the effects of land use changes on water quality using SWAT and CA–Markov models	Water Resources Management	10.1007/s11269-019-02427-0
2213	2021	Camara, M., Jamil, N.R., Abdullah, A.F. and Hashim, R.,	Analysis of time-space varying relationship between land use and water quality in a tropical watershed	Arabian Journal of Geosciences	10.1007/s12517-021-06596-4
2215	2014	Dunn, S.M., Sample, J., Potts, J., Abel, C., Cook, Y., Taylor, C. and Vinten, A.J.A.,	Recent trends in water quality in an agricultural catchment in Eastern Scotland: Elucidating the roles of hydrology and land use	Environmental Science: Processes & Impacts	10.1039/C3EM00698K
2219	2016	Hong, C., Xiaode, Z., Mengjing, G. and Wei, W.,	Land use change and its effects on water quality in typical inland lake of arid area in China	Journal of environmental biology	Not available
2251	2019	Bishwakarma, K., Pant, R.R., Pal, K.B., Ghimire, A., Thapa, L.B., Saud, P., Joshi, S. and Panthi, K.P.,	Water quality and land use/cover changes in the Phewa Watershed, Gandaki Province, Nepal	Nepal Journal of Environmental Science	10.3126/njes.v7i0.34473
2254	2017	Singh, S.K., Kumar, V. and Kanga, S.,	Land use/land cover change dynamics and river water	International Journal of	Not available

			quality assessment using geospatial technique: A case study of Harmu river, Ranchi (India)	Scientific Research in Computer Science and Engineering	
2261	2013	Aighewi, I.T., Nosakhare, O.K. and Ishaque, A.B.	Land use–Land cover changes and sewage loading in the lower eastern shore watersheds and coastal bays of Maryland: Implications for surface water quality	Journal of Coastal Research	10.2112/JCOASTRES-D-11-00195.1
2262	2021	Tromboni, F., Dilts, T.E., Null, S.E., Lohani, S., Ngor, P.B., Soum, S., Hogan, Z. and Chandra, S.	Changing land use and population density are degrading water quality in the lower mekong basin	Water	10.3390/w13141948
2263	2019	Qadir, J. and Singh, P.,	Land use/cover mapping and assessing the impact of solid waste on water quality of Dal Lake catchment using remote sensing and GIS (Srinagar, India)	SN Applied Sciences	10.1007/s42452-018-0027-6
2265	2012	Khare, Y.P., Martinez, C.J. and Toor, G.S.,	Water Quality and Land Use Changes in the Alafia and Hillsborough River Watersheds, Florida, USA	JAWRA Journal of the American Water Resources Association	10.1111/j.1752-1688.2012.00686.x
2292	2018	Effendi, H., Sabila, M.F. and Setiawan, Y.,	Correlation between water quality and land use change in Ciliwung watershed	Nature Environment and Pollution Technology	Not available
2295	2013	Merugu, C.S. and Seetharaman, R.	Comparative analysis of land use and lake water quality in rural and urban zones of south Chennai, India	Environment, development and sustainability	10.1007/s10668-012-9391-3
2304	2021	Lu, J., Cai, H., Zhang, X. and Fu, Y.,	Water quality in relation to land use in the Junshan Lake watershed and water quality predictions	Water Supply	10.2166/ws.2021.123
2307	2019	Gossweiler, B., Wesström, I., Messing, I., Romero, A.M. and Joel, A.	Spatial and temporal variations in water quality and land use in a semi-arid catchment in Bolivia	Water	10.3390/w11112227
2319	2014	Vushe, A., Haimene, E.P. and Mashauri, D.,	Namibian land use changes and nutrient water quality of the Okavango River	Journal of Agriculture and Environmental Sciences	Not available
2349	2020	Karakus, C.	Assessment of relationship between land use/cover and surface water quality trends within the riparian zone: a case study from Sivas, Turkey	Desalination and Water Treatment	10.5004/dwt.2020.25632
2354	2012	Verma, S., Verma, R.K., Tiwari, R.K.,	Relationship between land use/land-cover patterns and	Global Journal of Applied	Not available

		Patel, N. and Murthy, S.,	surface water quality in Damodar river basin, India	Environmental Sciences	
2381	2021	Che, N.S., Bett, S., Okpara, E.C., Olagbaju, P.O., Fayemi, O.E. and Mathuthu, M.,	An Assessment of Land Use and Land Cover Changes and Its Impact on the Surface Water Quality of the Crocodile River Catchment, South Africa	IntechOpen	10.5772/intechopen.95753
2406	2017	Xizhi, L., Peiqing, X. and Pan, Z.,	Correlation analysis between the water quality and land use composition in Chaobai River basin	Nature Environment and Pollution Technology	Not available
2440	2010	Pensuk, A.N.I.S.A.R.A., Shrestha, R.P. and Clemente, R.,	Effect of land use change on land quality and water resources in Phatthalung Watershed, Thailand	International Journal of Environment and Rural Development	Not available
2481	2015	Fazal S.A, Bhuiyan, M.A.H., Chowdhury, M.A.I. and Kabir, M.M	Effects of Industrial Agglomeration on Land-Use Patterns and Surface Water Quality in Konabari, BSCIC area at Gazipur, Bangladesh	International Research Journal of Environment Sciences	Not available
2486	2018	Karimipour, F., Madadi, A. and Bashough, M.H.	Extracting the spatio-temporal linkages between land use/land cover and water quality parameters using spatio-temporal weighted regression	Water Quality Research Journal	10.2166/wqrj.2018.004

Note. ID refers to the number assigned to articles that were returned via the systematic search. Publishing sources refers to the name of the journal or book.

Table A5. Geographical location of studies included in the systematic map database.

	Geographical Location			
ID	**Country**	**Specific Location**	**Climate zone)**	**Specific climate zone**
20	South Africa	Mangaung Municipality	Arid	BSk
29	India	Srinagar city	Temperate	Cfb
32	India	Srinagar city	Temperate	Cfb
46	China	Shaoxing City	Temperate	Cfa
54	Canada	Alberta	Continental	Dfc
55	Portugal	Ave River Basin	Temperate	Csb
82	South Korea	Geum River Basin	Temperate	Cwa
96	China	East, central, and west China	Continental, Polar, Temperate	Cfa, Cwa, Cwb, Dwc, ET
97	Sweden	Lake Bolmen	Continental	Dfb
114	China	Jilin Province	Continental	Dwa
132	Iran, Pakistan, Bangladesh, Myanmar	Baluchestan Province, Balochistan Province, Chittagong district, Rakhine Province	Arid, Tropical	Am, BWh

139	United States	Virginia	Temperate	Cfa
149	Thailand	Eastern Thailand	Tropical	Aw
162	China	Upstream Huai River Basin	Continental	Dwa
177	India	Srinagar city	Temperate	Cfb
209	China	Yuxi City	Temperate	Cfb
216	Brazil	Minas Gerais	Temperate	Cfa
218	Iran	Zayandeh-Rud basin	Arid	BWh
227	United States	Texas (Houston)	Temperate	Cfa
232	South Africa	Limpopo	Arid	BSh
309	Poland	Brda catchment	Temperate	Cfb
320	United States	Texas (Houston)	Temperate	Cfa
323	China	Across China	Continental, Temperate	Cfa, Cwb, Dwa
381	Iran	Ilam	Temperate	Csa
408	China	Liaoning Province	Continental	Dwa
427	China	Erhai Lake	Temperate	Cwb
564	Thailand	Mid-thailand	Tropical	Aw
587	Canada	Southern Ontario	Continental	Dfb
616	China	Shandong province	Continental	Dwa
685	United States	Southeast Louisiana	Temperate	Cfa
690	China	Shaanxi Province	Temperate	Cfa
694	United States	Florida	Temperate	Cfa
710	Iran	Northeast Iran	Arid	BSk
743	China	Eastern China	Continental	Dwa
759	China	Xiangyang City	Temperate	Cfa
766	China	Fujian Province	Temperate	Cfa
809	China	Hong Kong and Shenzhen	Temperate	Cfb
812	China	Shanghai	Temperate	Cfa
824	South Africa	North West province (Vryburg District)	Arid	BSh
826	South Africa	KZN Province	Temperate	Cwb
841	United States	Kansas	Temperate	Cfa
842	China	Shenzhen	Temperate	Cfb
843	South Korea	Yanggu County, Gangwon Province	Continental	Dwa
847	Malaysia	Kelantan	Tropical	Af
887	United States	Florida (Tampa Bay)	Temperate	Cfa
889	Poland	Beskid Sądecki	Temperate	Cfb
896	China	Anhui province	Temperate	Cfa
903	Thailand	Northern Thailand	Tropical	Am
983	China	Hubei and Henan provinces	Temperate	Cfa, Cwa
984	United States	Texas (Houston)	Temperate	Cfa
1029	United States	Florida	Temperate	Cfa
1034	South Africa	Cape Town	Temperate	Csa
1042	Brazil	São Paulo	Temperate	Cfa
1050	China	Shaanxi Province	Temperate	Cfa
1063	Brazil	Northweatern Brazil	Tropical	Af, Am

1066	New Zealand	Across New Zealand	Temperate	Cfa, Cfb
1074	China	Yuxi, Yunnan	Temperate	Cwa
1080	China	Sanjiang Plain	Continental	Dwa
1085	Chile	South-central Chile	Continental	Cfb
1115	Malaysia	Malacca state	Tropical	Af
1145	China	Henan, Hubei, Anhui, Shandong, Jiangsu province	Continental, Temperate	Cfa, Cwa, Dwa
1151	Greece	Northern Greece	Temperate	Csa
1240	England	Oxford	Temperate	Cfb
1287	China	Lianyungang	Continental	Dwa
1297	China	Lianyungang	Continental	Dwa
1307	Scotland	Northern Scotland	Temperate	Cfb
1324	China	Lianyungang	Continental	Dwa
1339	Portugal	Central Portugal	Temperate	Csa, Csb
1372	South Africa	Vaal River Catchment	Temperate	Cwb
1418	China	Heilongjiang Province	Continental	Dwa
1438	China	Taihu Lake	Temperate	Cfa
1443	Czech Republic	Jihlava administrative district	Continental	Dfb
1479	China	Henan, Shandong, Jiangsu, Anhui Provinces	Continental, Temperate	Cfa, Cwa, Dwa
1490	China	Sanjiang Plain	Continental	Dwa
1512	China	Hunan Province	Temperate	Cfa
1573	United States	Maine	Continental	Dfb
1576	China	Pengxi River	Temperate	Cfa
1603	Iran	Isfahan	Arid	BSk
1618	Chile	North Patagonia	Temperate	Cfb
1656	South Korea	Yongin watershed	Continental	Dwa
1685	Turkey	Izmir	Temperate	Csa
1691	Taiwan	Chiayi County	Temperate	Cwa
1717	Canada	Vancouver	Temperate	Cfb
1718	China	Fujian Province	Temperate	Cfa
1732	Spain	Galicia	Temperate	Csb
1754	China	Guangdong Province	Temperate	Cwa
1763	Spain	Lanjarón	Temperate	Csa
1784	India	Meghalaya	Temperate	Cwa
1789	China	Fujian Province	Temperate	Cfa
1795	Malaysia	Singapore	Tropical	Af
1802	United States	Florida	Temperate	Cfa
1824	Brazil	Western Central Brazil	Tropical	Aw
1889	China	Beijing	Continental	Dwa
1895	United States	Puerto Rico	Tropical	Af, Am, Aw
1948	United States	Georgia	Temperate	Cfa
1964	China	Nenjiang city	Continental	Dwc
1998	United States	Arkansas	Temperate	Cfa
2012	China	Yellow River Basin	Continental	Dwb
2038	Iran	West Iran	Arid, Temperate	BSh, Csa

2091	China	Beijing	Continental	Dwa
2098	India	Uttarakhand, Uttar Pradesh, Bihar and Himachal Pradesh states	Temperate	Cwa, Cwb
2105	Ghana	Northern region	Tropical	Aw
2109	China	Henan Province	Temperate	Cwa
2129	India	Punjab	Arid	BSh, BWh
2132	Algeria	Algerois Hodna Soummam	Temperate	Csa
2134	Kenya, Uganda, Tanzania	Lake Victoria	Tropical	Af, Aw
2152	Cameroon	East Cameroon	Tropical	Am, Aw
2162	Indonesia	Bali	Tropical	Af
2164	India	Srinagar city	Temperate	Cfb
2172	China	Central Yunnan Province	Temperate	Cwa
2203	South Africa	Southwestern Cape	Arid	BSk, BWk
2211	China	Jilin Province	Continental	Dwa
2213	Malaysia	Selangor	Tropical	Af
2215	Scotland	Forfar	Temperate	Cfb
2219	China	Western China	Arid	BWk
2251	Nepal	Gandaki Province	Temperate	Cwa
2254	India	Ranchi	Temperate	Cwa
2261	United States	Maryland	Temperate	Cfa
2262	Laos, Cambodia, Thailand	Southeast Asia	Tropical, Temperate	Am, Aw, Cwa
2263	India	Srinagar city	Temperate	Cfb
2265	United States	Florida	Temperate	Cfa
2292	Indonesia	Java	Tropical	Af
2295	India	South Chennai	Tropical	Aw
2304	China	Jiangxi Province	Temperate	Cfa
2307	Bolivia	Eastern Andes	Arid	BSk
2319	Namibia	Cuando-Cubango Province	Arid	BWh
2349	Turkey	Sivas	Continental	Dsb
2354	India	West Bengal	Tropical	Aw
2381	South Africa	Rustenburg	Arid	BSh
2406	China	Beijing	Continental	Dwa
2440	Thailand	Southern Thailand	Tropical	Am
2481	Bangladesh	Gazipur district	Tropical	Aw
2486	United States	Washington State	Temperate	Cfb, Csb

Note. Specific location refers to states or provinces. If this information was not available, cities, general regions or water body names were listed. Climate zones were defined by the Köppen–Geiger Classification and determined via the description of the study area location and visualization of maps. Studies were classified under more than one climate zone when relevant.

Table A6. Study type and population of studies included in the systematic map database.

	Study type and population		
ID	Study type	Surface water type	Specific surface water type
20	Case study	Tributary	River
29	Case study	Wetland	
32	Case study	Wetland	
46	Case study	Reservoir	
54	Case study	Tributary	Stream
55	Case study	Tributary	River
82	Case study	Tributary	River
96	Case study	Tributary	River
97	Case study	Lake	
114	Case study	Tributary	River
132	Case study	Coastal waters	Sea
139	Case study	Tributary	River
149	Case study	Tributary	River
162	Case study	Tributary	Headwaters
177	Case study	Wetland	
209	Case study	Lake	
216	Case study	Tributary	River
218	Case study	Tributary	River
227	Case study	Tributary	River
232	Case study	Tributary	River
309	Case study	Reservoir	
320	Case study	Wetland	Bayou
323	Case study	Lake, Reservoir	
381	Case study	Tributary	River
408	Case study	Tributary	River
427	Case study	Lake	
564	Case study	Tributary	River
587	Case study	Tributary	Stream
616	Case study	Tributary	River
685	Case study	Tributary	River
690	Case study	Tributary	River
694	Case study	Lake	
710	Case study	Tributary	River
743	Case study	Tributary	Headwaters
759	Case study	Tributary	River
766	Case study	Tributary	River
809	Case study	Tributary	River
812	Case study	Tributary	River
824	Case study	Lake	Pond
826	Case study	Tributary	River
841	Case study	Tributary	River
842	Case study	Tributary	Stream
843	Case study	Tributary	Headwaters
847	Case study	Tributary	River

887	Case study	Wetland	Estuary
889	Case study	Tributary	River
896	Case study	Tributary	River
903	Case study	Tributary	River
983	Case study	Reservoir	
984	Case study	Tributary	Stream
1029	Case study	Canal	
1034	Case study	Tributary	River
1042	Paired-catchment	Tributary	Headwaters
1050	Case study	Tributary	River
1063	Case study	Tributary	River
1066	Case study	Tributary	River
1074	Case study	Tributary	River
1080	Case study	Tributary	River
1085	Case study	Lake	
1115	Case study	Tributary	River
1145	Case study	Tributary	River
1151	Case study	Lake	
1240	Paired-catchment	Tributary	River
1287	Case study	Tributary	River
1297	Case study	Tributary	River
1307	Case study	Lake, Tributary	Loch, Headwaters
1324	Case study	Tributary	River
1339	Case study	Tributary	River
1372	Case study	Tributary	River
1418	Case Study	Wetland	
1438	Case Study	Lake	
1443	Case Study	Reservoir	
1479	Case Study	Tributary	River
1490	Case Study	Tributary	Stream
1512	Case Study	Tributary	River
1573	Case Study	Lake	
1576	Case Study	Tributary	River
1603	Case Study	Tributary	River
1618	Case Study	Lake	
1656	Case Study	Canal	Drainage network
1685	Case Study	Reservoir, Tributary	River
1691	Case Study	Reservoir	
1717	Case Study	Tributary	Stream
1718	Case Study	Tributary	Stream
1732	Case Study	Tributary	Stream
1754	Case Study	Tributary	River
1763	Case Study	Tributary	Headwaters
1784	Case Study	Tributary	Stream
1789	Case Study	Tributary	River
1795	Case Study	Coastal waters	Strait

1802	Case Study	Tributary	River
1824	Case Study	Tributary	River
1889	Case Study	Reservoir	
1895	Case Study	Tributary	Stream
1948	Case Study	Tributary	Headwaters
1964	Case Study	Tributary	River
1998	Case Study	Tributary	Stream
2012	Case Study	Tributary	River
2038	Case Study	Tributary	River
2091	Case Study	Tributary	River
2098	Case Study	Tributary	River
2105	Case Study	Tributary	River
2109	Case Study	Tributary	River
2129	Case Study	Wetland	
2132	Case Study	Tributary	River
2134	Case Study	Tributary	River
2152	Case Study	Tributary	River
2162	Case Study	Tributary	River
2164	Case Study	Lake	
2172	Case Study	Lake, Tributary	River
2203	Case Study	Tributary	River
2211	Case Study	Tributary	River
2213	Case Study	Tributary	River
2215	Case Study	Tributary	River
2219	Case Study	Lake, Tributary	River
2251	Case Study	Lake	
2254	Case Study	Tributary	River
2261	Case Study	Tributary	River
2262	Case Study	Tributary	River
2263	Case Study	Lake	
2265	Case Study	Tributary	River
2292	Case Study	Tributary	River
2295	Case Study	Lake	
2304	Case Study	Lake	
2307	Case Study	Tributary	River
2319	Case Study	Tributary	River
2349	Case Study	Tributary	River
2354	Case Study	Tributary	River
2381	Case Study	Tributary	River
2406	Case Study	Tributary	River
2440	Case Study	Tributary	River
2481	Case Study	Tributary	River
2486	Case Study	Tributary	River

Note. Studies classified as experimental employed the paired-catchment approach. Studies examining rivers, streams or headwaters were defined as ‘tributary’, estuaries were defined as ‘wetlands’.

Table A7. Spatial dimensions of land use for studies included in the systematic map database.

	Spatial dimension (Land use)					
ID	Spatial scale	Specific scale	# of sites	Total study area size (km2)	Size of sites (km2)	Spatial extent
20	Catchment		1	3,857.44	-	Macro
29	Multiple	Buffer, Catchment	2	-	6.903 – 18.023	Micro
32	Multiple	Buffer, Catchment	2	-	0.437 – 3.776	Micro
46	Multiple	Buffer, Catchment	1	550	-	Meso
54	Sub-Catchment		11	634,000	Not specified	Regional
55	Catchment		1	1,400	-	Macro
82	Sub-Catchment		14	9,866	Not specified	Macro
96	Multiple	Buffer, Catchment	1	1,800,000	-	Regional
97	Other	Counties	3	1,650	Not specified	Macro
114	Catchment		1	13,128.26	-	Macro
132	Other	Coastal zone	2	Not specified	Not specified	Not specified
139	Sub-Catchment		4	26,791.74	Not specified	Macro
149	Catchment		1	42,031		Macro
162	Multiple	Buffer, Sub-Catchment	1	Not specified	Not specified	Not specified
177	Multiple	Buffer, Other	1	1.098	-	Micro
209	Multiple	Buffer, Sub-Catchment, Catchment	3	Not specified	Not specified	Not specified
216	Catchment		1	82,427	-	Macro
218	Multiple	Buffer, Sub-Catchment, Catchment	1	41,485.65	-	Macro
227	Catchment		2	593.107	264.179-328.928	Meso
232	Not specified		1	4,268.67	-	Macro
309	Sub-Catchment		9	4,299	Not specified	Macro
320	Catchment		1	Not specified	-	Not specified
323	Catchment		12	965,800.02	Not specified	Regional
381	Catchment		1	1,216.58	-	Macro
408	Sub-Catchment		55	27,300	~350	Meso
427	Multiple	Catchment, Other (zones)	1	2,608	-	Meso
564	Multiple	Buffer, Sub-Catchment	3	71,060	17,439 - 30,308	Macro
587	Catchment		12	-	46.6 - 277.9	Meso
616	Sub-Catchment		1	-	82.85 - 7,079.23	Meso
685	Catchment		1	25,968	-	Macro
690	Catchment		3	-	327.5-	Meso

					6,870.8	
694	Catchment		3	-	0.168 - 1,800 (mean 67.98)	Meso
710	Catchment		1	117,966	41 - 16,427	Meso
743	Catchment		1	270,000	Not specified	Regional
759	Buffer	Multiple sizes	8	3,557	Not specified	Meso
766	Catchment		1	14,745	-	Macro
809	Buffer	Multiple sizes	1	726.72		Meso
812	Catchment		1	6,341	-	Meso
824	Sub-Catchment		5	-	6.222 - 64.806 (mean 19.4)	Meso
826	Catchment		12	4,349	18 - 353	Meso
841	Sub-Catchment		1	5,132	-	Meso
842	Sub-Catchment		5	Not specified	Not specified	Not specified
843	Catchment		7	61.52	Not specified	Meso
847	Sub-Catchment		4	13,100	Not specified	Macro
887	Catchment		4	6,500	822 - 3,192 (mean 1,003.5)	Meso
889	Sub-Catchment		4	1,580	85 - 456 (mean = 135.25)	Meso
896	Sub-Catchment		6	13,350	350 - 4,154 (mean = 750.66667)	Macro
903	Catchment		1	14,613.60	Not specified	Macro
983	Catchment		1	95,200	-	Macro
984	Multiple	Buffer, Catchment	2	Not specified	Not specified	Not specified
1029	Catchment		4		355.2 - 525.5 (mean = 220.175)	Meso
1034	Buffer		9	Not specified	Not specified	Not specified
1042	Catchment		2		0.13	Micro
1050	Multiple	Buffer, Catchment, Other (reach)	5		69.079 - 578.894 (mean =129.5946)	Meso
1063	Catchment		1	375,458	-	Regional
1066	Catchment		1		26 - 20,539 (mean 2,639)	Meso
1074	Buffer	Multiple sizes	1	Not specified	Not specified	Not specified
1080	Catchment		1	149.2	-	Meso
1085	Catchment		1	710	Not specified	Meso
1115	Sub-Catchment		7	670	Not specified	Meso
1145	Multiple	Buffer, Sub-Catchment	17	270,000	Not specified	Regional
1151	Catchment		1	Not specified	Not specified	Not specified
1240	Catchment		4	-	49.2 - 147.6 (mean =98.4)	Meso
1287	Other	Spatial zones	1	Not specified	Not specified	Not specified

1297	Other	Development zones	3	7,500	Not specified	Macro
1307	Catchment		5	9	Not specified	Micro
1324	Catchment		2	4,053	Not specified	Macro
1339	Catchment		4	5,063.90	Not specified	Macro
1372	Catchment		1	Not specified	-	Not specified
1418	Catchment		2	19,004	Not specified	Macro
1438	Buffer	Multiple sizes	1	10	-	Meso
1443	Sub-Catchment		2	34.5	16.17 - 18.33 (mean = 17.25	Meso
1479	Multiple	Buffer, Sub-Catchment	18	Not specified	Not specified	Not specified
1490	Catchment		1	2,205	-	Macro
1512	Catchment		31	85,383	Not specified	Macro
1573	Multiple	Buffer, Catchment	1	6,500	Not specified	Macro
1576	Catchment		2	5,172.50	Not specified	Macro
1603	Sub-Catchment		10	41,500	Not specified	Macro
1618	Sub-Catchment		4	-	19.2 - 54.8	Meso
1656	Catchment		2	-	0.634 - 1.398 (mean = 1.016)	Micro
1685	Catchment		1	550	-	Meso
1691	Multiple	Buffer, Catchment	3	481	Not specified	Meso
1717	Catchment		9	Not specified	Not specified	Not specified
1718	Sub-Catchment		11	14,700	Not specified	Macro
1732	Catchment		1	0.11	-	Micro
1754	Multiple	Buffer, Sub-Catchment, Catchment	3	-	3,387 - 4,588	Macro
1763	Catchment		1	6.697	-	Micro
1784	Sub-Catchment		3	39.51	Not specified	Meso
1789	Sub-Catchment		11	14,700	Not specified	Macro
1795	Not specified		11	Not specified	Not specified	Not specified
1802	Catchment		6	6,617	Not specified	Macro
1824	Catchment		ot specifi	5,790	Not specified	Meso
1889	Catchment		2	-	6,960 - 8,824	Macro
1895	Multiple	Buffer, Sub-Catchment, Catchment	1	Not specified	Not specified	Not specified
1948	Catchment		43	59,400	Not specified	Macro
1964	Catchment		1	27,633	-	Macro
1998	Sub-Catchment		3	32	11 - 21	Meso
2012	Catchment		1	34,284.47	-	Macro
2038	Other	Sub-region	5	-	5,350 - 16,411 (mean 10,152.8)	Macro
2091	Buffer	Multiple sizes	4	16,410	Not specified	Macro
2098	Multiple	Catchment, Other	1	238,348	-	Regional
2105	Catchment		1	357,089.50	-	Regional

2109	Sub-Catchment		1	39,075.30	-	Macro
2129	Other	Wetland boundary	1	222	-	Meso
2132	Catchment		7	5,400	92.968 - 1,453.503	Meso
2134	Catchment		3	-	181.72 - 933.388	Meso
2152	Sub-Catchment		6	-	Not specified	Not specified
2162	Sub-Catchment		16	426	Not specified	Meso
2164	Sub-Catchment		1	230	-	Meso
2172	Multiple	Buffer, Sub-Catchment, Catchment	9	Not specified	Not specified	Not specified
2203	Multiple	Buffer, Sub-Catchment	2	-	33.82 - 95.81	Meso
2211	Catchment		1	11,250	Not specified	Macro
2213	Buffer		1	2,200	-	Macro
2215	Multiple	Sub-catchment, Catchment	14	134	0.2- 121 (mean 11.94)	Meso
2219	Catchment		4	22,000	Not specified	Macro
2251	Catchment		1	150	-	Meso
2254	Catchment		1	49.2	-	Meso
2261	Catchment		1	5,597	-	Macro
2262	Catchment		3	Not specified	Not specified	Not specified
2263	Catchment		1	5.2906	Not specified	Micro
2265	Catchment		2	-	1,750 - 1,093	Macro
2292	Catchment		1	7,413.79	-	Macro
2295	Catchment		2	-	2.46 - 4.61	Micro
2304	Catchment		1	518	-	Meso
2307	Catchment		1	488	-	Meso
2319	Catchment		1	14,555.62	-	Macro
2349	Buffer		6	206.13	Not specified	Meso
2354	Catchment		1	23,170	-	Macro
2381	Catchment		1	5,560	-	Macro
2406	Catchment		1	15,360	-	Macro
2440	Catchment		1	Not specified	Not specified	Not specified
2481	Not specified		1	20.74	-	Meso
2486	Catchment		1	184.67	Not specified	Meso

Note. Areas listed as hectares, acres, or square miles were converted into square kilometers. Micro-scale (< 10 km2), Meso-scale (10–1,000 km2) Macro-scale (1,000–100,000 km2), Regional-scale (>100,000 km2). A 'watershed' or 'basin' was classified as a catchment, a "sub-watershed' or 'sub-basin' was classified as sub-catchments. Studies examining buffers at multiple scales were classified as buffers as opposed to mulitple.

Table A8. Temporal dimensions of land use for studies included in the systematic map database.

	Temporal dimension (Land use)				
ID	Start Year	Middle Year(s)	End Year	Change interval (years)	Time steps (#)
20	1988	2003	2018	30	3
29	1980		2017	37	2
32	1980		2017	37	2
46	2009		2019	10	2
54	2005	2010	2015	10	3
55	1995	2007, 2010, 2015,	2018	23	5
82	1985	1995, 2008	2019	34	4
96	2005	2010, 2015	2018	13	4
97	1960	1970, 1980, 1990, 2000	2010	50	6
114	2000		2020	20	2
132	1990	2000, 2010	2017	27	4
139	1992	2001, 2004, 2008, 2011	2016	24	6
149	2007		2015	8	2
162	2000		2010	10	2
177	1980		2017	37	2
209	2005	2008, 2011, 2014	2017	12	5
216	2000		2017	17	2
218	2002	2009	2015	13	3
227	1984	1994, 2004, 2009, 2014,	2019	35	6
232	2015		2020	5	2
309	1990	2006	2018	28	3
320	1984	1989, 1999, 2009,	2018	34	5
323	2005	2010	2015	10	3
381	1991	2007	2019	28	3
408	2004		2015	11	2
427	2000		2015	15	2
564	1995	2000, 2005	2010	15	4
587	1971	1982, 1983, 2000, 2001, 2002, 2009, 2010	2011	40	4
616	2010	2015	2018	8	3
685	1985		2015	30	2
690	2009		2013	4	2
694	1990		2010	20	2
710	1987	2001	2015	28	3
743	2000		2010	10	2
759	2009		2014	5	2
766	1990	1995, 2000, 2005, 2010	2015	25	6
809	1988	1993, 1998, 2003	2008	20	5
812	2007		2015	8	2
824	2004		2013	9	2
826	1994	2000, 2008	2011	17	4
841	2008		2014	6	2
842	1990	1995, 2000, 2005	2010	20	5
843	2009		2011	2	2

847	1984	2002	2013	29	3
887	1970	1996, 2001, 2006	2010	40	5
889	1980		2010	30	2
896	2000	2005, 2010	2015	15	4
903	2003		2009	6	2
983	2005	2010	2015	10	3
984	1984	1988, 1997, 1999, 2002	2010	26	6
1029	1988	1995, 1999, 2004	2009	21	5
1034	1977	1988, 2001	2010	33	4
1042	1995		2007	12	2
1050	2000	2005	2008	8	3
1063	2003		2007	4	2
1066	1996	2001, 2008	2012	16	4
1074	2005	2008	2013	8	3
1080	1979	1992, 1999	2009	30	4
1085	1,986	2001	2011	25	3
1115	2001	2009	2015	14	3
1145	2004		2009	5	2
1151	1972	1984, 2002	2011	39	4
1240	1960	1970, 1980, 1990, 2000	2010	50	6
1287	2000	2004	2008	8	3
1297	2000	2004	2008	8	3
1307	2011		2012	1	2
1324	2000		2008	8	2
1339	2000		2006	6	2
1372	1994	2000, 2005	2009	15	4
1418	1980	1990, 2000	2010	30	4
1438	1995		2006	11	2
1443	1990		2010	20	2
1479	2000		2005	5	2
1490	1976	1989, 2000	2006	30	4
1512	1986	1995, 2000	2005	19	4
1573	1986	1995, 1999, 2000, 2005	2008	22	6
1576	2000		2010	10	2
1603	1997		2008	11	2
1618	1998	2001	2006	8	3
1656	2011		2011	≤ 1	3
1685	1995		2005	10	2
1691	2001	2004, 2007	2010	9	4
1717	1976	1986	2000	24	3
1718	1996	2002	2007	11	3
1732	1997		1998	1	2
1754	1990	1998	2006	16	3
1763	1978		2009	31	2
1784	1981	1992, 2004	2007	26	4
1789	1996	2002	2007	11	3

1795	1991	2000, 2005	2008	17	4
1802	1996	2001	2006	10	3
1824	1954		2006	52	2
1889	1985		2000	15	2
1895	1977	1991	2000	23	3
1948	1974		2005	31	2
1964	1970	1985	2000	30	3
1998	1992	1994, 1996, 1999, 2001	2004	12	6
2012	1977	1996, 2000	2006	29	4
2038	1988		2002	14	2
2091	2000	2005	2010	10	3
2098	2001		2012	11	2
2105	2003	2013	2017	14	3
2109	2013	2014, 2015	2016	3	3
2129	2006	2014	2018	12	3
2132	2000	2010	2017	17	3
2134	1986	1995, 2001	2005	19	4
2152	1987	2000	2014	27	3
2162	2007	2013, 2014, 2015, 2017	2018	11	6
2164	1980	1990, 2000, 2010	2018	38	5
2172	2005	2008, 2011, 2014	2017	12	5
2203	1980	2006, 2010	2013	33	4
2211	1980	1995, 2005	2015	35	4
2213	2006	2010	2015	9	3
2215	2000	2002, 2004, 2006, 2008	2009	9	6
2219	1993	2000	2013	20	3
2251	2000		2010	10	2
2254	1992	2002	2009	17	3
2261	1986		2006	20	2
2262	2000		2017	17	2
2263	1981	2001	2011	30	3
2265	1974	1990, 1995, 2000	2007	33	5
2292	2011		2014	3	2
2295	1997		2009	12	2
2304	2005	2010, 2015	2019	14	4
2307	1991	1997	2017	26	3
2319	1990		2011	21	2
2349	1999		2015	16	2
2354	1997		2006	9	2
2381	1999	2009	2018	19	3
2406	1995	2005	2015	20	3
2440	1990		2006	16	2
2481	2004		2010	6	2
2486	1992	1996, 2001, 2006	2011	19	5

Table A9. Temporal dimensions of water quality for studies included in the systematic map database.

	Temporal dimension (Water quality)				
ID	Start Year	Middle Year(s)	End Year	Change interval (years)	Time steps (#)
20	1988	2003	2018	30	3
29	1980		2018	38	2
32	2018		2018	≤ 1	1
46	2017	2018	2019	2	3
54	2003		2017	14	2
55	1987	all years	2016	29	29
82	1985	1995, 2008	2019	34	34
96	2006	all years	2018	12	12
97	1987	all years	2018	31	31
114	2000	all years	2020	20	20
132	1990	2000, 2010	2017	27	4
139	1988	all years	2018	30	30
149	2007	all years	2016	9	9
162	2006	all years	2012	6	6
177	2002	2008	2018	16	3
209	2005	2008, 2011, 2014	2017	12	5
216	2000	all years	2017	17	17
218	2002	2009	2015	13	3
227	2017		2019	2	2
232	2016	all years	2020	4	4
309	1987	all years	2013	26	26
320	1969	all years until 1999	2017	48	31
323	2005	2010	2015	10	3
381	1991	all years	2019	28	28
408	2004		2015	11	2
427	2000	all years	2015	15	15
564	1995	all years	2010	15	15
587	1970	all years	2010	40	40
616	2009	all years	2017	8	8
685	1985		2015	30	2
690	2009	all years	2015	6	6
694	1989	all years	2010	21	20
710	1987	2001	2015	28	3
743	2003	all years	2010	7	7
759	2009	all years	2014	5	5
766	2005	all years	2015	10	10
809	1988	1989–1990, 1992–1994, 1997–1999, 2002–2004, 2006–2008	2008	20	10
812	2007	all years	2015	8	8
824	2014		2014	≤ 1	1
826	1987	all years	2013	26	27

841	2000	all years	2014	14	14
842	1990	all years	2010	20	20
843	2009		2010	1	2
847	1984	2002	2013	29	3
887	1974	all years	2011	37	37
889	1980	all years	2010	30	30
896	2000	2005, 2010	2015	15	15
903	2008	all years	2013	5	5
983	2005	all years	2014	9	9
984	Not specified		Not specified	Not specified	Not specified
1029	1979	all years	2014	35	35
1034	1980	all years	2010	30	30
1042	2011		2012	1	2
1050	2000	all years	2008	8	8
1063	1998	all years	2006	8	9
1066	1989	all years	2014	25	26
1074	2005	2008	2013	8	3
1080	1979	all years	2009	30	30
1085	1,986		2011	25	2
1115	2001	2009	2015	14	3
1145	2000	all years	2014	14	9
1151	1983	all years	2011	28	28
1240	1980	all years	2010	30	30
1287	2000	2004	2008	8	3
1297	2000	2004	2008	8	3
1307	2011		2012	1	2
1324	2000		2008	8	2
1339	2000		2006	6	2
1372	2000	all years	2012	12	12
1418	2010		2010	≤ 1	1
1438	1995	all years	2006	11	11
1443	1990	all years	2010	20	30
1479	1994	all years	2005	11	11
1490	1976	1989, 2000	2006	30	30
1512	1998	all years	2008	10	10
1573	1986	1995, 1999, 2000, 2005	2008	22	6
1576	2000		2010	10	2
1603	1997	all years	2008	11	11
1618	2008	all years	2009	1	2
1656	2011		2011	≤ 1	1
1685	1997	all years	2005	8	8
1691	2001	all years	2010	9	10
1717	1971	all years	2002	31	31
1718	1996	all years	2007	11	11
1732	1997	all years	2002	5	5
1754	1989	1990, 1991, 1997, 1998, 1999, 2005, 2006	2007	18	9

1763	2007	all years	2010	3	3
1784	Not specified		Not specified	Not specified	1
1789	1996	2002	2007	11	3
1795	1991	2006	2009	18	3
1802	1996	all years	2006	10	10
1824	2009	all years	2010	1	2
1889	1980	1985, 1990, 1995, 2000	2005	25	6
1895	1977	all years	2000	23	13
1948	1970	all years	2009	39	39
1964	1970	1985	2000	30	30
1998	1991	all years	2006	15	15
2012	1977	1996, 2000	2006	29	4
2038	1988		2002	14	2
2091	2000	all years	2010	10	10
2098	2001	all years	2012	11	11
2105	2007	all years	2017	10	10
2109	2013	all years	2016	3	3
2129	2014	all years	2018	4	4
2132	2000	2010	2017	17	3
2134	Not specified		Not specified	Not specified	Not specified
2152	1994	all years	2014	20	20
2162	2007	all years	2018	11	11
2164	1990	all years	2018	28	28
2172	2005	all years	2017	12	12
2203	1980	all years	2013	33	33
2211	1980	1995, 2005	2015	35	4
2213	2006	2010	2015	9	3
2215	2007	all years	2013	6	6
2219	1996	all years	2013	17	13
2251	2017		2017	≤ 1	2 months
2254	Not specified		Not specified	Not specified	Not specified
2261	1986	all years	2006	20	20
2262	2000	all years	2017	17	17
2263	1981	2001	2011	30	30
2265	1974	all years	2007	33	34
2292	2011		2014	3	2
2295	2009		2010	1	1
2304	2005	all years	2019	14	13
2307	1991	1997, 2005, 2011, 2014	2017	26	6
2319	1984	1990, 1993, 1994, 2002, 2011	2012	28	6
2349	1999	all years	2015	16	16
2354	1997		2006	9	2
2381	2017		2018	1	1
2406	1995	2000, 2005, 2010	2015	20	5
2440	1994	all years	2006	12	12
2481	2004		2010	6	Not specified

2486	1992		2011	19	19

Table A10. Data collection and processing for studies included in the systematic map database.

	Data collection and processing						
ID	**Land use measure**	**Specific measure**	**Water quality data source**	**Pollutant measure**	**Index or standard**	**# of sites**	**# of samples**
20	Area	% and km2	Monitoring	Concentrations	Water quality index	4	Not specified
29	Area	% and ha	Monitoring	Concentrations	Trophic state index	9	Not specified
32	Area	% and ha	Monitoring	Concentrations	Trophic state index	5	Not specified
46	Pattern and Area	%	Modeling	Concentrations	National standards	2	Not specified
54	Area	%	Monitoring	Concentrations	None	11	Not specified
55	Pattern and Area	%	Monitoring	Concentrations	None	52	Specified
82	Area	% and km2	Modeling	Concentrations	Water quality index	3	
96	Area	%	Monitoring	Concentrations	Water quality index	18	Not specified
97	Other	Volume (million m³ sk)	Monitoring	Concentrations	None	9	Not specified
114	Area	km2	Monitoring	Concentrations	Water quality grade/class	7	Not specified
132	Area	%	Estimates from remote sensing	Concentrations	None	2	
139	Area	%	Modeling	Concentrations	None		
149	Area	km2	Monitoring	Concentrations	None	68	Specified (1999)
162	Pattern and Area	%	Monitoring	Concentrations	National standards	24	Not specified
177	Area	ha	Monitoring	Concentrations	Water quality index, Trophic state index	8	Specified (768)
209	Pattern		Monitoring	Concentrations	None	9	Not specified
216	Area	% and km2	Monitoring	Concentrations	Water quality index	32	Not specified
218	Area	km2	Monitoring	Concentrations	None	7	Not specified
227	Area	km2	Monitoring	Concentrations	Pollution index	9	Specified (181)
232	Area	km2	Monitoring	Concentrations	Pollution index, Water quality index	5	Not specified
309	Area	%	Estimates	Loads	None	9	

			from remote sensing				
320	Area	%	Monitoring	Concentrations	Pollution index	4	Specified (12)
323	Area	% and km2	Monitoring	Concentrations	None	12	Not specified
381	Area	%	Monitoring	Concentrations	None	2	Not specified
408	Pattern and Area	%	Modeling	Loads	None	9	
427	Area	km2	Modeling	Exports	None		
564	Area	% and km2	Monitoring	Concentrations	National standards	18	Not specified
587	Area	%	Monitoring	Concentrations	None	12	Not specified
616	Pattern and Area	%	Monitoring	Concentrations	National standards	45	Not specified
685	Area	% and km2	Estimates from monitoring	Concentrations	None		
690	Pattern and Area	%	Monitoring	Concentrations	National standards	3	Not specified
694	Area	%	Monitoring	Concentrations	None	Not specified	Not specified
710	Area	% and km2	Monitoring	Concentrations	None	18	Not specified
743	Pattern and Area	%	Monitoring	Concentrations	None	31	Not specified
759	Pattern and Area	%	Monitoring	Concentrations	None	8	Not specified
766	Pattern and Area	%	Monitoring	Concentrations	None	2	Not specified
809	Pattern and Area	%	Monitoring	Concentrations	None	34	Not specified
812	Other	Urbanization values	Monitoring	Concentrations	National standards	53	Not specified
824	Area	% and ha	Monitoring	Concentrations	National standards, Global guidelines (WHO)	5	Not specified
826	Area	% and km2	Monitoring	Concentrations	None	9	Not specified
841	Area	% and acres	Estimates from monitoring	Fluxes	None		
842	Pattern and Area	%	Monitoring	Concentrations	National standards	27	Not specified
843	Area	% and km2	Estimates from monitoring	Loads	National standards	7	
847	Area	% and km2	Estimates from monitoring	Loads	None		
887	Area	%	Monitoring	Concentrations	None	60	Not

							specified
889	Area	%	Estimates from monitoring	Loads	National standards	1-6	
896	Pattern		Modeling	Loads	Water quality grade/class		
903	Area	% and km2	Modeling	Concentrations	National standards	1-13	Not specified
983	Area	% and km2	Monitoring	Concentrations	Water quality grade/class	20	Not specified
984	Area	acres	Monitoring	Concentrations	None	7	Specified (21)
1029	Area	%	Monitoring	Concentrations	None	4	Not specified
1034	Area	km2	Monitoring	Concentrations	National standards	Not specified	Not specified
1042	Area	%	Monitoring	Concentrations	None	2	Not specified
1050	Pattern and Area	% and ha	Monitoring	Concentrations	National standards	5	Not specified
1063	Area	% and km2	Monitoring	Concentrations	None	4	Not specified
1066	Area	%	Monitoring	Concentrations	National standards	77	Not specified
1074	Pattern		Monitoring	Concentrations	Water quality grade/class	39	Not specified
1080	Area	%	Modeling	Loads	None		
1085	Pattern and Area	% and ha	Modeling	Concentrations	None	38	
1115	Area	% and km2	Monitoring	Concentrations	None	9	Not specified
1145	Area	%	Monitoring	Concentrations	None	17	Not specified
1151	Pattern and Area	%	Monitoring	Concentrations	None	4	Not specified
1240	Area	Grid-cells	Monitoring	Concentrations	None	4	Not specified
1287	Pattern and Area	%	Monitoring	Concentrations	National standards	18	Not specified
1297	Pattern and Area	%	Monitoring	Concentrations	National standards	18	Not specified
1307	Area	km2	Monitoring	Concentrations	None	13	Not specified
1324	Area	%	Monitoring	Concentrations	Pollution index	33	Not specified
1339	Area	%	Monitoring	Concentrations	None	4	Not specified
1372	Area	%	Monitoring	Concentrations	National standards	12	Not specified
1418	Pattern and Area	ha	Monitoring	Concentrations	Trophic state index	344	Specified (12)
1438	Pattern and Area	%	Monitoring	Concentrations	National standards	5	Not specified
1443	Area	% and ha	Monitoring	Concentrations	None	2	Not specified

1479	Area	%	Monitoring	Concentrations	National standards	18	Not specified
1490	Pattern and Area	% and km2	Modeling	Concentrations	None		
1512	Area	km2	Monitoring	Concentrations	National standards, Pollution index	31	Not specified
1573	Area	%	Estimates from remote sensing	Concentrations	None	40	
1576	Area	km2	Modeling	Concentrations	Pollution index	2	Not specified
1603	Pattern and Area	%	Monitoring	Concentrations	None	10	Not specified
1618	Pattern and Area	%	Monitoring	Concentrations	Management targets	4	Not specified
1656	Area	%	Estimates from monitoring	Loads	None	2	
1685	Area	%	Monitoring	Concentrations	None	7	Not specified
1691	Area	%	Monitoring	Concentrations	None	3	Not specified
1717	Area	%	Monitoring	Concentrations	Stream habitat score	9	Specified (55)
1718	Pattern and Area	%	Monitoring	Concentrations	None	11	Not specified
1732	Other	Type (full conversion)	Monitoring	Concentrations	None	1	Specified (102)
1754	Pattern and Area	%	Monitoring	Concentrations	None	3	Not specified
1763	Pattern and Area	ha	Monitoring	Concentrations	None	6	Not specified
1784	Area	ha	Monitoring	Concentrations	None	3	Specified (3 for each parameter)
1789	Pattern and Area	%	Monitoring	Concentrations	None	11	Not specified
1795	Not specified		Monitoring	Concentrations	National standards	11	Specified (3)
1802	Area	%	Monitoring	Concentrations	None	4	Specified (510)
1824	Area	ha	Monitoring	Concentrations	National standards	17	Not specified
1889	Area	% and km2	Modeling	Loads	None	8	Not specified
1895	Area	%	Monitoring	Concentrations	None	55	Specified
1948	Area	%	Monitoring	Concentrations	None	43	Not specified
1964	Area	%	Modeling	Loads	None		
1998	Area	%	Estimates from monitoring	Loads	None	3	
2012	Pattern	ha	Modeling	Loads	None		

	and Area						
2038	Area	ha	Monitoring	Concentrations	None	Not specified	Not specified
2091	Area	% and km2	Monitoring	Concentrations	None	13	Not specified
2098	Area	%	Monitoring	Concentrations	Pollution index	5	Not specified
2105	Area	% and ha	Monitoring	Concentrations	None	Not specified	Not specified
2109	Area	% and km2	Monitoring	Concentrations	Water quality index, Water ecological index	7	Not specified
2129	Area	% and ha	Monitoring	Concentrations	None	14	Not specified
2132	Area	% and ha	Monitoring	Concentrations	Water quality index	7	Not specified
2134	Area	km2	Monitoring	Concentrations	National standards	12	Not specified
2152	Area	%	Monitoring	Concentrations	Global guidelines (WHO)	6	Not specified
2162	Area	%	Monitoring	Concentrations	Water quality grade/class	500	Specified (500)
2164	Area	% and km2	Monitoring	Concentrations	None	Not specified	Not specified
2172	Area	%	Monitoring	Concentrations	Water quality index	17	Specified (45)
2203	Area	% and ha	Monitoring	Concentrations	National standards	2	Not specified
2211	Area	%	Modeling	Loads	None	20	
2213	Area	%	Estimates from monitoring	Concentrations	Water quality index	9	
2215	Area	%	Estimates from monitoring	Loads	None	6	
2219	Area	% and km2	Monitoring	Concentrations	Water quality index	Not specified	Not specified
2251	Area	km2	Monitoring	Concentrations	Water quality index, Global guidelines (WHO)	10	Specified (20)
2254	Area	% and km2	Monitoring	Concentrations	None	5	Not specified
2261	Area	% and km2	Monitoring	Concentrations	None	9	Not specified
2262	Area	%	Monitoring	Concentrations	None	25	Specified (100-297)
2263	Area	% and ha	Monitoring	Concentrations	None	4	Not specified
2265	Area	%	Monitoring	Concentrations	National standards	12	Not specified
2292	Area	% and ha	Monitoring	Concentrations	Water quality grade/class	8	Not specified

2295	Area	ha	Monitoring	Concentrations	None	2	Not specified
2304	Area	%	Monitoring	Concentrations	Water quality index	Not specified	Not specified
2307	Area	% and km2	Monitoring	Concentrations	Pollution index, Water quality index	6	Not specified
2319	Area	% and km2	Monitoring	Concentrations	None	Not specified	Not specified
2349	Area	%	Monitoring	Concentrations	Water quality index	6	Not specified
2354	Area	% and km2	Monitoring	Concentrations	None	19	Specified (76)
2381	Area	ha	Monitoring	Concentrations	Global guidelines (WHO)	4	Specified (72)
2406	Area	% and km2	Monitoring	Concentrations	Water quality index	Not specified	Not specified
2440	Area	%	Monitoring	Concentrations	Water quality index	Not specified	Not specified
2481	Area	acres	Monitoring	Concentrations	National standards	13	Not specified
2486	Area	%	Monitoring	Concentrations	None	45	Not specified

Table A11. Seasonal and spatial considerations for studies included in the systematic map database.

	Seasonal consideration		Spatial considerations		
ID	**Variation in water quality**	**Seasons**	**Spatial considerations (Yes or No)**	**Land use**	**Water quality**
20	No		No		
29	Yes	4 seasons	Yes- WQ	Multiple spatial scales	Distribution maps
32	Yes	4 seasons	Yes- WQ	Multiple spatial scales	Distribution maps
46	No		Yes- LU and WQ	Multiple spatial scales	Distribution maps
54	Yes	Wet and dry seasons	Yes- LU and WQ	Pattern	One-way ANOVA, Cluster analysis
55	No		Yes- LU	Pattern change	
82	No		Yes- LU	Distribution maps	
96	Yes	Wet and dry seasons	Yes- LU	Multiple spatial scales	
97	Yes	4 seasons	No		
114	No		Yes- LU	Distribution maps	
132	No		Yes- WQ		Distribution maps
139	No		Yes- LU		
149	Yes	4 seasons	No		
162	No		Yes- LU	Multiple spatial scales,	

				Pattern change	
177	Yes	4 seasons	Yes- WQ	Multiple spatial scales	Distribution maps, Cluster analysis
209	No		Yes- LU	Multiple spatial scales, Pattern change	
216	Yes	4 seasons	Yes- WQ		Cluster analysis
218	No		Yes- LU	Multiple spatial scales	
227	Yes	2 seasons (Summer and fall)	Yes- WQ		Comparison between the upstream and downstream continuum
232	No		Yes- WQ		Comparison between the upstream and downstream continuum
309	No		Yes- LU	Distribution maps	
320	Yes	2 seasons (Summer and fall)	Yes- WQ		Comparison between the upstream and downstream continuum
323	No		No		
381	Yes	Wet and dry years	No		
408	No		Yes- LU and WQ	Pattern change	Distribution maps
427	No		Yes- LU and WQ	Multiple spatial scales	Distribution maps
564	Yes	Wet and dry seasons	Yes- LU and WQ	Multiple spatial scales	Cluster analysis, Comparison between the upstream and downstream continuum
587	Yes	2 seasons (Growing and dormant)	No		
616	Yes	Wet and dry seasons	Yes- LU and WQ	Pattern	Global and local Moran's I
685	Yes	Not specified	Yes- LU and WQ	Distribution maps	Distribution maps
690	Yes	4 seasons	Yes- LU	Pattern change	One-way ANOVA
694	No		No		
710	No		No		
743	Yes	Wet and dry seasons	Yes- LU and WQ	Pattern	Comparison between the upstream and downstream continuum
759	No		Yes- LU and WQ	Pattern change	Comparison between the upstream and downstream continuum
766	No		Yes- LU	Pattern change	
809	No		Yes- LU	Pattern change	
812	Yes	4 seasons	Yes- LU and WQ	Distribution maps	Distribution maps
824	No		No		
826	Yes	Wet and dry seasons	Yes- WQ		Comparison between the upstream and downstream continuum

841	Yes	2 seasons (Fall/Winter, Spring)	No		
842	No		Yes- LU and WQ	Pattern change	Cluster analysis
843	Yes	Wet and dry seasons	No		
847	No		Yes- WQ		One-way ANOVA
887	Yes	4 seasons	No		
889	No		No		
896	No		Yes- LU and WQ	Pattern change, Distribution maps	Distribution maps
903	Yes	Wet and dry seasons	No		
983	Yes	Wet and dry seasons	Yes- WQ		Comparison between the upstream and downstream continuum
984	No		Yes- LU and WQ	Multiple spatial scales, Distribution maps	Comparison between the upstream and downstream continuum
1029	Yes	Wet and dry seasons	No		
1034	No		Yes- WQ		Comparison between the upstream and downstream continuum
1042	Yes	Wet and dry seasons	No		
1050	Yes	Wet and dry seasons	Yes- LU	Multiple spatial scales, Pattern	One-way ANOVA
1063	No		Yes- WQ		Comparison between the upstream and downstream continuum
1066	No		No		
1074	No		Yes- LU		
1080	No		Yes- WQ	Distribution maps	
1085	No		Yes- LU and WQ	Pattern change	Distribution maps
1115	No		Yes- WQ		Cluster analysis
1145	No		Yes- LU and WQ	Multiple spatial scales	Global and local Moran's I, Distribution maps
1151	No		Yes- LU	Pattern change	
1240	Yes	2 seasons (Winter and summer)	No		
1287	No		Yes- LU	Pattern change	
1297	No		Yes- LU	Pattern change	
1307	Yes	Not specified	No		

1324	No		Yes- LU	Distance (via weighting scheme)	
1339	No		Yes- LU and WQ		Cluster analysis
1372	No		No		
1418	No		Yes- LU and WQ	Pattern change	Distribution maps
1438	No		Yes- LU	Pattern change	
1443	No		No		
1479	Yes	Wet and dry seasons	Yes- LU and WQ	Multiple spatial scales	Global and local Moran’s I
1490	No		Yes- LU and WQ	Pattern change	Distribution maps
1512	Yes	High and low flow periods	Yes- WQ		Comparison between the upstream and downstream continuum
1573	No (Summer only)		Yes- LU	Multiple spatial scales	
1576	No		Yes- LU and WQ	Distribution maps	Distribution maps
1603	No		Yes- LU	Pattern change	
1618	No		Yes- LU	Pattern, Distribution maps	Helmert contrasts, ANOVA
1656	No		No		
1685	Yes	2 seasons (Winter and summer)	Yes- LU	Distribution maps	
1691	No		Yes- LU and WQ	Multiple spatial scales	
1717	No		Yes- LU	Distance (via weighting scheme)	
1718	Yes	Wet and dry years	Yes- LU	Pattern change	
1732	No		No		
1754	No (Dry season only)		Yes- LU and WQ	Multiple spatial scales, Pattern change	One-way ANOVA
1763	Yes	4 seasons	No		
1784	No		No		
1789	Yes	Wet and dry years	Yes- LU	Pattern change	
1795	No		No		
1802	No		Yes- WQ		
1824	No		No		
1889	No		No		
1895	No		Yes- LU	Multiple spatial scales	
1948	No		No		
1964	No		No		
1998	No		Yes- LU	Distribution maps	

2012	No		Yes- LU and WQ	Pattern change	Distribution maps
2038	No		No		
2091	No		Yes- LU and WQ		One-way ANOVA
2098	Yes	Pre Monsoon, monsoon, post monsoon	Yes- LU and WQ	Multiple spatial scales	Distribution maps
2105	No		No		
2109	Yes	2 seasons (Winter and summer)	Yes- WQ		One-way ANOVA
2129	No		Yes- WQ		Distribution maps
2132	No		Yes- WQ		Cluster analysis, Comparison between the upstream and downstream continuum
2134	No		No		
2152	No		Yes- WQ		One-way ANOVA
2162	Yes	Wet and dry seasons	Yes- LU and WQ	Distance (via weighting scheme)	Comparison between the Upstream and downstream continuum, Distance (via weighting scheme)
2164	No		No		
2172	No		Yes- LU	Multiple spatial scales	
2203	Yes	Wet and dry years	Yes- LU and WQ	Multiple spatial scales	
2211	No		Yes- WQ		Distribution maps
2213	No		Yes- LU and WQ		
2215	No		Yes- LU	Multiple spatial scales	
2219	No		No		
2251	Yes	2 seasons (Winter and summer)	No		
2254	No		No		
2261	No		No		
2262	Yes	Wet and dry seasons	No		
2263	No		No		
2265	No		No		
2292	No		No		
2295	Yes	4 seasons	Yes- WQ		Two-way ANOVA
2304	No		No		
2307	No (Dry season only)		Yes- WQ		Comparison between the upstream and downstream continuum

2319	Yes	2 seasons (Autumn and winter)	Yes- WQ		One-way ANOVA
2349	Yes	Wet and dry seasons	Yes- WQ		Distribution maps
2354	No (Winter only)		No		
2381	Yes	Wet and dry seasons	Yes- WQ		Distribution maps
2406	No		No		
2440	No		No		
2481	No		Yes- LU	Distribution maps	
2486	Yes	4 seasons	Yes- LU		Global Moran's Index, Local Indicator of Spatial Association (LISA)

Note. LU= land use; WQ= water quality.

Table A12. Independent variables examined within studies included in the systematic map database.

	Independent variables					
ID	**Climate**	**Hydrology**	**Management**	**Socio-economic**	**Soil**	**Topography**
20						
29						
32						
46						
54						
55						
82						
96						
97	Air temperature, Precipitation	Discharge		Sewage (discharge)		
114						
132						
139	Precipitation				Sediment yield	Runoff
149						
162						
177						
209						
216						
218						
227						
232	Air					

	temperature, Rainfall					
309					Soil loss, Erosion (power)	Slope, Flow accumulation
320						
323						
381						
408						
427						
564						
587						
616						
685				Housing, Population		
690		Discharge, Water level, Water temperature				
694	Rainfall					Regional conditions
710						
743						
759						
766						
809						
812						
824						
826						
841	Precipitation, Growing degree days		Irrigation			
842						
843	Rainfall	Discharge				
847						
887	Precipitation, Wind stress					
889			Management changes (sowing and yielding of crops), Fertilizer application	Livestock population, Livestock density, Population density, Sewage usage		
896						
903						
983			Fertilizer application	Sewage (discharge)		
984						
1029	Rainfall	Discharge				
1034						

1042						
1050						
1063						
1066	Precipitation, Air temperature, Sunshine	Discharge, Water storage	Fertilizer application	Livestock density	Soil properties, Land disturbance	Area, Ruggedness, Slope
1074						Landform Type
1080					Soil properties	
1085						
1115						
1145		Water temperature, Discharge				Elevation, Slope
1151	Air temperature, Aridity index, Evapotranspiration, Precipitation					
1240	Rainfall					
1287						
1297						
1307	Air temperature, Rainfall	Water table depth				
1324			Management changes	Industrial zones, Urbanization level		
1339						
1372	Rainfall, Evaporation	Discharge				
1418						
1438						
1443			Fertilizer application, Erosion control			
1479		Discharge, Water temperature		Point source emission		
1490						
1512	Rainfall	Discharge				
1573						
1576						
1603						
1618				Aquaculture (salmon farming)		
1656	Rainfall					
1685						

1691						
1717						Slope
1718						
1732			Fertilizer application			
1754				Population, Gross domestic product (GDP)		
1763						
1784						Basin shape, Slope
1789						
1795						
1802						
1824	Air temperature, Rainfall					
1889	Precipitation, Air temperature					
1895	Precipitation	Discharge				
1948						
1964						
1998	Precipitation		Management changes			
2012						
2038		Discharge			Erosion (patterns)	
2091						
2098				Population growth		
2105						
2109				Gross Domestic Product, Urbanization rate		
2129						
2132						
2134						
2152				Population growth		Elevation, Slope
2162				Population growth		
2164						
2172						
2203	Rainfall					
2211						
2213						
2215						Runoff
2219						
2251						
2254						

2261	Air temperature, Precipitation			Sewage (discharge)		
2262				Population density		
2263				Solid waste		
2265						
2292						
2295						
2304				Economic growth, Population growth		
2307						
2319		Discharge				
2349					Soil type	Slope
2354						
2381						
2406						
2440		Water sufficiency			Erosion (status), Cation exchange capacity, Soil texture, Soil water holding capacity	
2481						
2486						

Note. The term 'discharge' was used for water flow, streamflow or river flow.

Table A13. Response variables examined within studies included in the systematic map database.

	Response variables				
ID	**Climate**	**Hydrology**	**Soil**	**Topography**	**Other**
20	Air temperature, Rainfall	Water quantity			
29		Wetland depth		Wetland area	
32		Wetland depth		Wetland area	
46					
54					
55					
82	Evapotranspiration	Groundwater flow	Soil water	Runoff	
96					
97		Residence time			
114					
132					

139					
149					
162					
177				Wetland area	
209					
216					
218					
227		Discharge	Soil concentrations		
232					
309		Discharge	Sediment load		
320			Soil concentrations		
323					
381	Rainfall	Discharge			
408		Water yield			
427		Water yield	Soil retention		Carbon storage
564			Chemical flux (loading rate)		
587					
616					
685					
690					
694					
710					
743					
759					
766					
809					
812					Wastewater discharge
824		Water depth			
826					
841					
842					
843			Sediment exports		
847					
887					
889					
896					
903		Discharge	Sediment yield		
983					
984		Discharge	Sediment concentrations		
1029					
1034					Ecosystem services
1042					
1050					
1063					

1066					
1074					
1080					
1085					
1115					
1145					
1151		Water level			
1240		Water quantity			
1287					
1297					
1307					Groundwater quality
1324					
1339					
1372					
1418					
1438					
1443					
1479					
1490					
1512					
1573					
1576					
1603					
1618		Discharge	Sediment concentrations		
1656				Runoff	
1685			Soil loss		
1691					
1717					Aquatic organisms (Benthic macroinvertebrate species richness)
1718					
1732					
1754		Discharge			
1763	Rainfall	Discharge	Sediment yield		
1784			Sedimentation production rate		
1789				Runoff	
1795					
1802					
1824		Groundwater recharge, Discharge			
1889		Discharge	Sediment load		
1895					
1948					
1964					Economic loss (treatment costs)

1998			Sediment load		
2012			Sediment load		
2038					
2091					
2098					
2105					
2109					Aquatic organisms (Phytoplankton, Zooplankton, Zoobenthos)
2129				Wetland area	
2132					
2134			Sediment properties		Industrial wastewater
2152					
2162					
2164					
2172					
2203		Discharge			
2211		Discharge	Sediment discharge		
2213					
2215					Groundwater quality
2219					
2251					
2254					
2261					
2262					
2263					
2265		Discharge			
2292					
2295				Water spread area	
2304					
2307		Discharge			
2319					
2349					
2354					
2381					
2406					
2440		Water quantity			
2481					
2486					

Note. The term 'discharge' was used for water flow, streamflow or river flow.

Table A14. Analysis of temporal changes in land use and water quality for studies included in the systematic map database.

	Analysis of Temporal Changes	
ID	**Change detection measure of land use data**	**Temporal trend of water quality data**
20	Absolute change	Visualized
29	Absolute change	Compared with reference values
32	Absolute change	None
46	Change in landscape metrics	None
54	Absolute change	Visualized
55	Change in landscape metrics	Visualized
82	Absolute change	Visualized
96	Growth rate	Mann–Kendall trend test
97	Relative change	Visualized
114	Land use change index	Visualized
132	Growth rate	Visualized
139	Absolute change	None
149	Urbanization index	Linear regression
162	Change in landscape metrics	None
177	Absolute change, Relative change	Compared with reference values
209	Change in landscape metrics	Visualized
216	Absolute change	Mann–Kendall trend test, Seasonal Mann–Kendall test, Spearman's Rank correlation
218	Absolute change	Visualized
227	Relative change	ANOVA, Tukey’s multiple range test
232	Absolute change	Visualized
309	Absolute change	Visualized
320	NDVI index	ANOVA, Tukey’s multiple range test
323	Rate of change	Visualized
381	Absolute change	Mann–Kendall trend test
408	Absolute change, Change in landscape metrics	Visualized
427	Absolute change	Visualized
564	Absolute change	Shown in table
587	Absolute change	Kruskal-Wallis rank sum test, Dunn post-hoc test
616	Growth rate	Seasonal Mann-Kendall’s test
685	Absolute change	Visualized
690	Change rate in NDVI	Mann-Kendall trend test (for spatial-temporal change)
694	Absolute change	Linear regression
710	Absolute change	Mann-Kendall, Seasonal Kendall or Linear regression
743	Net changes (change matrix)	Seasonal Mann-Kendall test, Kendall’s S, One-way ANOVA
759	Absolute change, Change in landscape metrics	One-way ANOVA
766	Absolute change, Transition matrix, Change in landscape metrics	Visualized
809	Change in landscape metrics	One-way ANOVA
812	Urbanization index	Visualized
824	Absolute change, Relative change	None
826	Absolute change	Visualized

841	Absolute change	Visualized
842	Change in landscape metrics	Visualized (box plots)
843	Absolute change	Shown in table
847	Absolute change	Visualized
887	Absolute change	Mann–Kendall trend test
889	Absolute change	Visualized
896	Change in landscape metrics	Visualized
903	Absolute change	Visualized
983	Absolute change	Visualized
984	NDVI index	None
1029	Absolute change	LOESS (LOcally weighted regrESSion)
1034	Absolute change	Levene's test of homogeneity of variances, ANOVA, Kruskal-Wallis tests, Tukey post hoc tests (spatial-temporal changes)
1042	Absolute change	None
1050	Absolute change	None
1063	Relative change, Rate of change	None
1066	Absolute change	Seasonal Kendall test
1074	Absolute change	Compared with reference values
1080	Absolute change	Visualized
1085	Absolute change, Change in landscape metrics, Change rate	Visualized
1115	Absolute change, Relative change	None
1145	Absolute change	Seasonal Mann–Kendall test
1151	Relative change, Change rate, Change in landscape metrics	Visualized
1240	Index of urban extent (URBEXT)	Regression models
1287	Absolute change, Change in landscape metrics	Visualized
1297	Absolute change, Change in landscape metrics	None
1307	Absolute change	Visualized
1324	Land change intensity index	Water change intensity index
1339	Absolute change, Change rate, Rate of change	Visualized
1372	Absolute change	Shown in table
1418	Absolute change, Change in landscape metrics	None
1438	Absolute change, Change in landscape metrics	Visualized
1443	Absolute change	Linear regression, Visualized
1479	Absolute change	Seasonal Mann–Kendall test
1490	Absolute change, Change in landscape metrics	Visualized
1512	Linear interpolation	Visualized
1573	Absolute change	Multi-variate regression
1576	Absolute change	Visualized
1603	Absolute change, Change in landscape metrics	Percent change
1618	Absolute change	None
1656	Absolute change	Visualized
1685	Absolute change	Seasonal Kendall test
1691	Absolute change	Visualized
1717	Not specified	None

1718	Absolute change, Change in landscape metrics	One-way ANOVA
1732	Absolute change	Visualized
1754	None	T-test
1763	Absolute change	None
1784	Absolute change	None
1789	None	None
1795	Absolute change	Visualized
1802	Absolute change	Linear regression (spatial-temporal change)
1824	Absolute change	None
1889	Absolute change	Visualized
1895	Absolute change	None
1948	Absolute change	Simple linear bivariate regression, Scatter plot of time series data
1964	Absolute change	Shown in table
1998	Absolute change, Transition matrix	Straight line regression
2012	Absolute change, Change in landscape metrics	Shown in table
2038	Absolute change	Visualized
2091	Absolute change	Paired t-tests
2098	Relative change, Net changes (change matrix)	Mann–Kendall rank test
2105	Absolute change, Rate of change	ANOVA, Visualized
2109	Absolute change, Transition matrix	Visualized
2129	Absolute change, Rate of change	Shown in table
2132	Absolute change	Visualized
2134	Absolute change	None
2152	Absolute change	Mann-Kendall trend test
2162	Absolute change	None
2164	Absolute change, Relative change	Shown in table
2172	Absolute change	None
2203	Absolute change	Seasonal Mann-Kendall trend test, Line chart of temporal data
2211	Absolute change	Shown in table
2213	Absolute change	Shown in table
2215	Absolute change	Regression analysis, Mann–Kendall test, Line chart of temporal data
2219	Absolute change, Relative change, Transition matrix	None
2251	Absolute change	None
2254	Relative change	None
2261	Relative change	Visualized
2262	Absolute change	Compared with reference values
2263	Absolute change	Shown in table
2265	Absolute change	Seasonal Kendall trend detection, Visualized (line chart)
2292	Absolute change	Shown in table
2295	Absolute change	None
2304	Absolute change, Transition matrix	Visualized
2307	Absolute change, Change rate	Mann–Kendall trend test, Shown in table

2319	Absolute change	One-way ANOVA
2349	Absolute change	Mann–Kendall trend test
2354	Absolute change	ANOVA
2381	Absolute change, Change rate	None
2406	Transition matrix	Shown in table
2440	Absolute change	Visualized
2481	Relative change	None
2486	Linear interpolation	Visualized

Table A15. Type of analysis employed for studies included in the systematic map database and Quartile.

	Analysis		
ID	**Type**	**Statistical**	**Quartile**
20	Comparative		Q4
29	Comparative		Q3
32	Comparative		Q3
46	Statistical	RDA	Q2
54	Statistical	R, RDA	Q2
55	Statistical	RS	Q1
82	Comparative		Q3
96	Statistical	RS	Q2
97	Statistical	RS, LWR	Q1
114	Statistical	GCo	Q3
132	Comparative		Q3
139	Statistical	CM, PCA	Q3
149	Statistical	LR, MR, LME	Q1
162	Statistical	NLR	Q1
177	Comparative		Q2
209	Statistical	RDA, MLR	Q1
216	Comparative		Q2
218	Statistical	R	Q4
227	Comparative		Q2
232	Comparative		Q3
309	Comparative		Q2
320	Comparative		Q3
323	Statistical	RS, RDA	Q1
381	Statistical	RS, R	Q2
408	Statistical	RDA, BRT	Q2
427	Statistical	R	Q1
564	Statistical	R, MR, ANOVA	Q3
587	Comparative		Q2
616	Statistical	R, MLR	Q2
685	Comparative		Q1
690	Statistical	RDA	Q1
694	Statistical	MLR, MOLR	Q4

710	Statistical	RS, MLR	Q4
743	Statistical	RS, LR, OLS, MLR	Q2
759	Statistical	RDA, MLR	Q1
766	Comparative		Q2
809	Statistical	RDA	Q1
812	Statistical	R, LR	Q1
824	Statistical	MLR	Q2
826	Statistical	R	Q3
841	Statistical	LR	Q2
842	Statistical	PRA	Q2
843	Statistical	PCA	Q2
847	Statistical	ANOVA	Q4
887	Statistical	RDA, MR	Q4
889	Statistical	RS, MR	Q4
896	Statistical	R	Q4
903	Comparative		Q2
983	Comparative		Q2
984	Comparative		Q3
1029	Comparative		Q1
1034	Comparative		Q1
1042	Statistical	ANOVA	Q1
1050	Statistical	RDA	Q1
1063	Statistical	R, RS	Q4
1066	Statistical	RS, SWR	Q1
1074	Statistical	RS	Q2
1080	Statistical	F-test	Q1
1085	Statistical	GLM	Q2
1115	Statistical	CCA, PCA, ANOVA	Q3
1145	Statistical	MLR	Q2
1151	Comparative		Q2
1240	Statistical	MLR	Q1
1287	Statistical	PR, ER, LR	Q1
1297	Statistical	R	Q2
1307	Comparative		Q1
1324	Statistical	GWR	Q2
1339	Statistical	FA	Q1
1372	Statistical	PLSR	Q2
1418	Comparative		Q2
1438	Statistical	SWR	Q4
1443	Statistical	ANOVA	Q4
1479	Statistical	LR	Q1
1490	Statistical	RDA	Q1
1512	Statistical	R	Q1
1573	Statistical	MLR	Q4
1576	Statistical	RS, PLSR	Q2
1603	Statistical	R, LR	Q2

1618	Statistical	LME	Q1
1656	Comparative		Q3
1685	Comparative		Q3
1691	Comparative		Q2
1717	Statistical	RS	Q3
1718	Statistical	R, MLR, SWR	Q3
1732	Comparative		Q4
1754	Statistical	MLR	Q1
1763	Comparative		Q3
1784	Comparative		Q4
1789	Statistical	SWR	Q4
1795	Comparative		Q3
1802	Statistical	LME	Q3
1824	Comparative		Q3
1889	Modeled		Q1
1895	Statistical	LME	Q2
1948	Comparative		Q4
1964	Comparative		Q4
1998	Comparative		Q3
2012	Statistical	R	Q1
2038	Comparative		Q2
2091	Statistical	R, RDA, MR	Q2
2098	Statistical	R, MLR	Q1
2105	Statistical	RS, MLR	Q1
2109	Statistical	CCA, R	Q1
2129	Comparative		Q1
2132	Statistical	R, MLR	Q2
2134	Comparative		Not available
2152	Statistical	R, MLR	Q3
2162	Statistical	GWR	Q2
2164	Statistical	R	Q1
2172	Statistical	R	Q2
2203	Statistical	RS, PCA	Q4
2211	Statistical	R	Q2
2213	Statistical	OLS, GWR	Q3
2215	Statistical	MR	Q2
2219	Statistical	R	Q4
2251	Comparative		Not available
2254	Comparative		Not available
2261	Statistical	PCA, SWR, MR	Q4
2262	Statistical	MR	Q3
2263	Comparative		Q2
2265	Comparative		Q2
2292	Statistical	R, MLR	Not available
2295	Comparative		Q3
2304	Statistical	LR	Q4

2307	Statistical	RS	Q2
2319	Comparative		Not available
2349	Statistical	R	Q4
2354	Statistical	R, LR	Not available
2381	Comparative		Not available
2406	Statistical	RS, RDA	Not available
2440	Comparative		Not available
2481	Comparative		Not available
2486	Statistical	R, GWR	Not available

Note. ANOVA = Analysis of variance; BRT = Boosted regression tree; CCA = Canonical correlation analysis; CM = Correlation matrix; ER = Exponential regression; FA = Factor analysis; GCo = Grey correlation; GLM = Generalized linear model; GWR = Geographically weighted regression; LME = Linear mixed-effects models; LR = Linear regression; LWR = Locally weighted regression; MOLR = Multivariate ordinal logistic regression; MLR = Multiple linear regrression; MR = Multiple regression; NLR = Nonlinear regression; OLS = Ordinary least squares; PCA = principal component analysis; PLSR = partial least squares regression; PR = power regression; PRA = Panel regression analysis; R = Pearson correlation; RDA = Redundancy analysis; RS = Spearman's rank correlation; SWR = Stepwise regression. Quartile = The rank for the journal impact factor according to the Journal Citation Reports (Clarivate), assigned according to the year of publication and relevant category. If data was not listed for the year published, the most recently available year was used.

Table A16. Outcomes for studies included in the systematic map database.

	Notable land use changes		**Water quality changes**
ID	**Expansion (increase)**	**Loss (decrease)**	**Direction**
20	Urban	Vegetation	Degradation
29	Urban	Wetland	Degradation
32	Urban, Vegetation	Wetland	Not examined
46	Urban	Agriculture, Forest	Not examined
54	Urban	Agriculture	No change
55	Agriculture, Urban	Forest	Degradation
82	Agriculture, Urban	Forest	Degradation
96	Urban	Bare land	Improvement
97	Forest	Not specified	Diverging trends
114	Various (Agriculture, Grassland, Urban)	Various (Bare land, Forest, Water)	Diverging trends
132	Agriculture, Urban	Wetland	Degradation
139	Urban	Forest	Not examined
149	Urban	Agriculture	No change
162	Urban	Forest	Not examined
177	Urban	Wetland	Degradation
209	Not specified	Not specified	No change

216	Forest, Urban	Agriculture	Diverging trends
218	Urban	Vegetation	Degradation
227	Urban	Vegetation	Degradation
232	Urban	Bare land, Water	Degradation then Improvement
309	Forest, Urban	Agriculture	Improvement
320	Urban	Vegetation	Degradation
323	Urban	Agriculture	Degradation
381	Urban	Grassland	Degradation
408	Agriculture, Urban	Various (Agriculture, Forest, Grassland)	Degradation
427	Urban	Various (Agriculture, Forest, Grassland)	Degradation
564	Forest, Urban	Agriculture	Degradation
587	Urban	Agriculture	Degradation
616	Urban	Forest, Grassland	Diverging trends
685	Urban	Not specified	Diverging trends
690	Forest	Agriculture, Grassland	Improvement
694	Urban, Wetland	Agriculture	Diverging trends
710	Grassland	Grassland	Not specified
743	Urban	Agriculture	Diverging trends
759	Urban	Agriculture, Forest	Diverging trends
766	Agriculture, Urban	Bare land, Forest	Degradation
809	Urban	Agriculture, Water	Diverging trends
812	Urban	Not specified	Diverging trends
824	Urban	Bare land, Grassland	Not examined
826	Agriculture, Urban	Vegetation	Degradation
841	Grassland	Agriculture, Other	Not specified
842	Other, Urban	Agriculture, Forest	Degradation
843	Agriculture	Agriculture	Improvement
847	Agriculture	Forest	Degradation
887	Urban	Not specified	Improvement
889	Grassland	Agriculture	Improvement
896	Forest, Urban	Agriculture	Degradation
903	Agriculture, Urban	Forest	Degradation
983	Urban	Forest	Degradation
984	Vegetation	Urban	Not examined
1029	Agriculture	Forest, Wetland	Diverging trends
1034	Urban	Not specified	Degradation
1042	Agriculture	Grassland	Degradation
1050	Forest	Agriculture	Not examined
1063	Agriculture	Forest	Not examined
1066	Forest	Grassland	Diverging trends
1074	Other	Bare land, Vegetation	Degradation
1080	Agriculture	Forest, Wetland	Degradation
1085	Agriculture	Forest	Degradation
1115	Urban	Water	Not examined

1145	Urban	Not specified	Improvement
1151	Agriculture	Water	Degradation
1240	Urban	Bare land	Degradation
1287	Urban	Agriculture, Wetland	Diverging trends
1297	Urban	Agriculture, Wetland	Not examined
1307	Wetland	Forest	Diverging trends
1324	Urban	Not specified	Diverging trends
1339	Forest, Urban	Agriculture	Diverging trends
1372	Urban	Agriculture, Forest	Degradation
1418	Agriculture, Urban	Wetland	Not examined
1438	Urban	Agriculture	Degradation
1443	Grassland	Agriculture	Improvement
1479	Forest, Urban	Agriculture	Improvement
1490	Agriculture	Wetland	Diverging trends
1512	Agriculture, Urban	Not specified	Degradation
1573	Not specified	Not specified	No change
1576	Not specified	Not specified	Diverging trends
1603	Bare land	Grassland	Degradation
1618	Agriculture	Vegetation	Degradation
1656	Bare land	Various (Agriculture, Urban, Other)	No change
1685	Agriculture, Urban	Not specified	Diverging trends
1691	Grassland, Other	Forest	Diverging trends
1717	Urban	Agriculture, Forest	Not examined
1718	Urban	Agriculture	Diverging trends
1732	Forest	Agriculture	Improvement
1754	Not specified	Not specified	Degradation
1763	Grassland, Other	Agriculture, Forest	Not examined
1784	Agriculture, Urban	Forest	Not examined
1789	Not specified	Not specified	Not examined
1795	Urban	Agriculture, Wetland	Degradation
1802	Urban	Various (Agriculture, Vegetation, Wetland)	Improvement
1824	Agriculture, Urban	Forest, Grassland	Not examined
1889	Forest	Agriculture, Grassland	Degradation then Improvement
1895	Grassland, Urban	Agriculture, Forest	Not specified
1948	Urban	Forest	Diverging trends
1964	Agriculture, Urban	Forest, Grassland	Diverging trends
1998	Urban	Grassland	No change
2012	Agriculture	Grassland	Diverging trends
2038	Bare land	Agriculture, Grassland	Degradation
2091	Urban	Not specified	Diverging trends
2098	Urban	Bare land	No change
2105	Agriculture, Bare land	Grassland	Diverging trends
2109	Urban	Agriculture	Diverging trends
2129	Agriculture	Wetland	Degradation

2132	Urban	Agriculture, Bare land	Degradation
2134	Agriculture, Urban	Vegetation, Wetland	Not examined
2152	Agriculture	Forest	Diverging trends
2162	Urban	Agriculture	Not examined
2164	Urban, Wetland	Agriculture, Forest	Degradation
2172	Other, Urban	Agriculture	Not examined
2203	Not specified	Not specified	Diverging trends
2211	Agriculture, Urban	Forest, Grassland	Degradation
2213	Agriculture, Urban	Forest	Not specified
2215	Not specified	Not specified	Diverging trends
2219	Agriculture, Urban	Bare land, Grassland	Not examined
2251	Forest	Agriculture	Not examined
2254	Agriculture, Urban	Various (Bare land, Forest, Vegetation)	Not examined
2261	Urban	Agriculture, Bare land	Diverging trends
2262	Agriculture, Urban	Forest	Degradation
2263	Urban, Wetland	Agriculture	Diverging trends
2265	Urban	Agriculture	Improvement
2292	Urban	Agriculture	Not specified
2295	Urban	Vegetation	Not examined
2304	Urban	Agriculture, Forest	Degradation
2307	Forest, Urban	Various (Bare land, Grassland, Vegetation, Other)	Degradation
2319	Agriculture	Grassland, Vegetation	Diverging trends
2349	Agriculture, Urban	Bare land	Diverging trends
2354	Urban	Forest, Vegetation	Degradation
2381	Agriculture, Grassland	Bare land	Not examined
2406	Forest	Agriculture	Diverging trends
2440	Agriculture	Forest	Degradation
2481	Urban	Water	Not examined
2486	Grassland, Urban	Forest, Wetland	Diverging trends

Note. The overall direction of change over time as compared to inital/reference condition: Improvement, degradation, diverging trends (i.e., some parameters increase while others decrease), no change or not examined.

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