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The impact of land use and spatial mediated processes on the water quality in a river system.

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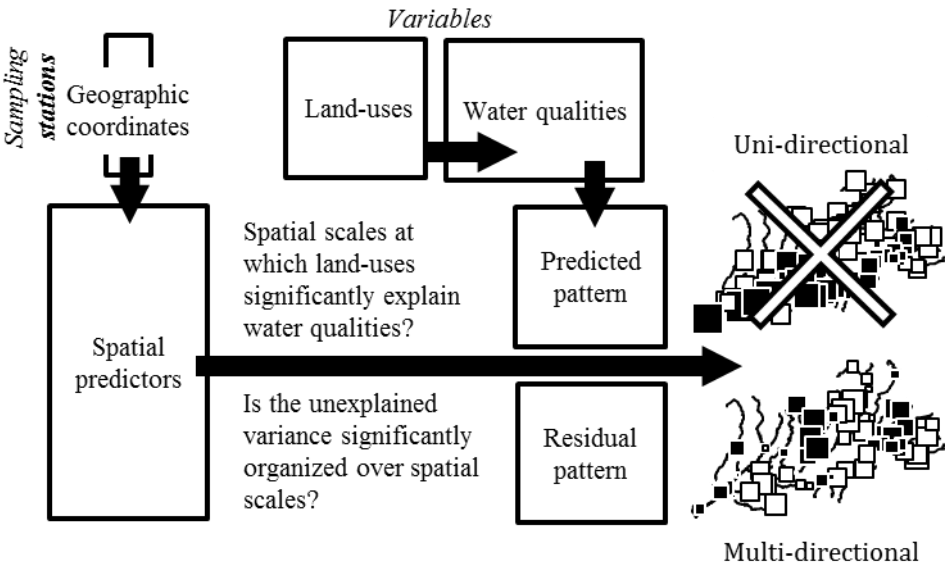
Abstract

River systems are highly complex, hierarchical and patchy systems which are greatly influenced by both catchment surroundings and in-stream processes. Natural and anthropogenic land uses and processes effect water quality (WQ) through different pathways and scales. Understanding under which conditions these different river and catchment properties become dominant towards water chemistry remains a challenge. In this study we analyzed the impact of land use and spatial scales on a range of WQ variables within the Kleine Nete catchment in Belgium. Multivariate statistics and spatial descriptors (Moran's and asymmetric eigenvector maps) were used to assess changes in water chemistry throughout the catchment. Both land use and complex mixes of spatial descriptors of different scales were found to be significantly associated to WQ parameters. However, unidirectional, upstream-downstream changes in water chemistry, often described in river systems, were not found within the Kleine Nete catchment. As different sources and processes obscure and interact with each other, it is generally difficult to understand the correct impact of different pollution sources and the predominant pathways. Our results advocate for WQ management interventions on large and small scales where needed, taking the predominate pathways in to account.

Graphical abstract



Keywords: Water quality; Land use; River management; Spatial process; Asymmetric eigenvector maps (AEM); Moran's eigenvector maps (MEM).

Abbreviations

Water quality (WQ), River Continuum Concept (RCC), Principal Component Analysis on Instrumental Variables (PCAIV), Moran's Eigenvector Map (MEM), Redundancy Analysis (RDA), Asymmetric Eigenvector Maps (AEM).

1. Introduction

River systems are complex and patchy systems which are greatly influenced by both catchment surroundings and in-stream processes (Poole, 2002). This results in a hierarchical system, ranging from the largest spatial scale of landscape or basin to successively smaller scales such as the valley segment, channel reach and sediment pools and riffles (Allan, 2004; Townsend et al., 2003). Different geomorphological, ecological and anthropogenic factors affect river water quality (WQ), with changing influence over temporal and spatial scales (Baker, 2003; Poole, 2010). Under natural conditions, river systems already demonstrate a high level of complexity which has increased further due to land development. Anthropogenic activities have disrupted and changed existing processes and/or included new water and pollution sources through different pathways (sewers, runoff, seepage, etc.). As a result, carbon, nutrient and other contaminants, such as chloride and calcium, have become more dynamic (Kaushal and Belt, 2012; Kaushal et al., 2014; Steele and Aitkenhead-Peterson, 2011).

Since the beginning of the 20th century, scientists have attempted to translate these dynamics into theoretical concepts (Melles et al., 2012). Vannote et al. (1980) observed that physical variables changed along a continuous gradient from headwaters to river mouth, determining stream communities (River Continuum Concept: RCC). In the following decades, additional concepts were developed that increased our understanding of the rivers complexity, amongst others: the serial discontinuity concept (Wards and Stanford, 1983), nutrient spiraling (Webster and Patten, 1979) , catchment hierarchy (Townsend, 1996) and patch dynamics (Townsend, 1989). Which were later integrated and extended by Poole (2002), Thorp et al. (2006) and Humphries et al. (2014) to explain

different types of discontinuities in natural systems. Statzner and Higler (1986) evidenced the universal influence of hydraulics on the longitudinal river gradient, and mentioned that natural zonation patterns over long stream reaches are usually obscured by human influences. The integration of anthropogenic influences in these concepts is still progressing; e.g. “Urban Stream Syndrome” by Walsh et al. (2005) and “Urban Watershed Continuum” by Kaushal and Belt (2012). Under what conditions these concepts can be applied is often less clear.

Many river processes occur at different spatial scales, taking directional movements into account. Both natural and anthropogenic patterns and processes in river systems are generally strongly oriented to downstream reaches (longitudinal connectivity vectors) (Ward, 1989). But also lateral (e.g. runoff) and vertical (e.g. seepage) vectors can have important effects (Stanford and Ward, 1993; Townsend, 1996). The relative magnitude of these vectors can differ among river systems and investigating which of these vectors are predominant within a river system remains challenging.
Catchment characteristics like land uses and geomorphological properties are connected to a river system through all three vectors and have profound effects on the river characteristics. These characteristics are therefore widely used as landscape metrics to explain WQ variation and applied as predictors for ecosystem health and river functioning (Jones et al., 2001; Stanfield et al., 2009). As these landscape metrics depend on a good delineation of the upstream area and correct incorporation of the hydrological flow paths and solute deliveries (Gergel et al., 2002), much research has gone to improve their calculation (e.g. Baker et al., 2007; Van Sickle and Johnson, 2008; Vrebos et al., 2015). Nevertheless, landscape metrics can only explain part of the observed variation, as they describe only a limited portion of all processes present in a catchment. For example, in-stream processes can have a profound impact on different WQ parameters (e.g. (Caissie, 2006; Withers and Jarvie, 2008) and also ground water contributions to stream chemistry can be scale dependent (Peralta-Tapia et al., 2015). Up to now, it remains difficult to define and select structures, connectivity vectors and scales on which these processes take place and to translate them into functional indicator metrics.

In general, ecological variables strongly depend on environmental conditions which change often gradually in space (Dray et al., 2012; Legendre, 1993). Although a catchment can extend over a large area and can be marked by strong upstream-downstream gradients, sub-gradients at smaller scales can result from sub-catchment properties, local pollution sources or in-stream processes. As a result, the WQ pattern of the whole catchment might encompass various spatial scales. In this respect, WQ descriptors can exhibit different “spatial waves”, where these descriptors increase and decrease along a river stretch. These changes depend on particular physical, chemical or human-mediated drivers and/or local independent processes. Basically, there is no single scale at which ecological phenomena should be studied as the observer imposes a perceptual bias (i.e. the spatial extent of his work) through which the system is viewed (Levin, 1992). Many scales can be perceived in any spatial extent and recent developments in spatial analysis enlarged exploratory perspectives in scale-dependent processes (Dray et al., 2012). Scales can be materialized by spatial variables derived from geographic coordinates of sampling units in order to explore the spatial nature of ecological variables by a correlative approach. Two types of spatial predictors were recently developed: those accounting for spatial patterns resulting from multi-directional processes (Griffith and Peres-Neto, 2006) and those accounting for unidirectional ones (Blanchet et al., 2008b). Both types can be combined within one analysis, to test a community or species for both directional and non-directional processes and flows at different spatial scales (Blanchet et al., 2011).

Natural lotic systems are expected to generate longitudinal gradients. However, intensive land uses should strongly disrupt the spatial extent of natural processes and these longitudinal gradients. Focusing on a strongly anthropogenically affected river system in northern Belgium, we hypothesized that (1) land use should drive a substantial amount of WQ variance; (2) spatial variables accounting for unidirectional processes should weakly predict WQ patterns; and (3) human-mediated processes should take place over complex mixes of spatial scales.

2. Methodology

2.1. Study Area

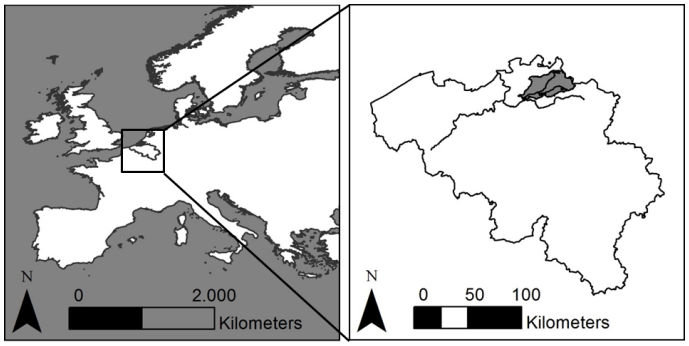


Fig. 1: Location of the study area.

The Kleine Nete Catchment (approximately 780 km²) is situated in in Northern Belgium and is a sub-catchment of the Scheldt river basin (Fig. 1). It has a marine temperate climate with an average precipitation of 800 mm/year. Topographic heights range between 3m and 57m above sea level. As a result of weak elevation gradients, average water current velocities are limited (0.2 m/s in winter, 0.06 m/s in summer) (De Doncker et al., 2009). The catchment consists mainly of sandy soils, with loamy sand soils in the floodplains. Due to permeable soils, the river system is mainly groundwater fed and natural surface runoff takes only place during wet periods when the soils are water saturated. Some of the upstream geophysical characteristics of the catchment, used in the analysis, are summarized in the supplementary material (Fig. S1).

Land use within the catchment is dominated by pasture (24%), croplands (20%), broadleaved woodland and evergreen needle leaf forests (22%) and houses and roads (13%). The other 21% consists mainly out of open waters, gardens, shrubs, etc. In total 27 cities and municipalities are fully or partially located within the catchment, with a total population of +/- 524 000 inhabitants in 2012 and an average population density of 455 inh./km². Typical ribbon development is present between villages in the catchment (De Decker, 2011).

The hydrological system within the catchment has been strongly transformed by human interventions. Streams no longer follow their natural flow paths and their flow regimes are heavily altered. Although the Kleine Nete is considered to be one of the lesser polluted catchments in Flanders, almost none of the streams within the catchment meet the European Water Framework Directive (Directive 2000/60/EC) quality standards. At the moment 20 wastewater treatment plants (WWTP) are located within the catchment. In 2012 75% of the households in the region were connected to a WWTP. The

rest of the population discharges its wastewater directly into the river system through ditches and sewer pipes.

2.2. Water quality sampling

Between June 2010 and the end of 2012, monthly samples were taken on 73 locations within the Kleine Nete catchment (Fig. S2). Fifty-seven of those sample points are part of the long term monitoring network of the Flemish government. An additional 16 locations were selected to better represent the different land uses and improve the spatial coverage within the catchment. Because of the number of sampling points, monthly sampling took 3 days.
Samples were analyzed to quantify 25 different parameters: temperature (T; °C), pH, oxygen concentration (O2 Conc; mg/L) and saturation (O2Sat %) were measured on location. Concentrations (mg/L) of nitrate (NO_3), nitrite (NO_2), ammonium (NH_4), Kjeldahl nitrogen (KjN), orthophosphate (oPO4), total phosphorus (Ptot), chloride (Cl^-), carbon dioxide (CO_2) biogenic silica (BSi), calcium (Ca), iron (Fe), potassium (K), manganese (Mg), sodium (Na), dissolved silica (SiO2), zinc (Zn), biological oxygen demand (BOD), chemical oxygen demand (COD), suspended solids (SS), chlorophyll a concentrations (Chla; mg/L) and conductivity (Cond; µS/cm) were measured in the lab following different national and international standards. An overview of these is given in the supplementary materials.

2.3. Upstream area analysis

For each of the sampling points the characteristics of the upstream area were calculated following the procedure of Vrebos et al. (2015), taking the sewer system into account where needed. All GIS-calculations were performed in ArcGIS 9.3 (ESRI Inc., 2009).

2.3.1. Land use and soil map

Land use maps (1:10.000 vector-layers) were obtained from the National Geographic Institute and consist of 49 categories (NGI, 2007). These, high accuracy maps (1:21.000) were created between 1998 and 2007. The vector layers were converted to a 1m-raster and the land use categories were aggregated to 8 different classes. woodland, cropland, pasture, buildings, paved area, water, greenhouses and others. A description of the land use categories can be found in the supplementary materials (Table S1). A distinction was made between buildings and other impervious areas (roads, concrete areas, etc.) buildings can be an important source of wastewater, while other impervious areas mainly collect rainwater.

2.3.2. Soil map

Soil properties were obtained from the digital soil map (1:20.000) of Flanders (AGIV, 2006). 1m-rasters for soil texture and soil drainage were calculated. Soil texture characteristics were aggregated to 8 classes: sand (Z), dunes (X), loamy sand (S), sandy loam (P and L), loam (symbol A), clay (symbol E and U) and peat (symbol V). Soil drainage characteristics were aggregated in five classes: well drained (symbol a and b), moderately drained (symbol c and d), poorly drained (symbol e, f, and g) and poorly drained with stagnating water (symbol h and i) and others (areas without symbol).

2.3.3. Upstream area calculation

Upstream areas and sub-catchments were delineated for each sample point from a 1:5000 digital elevation model expressed as a 5m-raster (FEA, 2006) using a D8-runoff model (Jenson and Domingue,

1988). The sub-catchment raster was used to calculate initial upstream land use, soil texture and soil drainage acreages. These datasets were then adapted to include effects of sewer infrastructure. Maps, that indicate which buildings are currently connected to a WWTP, were used to virtually remove them from their sub-catchment and add them to the connected WWTP receiving sub-catchment. As result a distinction between WWTP connected and not connected buildings could be made. For each sample point total upstream areas and subsequent land use percentages were calculated. A more detailed description of the used methodology can be found in Vrebos et al. (2015).
Since the same area is taken into account for several WQ sample points, there is double counting in the land use conditions. This can lead to some autocorrelation in the results. Using independent sample points on different streams, often used in land use – WQ studies, was not an option. As this would not generate adequate MEMs and AEMs. To our knowledge, there are currently no statistical methods that are able to adequately address this issue of spatial autocorrelation in lotic systems.

2.4. Data Analysis

Initially WQ was statistically compared (Tukey's HSD) between seasons (winter = December, January, February; spring = March, April, May; summer = June, July, August and autumn = September, October, November). WQ parameters were found to be similar in spring, summer and autumn, but differed drastically in winter (Fig. S3). Winter concentrations were mainly distinct due to higher chemical loads, while some parameters, such as pH, were lower. At the same time, river discharges strongly varied from winter (high) to summer (low) (Fig. S4). Hence, data analyses were conducted separately on winter data and on averaged values of the three other seasons; hereafter called "summer". Many WQ parameters have a diurnal variability (Vandenberghe et al., 2005). For most of our samples, the sampling time was not available, although sampling always took place during the day. As a consequence, we were not able to adjust for diurnal variability. However, we computed mean values per season from monthly values spread over two years. Between-month and between-year variabilities may have affected samples more than sampling time within the few sampling days. An overview of the ranges of the different WQ variables in both periods is given in supplementary materials (Fig. S5). Both periods were further analysed in the same way. Three data tables; land uses, water qualities and spatial predictors, were further considered and processed in two steps.

Firstly, significant relationships between land uses and water quality parameters were drawn from a Principal Component Analysis on Instrumental Variables (PCAIV; Lebreton et al., 1991; Sabatier et al., 1989) also known as Redundancy Analysis (RDA). This enabled us to consider the WQ variations due to land use related processes. The significance of these relationships was tested with a permutation test (9999 iterations; Manly, 1991).

Secondly, spatial scales of the resulting predicted pattern were determined using recent statistical developments (Blanchet et al., 2011; Griffith and Peres-Neto, 2006). Spatial scales are not controlled by the observer, but deduced from the spatial extent of the dataset. Geographic coordinates of n sampling stations are used to build a weighted distance matrix (n stations × n stations) which is diagonalized to generate $n - 1$ orthogonal eigenvectors and $n - 1$ orthogonal associated spatial predictors composed of n observations (principal coordinates). In a conservative way, this enabled us to consider the WQ variations only due to land use related processes. The significance of these relationships were tested using a permutation test (9999 iterations; Griffith and Peres-Neto, 2006). This procedure offers several advantages, compared to older statistical methods. First, it builds independent predictors, a necessary condition in regression analyses. Second, the variances of these

spatial predictors equal associated spatial autocorrelation following Moran's I (Moran, 1950). Third, predictors are hierarchized from the largest (largest scale, positive autocorrelation) to the smallest one (smallest scale, negative autocorrelation). Here, the spatial decomposition of the 73 stations results in 72 spatial descriptors, called Moran's Eigenvector Map (MEM; Griffith and Peres-Neto, 2006). MEMs provide anisotropic spatial descriptors as they enable to identify multi-directional processes. Since lotic systems experience strong directional patterns, isotropic spatial descriptors were proposed by Blanchet et al. (2008b). These descriptors, called Asymmetric Eigenvector Maps (AEM), can be built from a PCA on a weighted matrix containing affinities between sampling stations and connections among them. Hereby links among sampling stations not connected by possible upstream-downstream paths are prevented. This calculation also resulted in 72 different AEMs.

Although both methods were initially developed for community ecology, they have a great potential in other research fields like river landscape ecology. In recent years, they have been used to analyse different types of species and communities within river systems (e.g. Bertolo et al., 2012; Bourgeois et al., 2016; Landeiro et al., 2011; Liu et al., 2013; Massicotte and Frenette, 2011). Investigating such scale-dependent processes should improve our understanding of fundamental river ecosystem functioning and underline the importance of the different concepts. For example, although the RCC is considered to be largely falsified (Poole, 2010), recent applications of the methodology of Blanchet et al. (2008b) seem to prove the validity of the concept in at least some rivers (e.g. Mortillaro et al., 2012)) Combining both types of structures within one analysis should allow us to distinguish the relevant types (isotropic and anisotropic) and their size (Blanchet et al., 2011).

The most significantly correlated spatial scales to the predicted WQ pattern were identified by PCAIV with a forward selection following the method from Blanchet et al. (2008a), based on both alpha significance level and adjusted coefficient of multiple determination (adjusted R2) as stopping criteria. This strongly conservative procedure lowers type I error inflation and was designed for variable selection in general, and more specifically for spatial variables, always in high numbers. In order to assess the relevance of land use predictors, the whole analytical procedure was also conducted on the residual pattern between land uses and WQ parameters. This procedure, using the predicted pattern of water qualities by land uses, focuses only on the spatial scales of human-mediated processes.

Fig. 2 summarizes the analytical procedure. Computations and associated graphical representations were implemented under R version 3.2.0 (R Core Team, 2015) with the packages "ade4" (Chessel et al., 2004; Dray et al., 2007) for PCAIV, and "adespatial", "AEM" (Blanchet et al., 2008b) and "packfor" packages for MEM and AEM computations and forward selection, respectively.

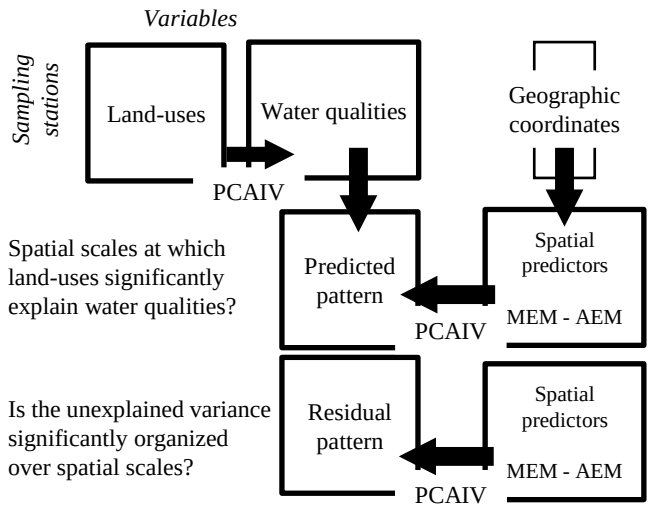


Fig. 2: Conceptual schema of the analytical procedure.

3. Results

3.1. Water quality and land uses

Water quality was significantly influenced by land uses in winter and summer (Fig. 3). Land use explained 29% (winter) and 32% (summer) of WQ variation ($p < 0.001$). In both periods, water quality predictions were structured along three main axes on which covariances between land uses and WQ were mostly similar.

Axis 1 expressed in both periods a size effect in most of the WQ parameters, explaining more of the variation in winter than in summer. This size effect was mainly explained by land uses that are related to urbanization: paved areas, WWTP connected and not-connected houses and other land uses. These land uses covaried with a large group of WQ parameters that had a stronger clustering in winter. In winter, Axis 2 was mainly explained by open water and woodland covarying with O_2 and pH, and opposed to grassland and arable land covarying with T, PO_4, SiO_2, K and Fe. WWTP connected houses, paved areas and other land uses were opposed to not connected houses and greenhouses along the second axis. With NH_4, KjN and Ptot covarying with one group and Na, CO_2, Cl^- and BSi covarying with the other. In summer, Axis 2 described more variation compared to winter and was also explained by open water, woodland and paved areas; whereas grassland and arable land were still in opposition. Temperature shifted to covary in a positive way to O_2 and pH, and other elements such as NO_2, NO_3, CO_2, Na and Cl. The opposition between WWTP connected and not connected houses along Axis 2 appeared to be stronger compared to winter. With WTTP connected houses covarying with NO_3, Na, Cl, CO_2 and NO_2 and not connected houses with K, KjN, NH_4, Ptot, SIO_2 and BOD.

Axis 3 expressed mainly an opposition between arable land and grassland with greenhouses, whereas Mg, O_2, K, NO_3, ZS, Zn and Fe strongly covaried with arable land in both seasons. O_2 was less variable; SiO_2, CO_2, pH and Ca were mainly explained by grassland and glasshouses.

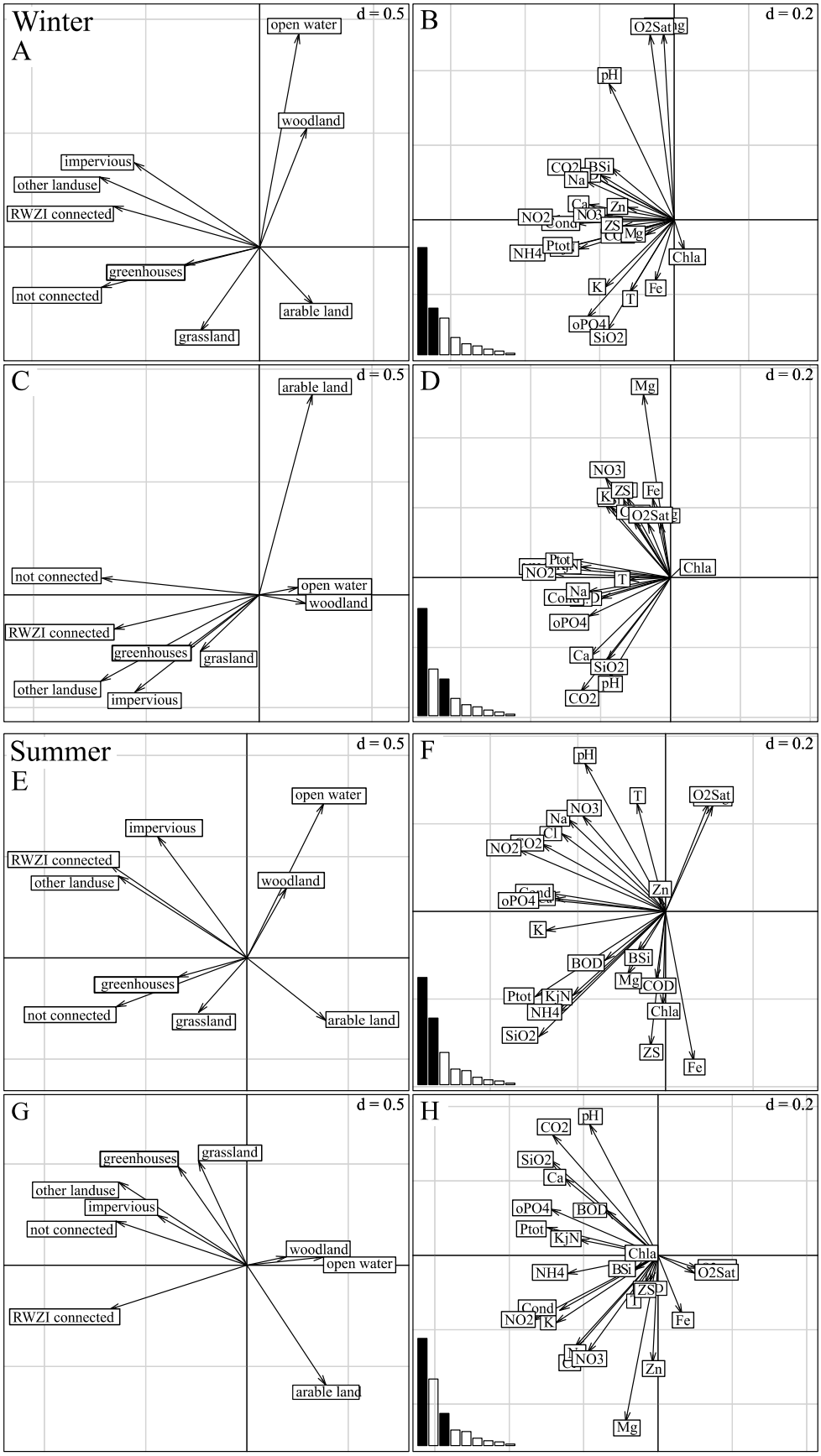


Fig 3: PCAIVs of the pure relationships between land uses and water qualities. A-B) and E-F) Axes 1 (horizontal) and 2 (vertical). C-D) and G-H) Axes 1 and 3 (vertical). Bar diagrams, eigenvalues. Winter:

Axis 1, 45%; Axis 2, 20%; Axis 3, 15%. Summer: Axis 1, 42%; Axis 2, 26%; Axis 3, 13%. “d” indicates the grid scale.

3.2. Explained water quality variation and spatial patterns

WQ within the Kleine Nete catchment was highly variable both between and within the two periods (Fig. S5). In both periods more or less halve of the parameters was higher compared to the other period: summer, 12; winter, 13. WQ parameters alone were first spatially modelled to describe their raw pattern. As winter and summer WQ tables were significantly correlated to the geographic coordinates of the sampling station (PCAIV of water qualities on geographic coordinates; $p < 0.001$), the tables were detrended to avoid spurious correlations (Sharma et al., 2011). No AEM was found to be significant for the WQ data, while several MEMs explained only 11% of winter and summer pattern variances respectively ($p < 0.001$; Table 1). PCAIVs plots can be found in the supplementary materials (Fig. S6).

Table 1: Results of spatial modelling displaying the significant spatial predictors explaining significantly the raw water quality patterns.

Season	Spatial predictor	R^2	Adjusted R^2	Cummulated explained variance	F	p-value
Winter	MEM9	0.052	0.052	0.039	3.91	0.002
	MEM2	0.041	0.093	0.067	3.15	0.006
	MEM7	0.040	0.133	0.095	3.15	0.003
	MEM6	0.029	0.162	0.112	2.35	0.013
Summer	MEM2	0.046	0.046	0.033	3.46	0.003
	MEM7	0.039	0.086	0.060	3.00	0.007
	MEM49	0.030	0.116	0.077	2.34	0.018
	MEM20	0.027	0.143	0.093	2.18	0.024
	MEM11	0.027	0.170	0.108	2.20	0.034

After modelling WQ and spatial predictors, also land use was taken into account. In this analysis both seasonal patterns were significantly organised in space ($p < 0.001$; Table 2). Space explained for both analyses circa 22% of variance. A first result was the absence of significance of AEMs in both patterns, the essential of the spatial structure being explained by multi-directional waves (MEMs). Second, the results showed that these seasonal analyses of human-mediated processes (i.e. land uses vs WQ relationships) were twice more significantly spatialized (22% of explained variance) than the WQ pattern alone (10 %). Third, broad scales had no dominant contributions to the observed patterns which were rather explained by mixes of scales ranging from a few km to the maximum, with summer having both larger (20-50km, MEM1 and MEM2; Fig. 4 and 5) and smaller scales (a few kilometres, MEM 59).

Table 2: Results of spatial modelling displaying the significant spatial predictors retained in PCAIV and their contributions to the land uses – water qualities relationships.

Season	Spatial predictor	R^2	Adjusted R^2	Cummulated explained variance	F	p-value
Winter	MEM36	0.052	0.052	0.038	3.87	0.008
	MEM7	0.041	0.092	0.066	3.13	0.020
	MEM10	0.038	0.130	0.092	3.01	0.030
	MEM4	0.038	0.168	0.119	3.08	0.021
	MEM12	0.037	0.205	0.145	3.10	0.023
	MEM2	0.035	0.240	0.171	3.08	0.017
	MEM9	0.032	0.272	0.194	2.85	0.029
	MEM48	0.031	0.303	0.215	2.80	0.027
Summer	MEM10	0.051	0.051	0.037	3.80	0.006
	MEM7	0.040	0.091	0.065	3.07	0.018
	MEM2	0.039	0.130	0.092	3.12	0.016
	MEM36	0.034	0.164	0.115	2.79	0.031
	MEM6	0.032	0.196	0.136	2.65	0.048
	MEM1	0.031	0.227	0.157	2.68	0.032
	MEM5	0.030	0.258	0.178	2.65	0.036
	MEM15	0.029	0.286	0.197	2.57	0.047
	MEM59	0.028	0.315	0.217	2.61	0.037

The winter WQ pattern was similar to previously described by the WQ – space analysis; the largest scales (MEM2, MEM4 and MEM7) were mainly expressed along the first axis, explaining the size effect which appears to be mostly related to increases in urbanization. The opposition along the second axis was mainly explained by smaller scales and the opposition along the third axis by a mix of different scales. Both second and third axis showed oppositions between different types of urbanisation, RWZI-connected and not connected houses, and types of agriculture, greenhouses, grassland and arable land. These oppositions along the second and third axis could be related to differences in nutrient concentrations, but also to other WQ parameters.

The summer WQ pattern, was also similar as previously described, but encompassed only two axes. Both size effect and opposition were explained by mixes of different scales. Compared to winter the effects were more diffuse with all WQ parameters changing over different sizes of scales.

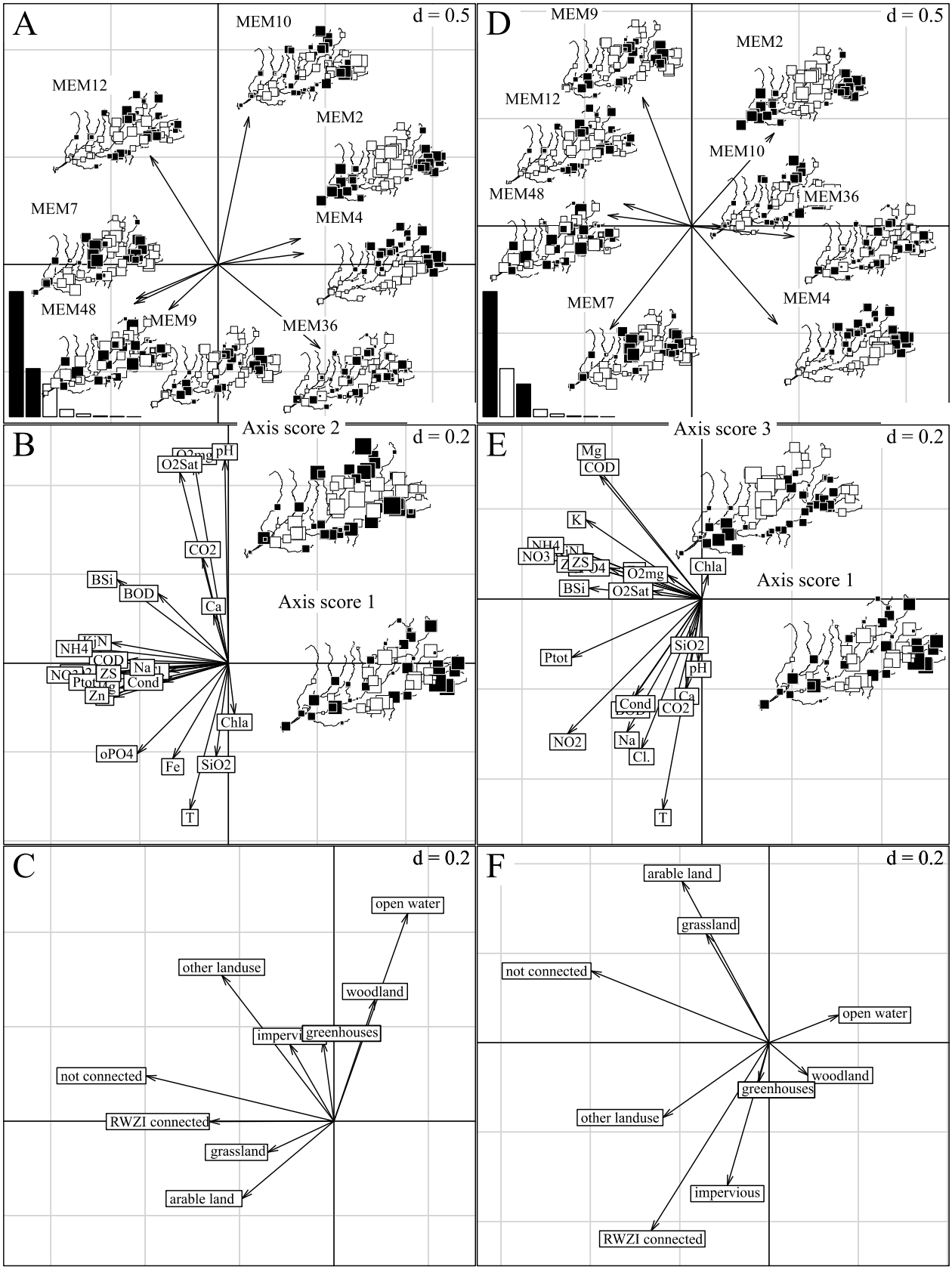


Fig. 4: PCAIV of the winter relationships between human-mediated processes (relationships between land uses and water qualities) and spatial descriptors. A-C) Axes 1 and 2. D-F) Axes 1 and 3. Bar diagrams, eigenvalues. Axis 1 (horizontal), 58%; Axis 2 (vertical), 22%; Axis 3 (vertical), 15%. A and D) Spatial predictors;

inserts illustrate spatial wave length expressed by MEM score distributions; large white squares, low values; large black squares, high values; small squares, intermediate values. "d" indicates the grid scale.

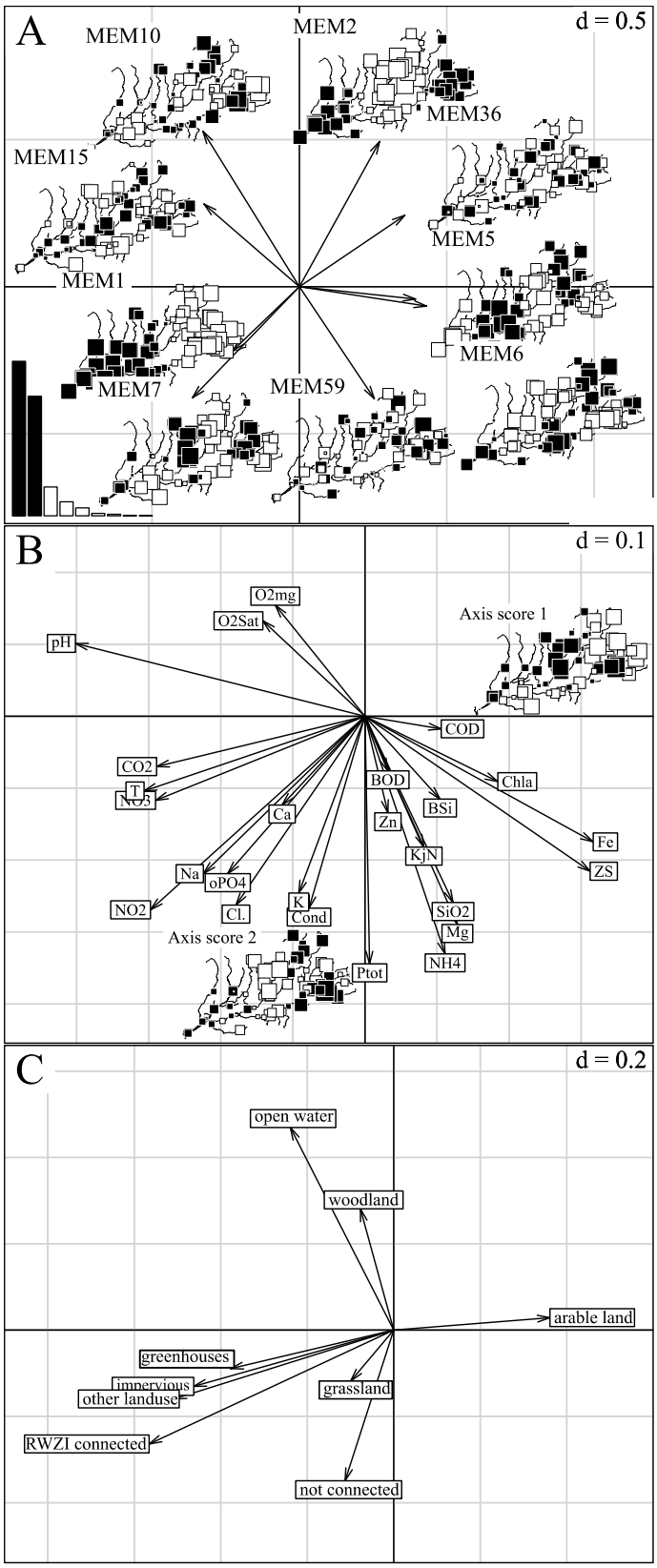


Fig. 5: PCAIV of the summer relationships between human-mediated processes (relationships between land uses and water qualities) and spatial descriptors. Bar diagram, eigenvalues. Axis 1 (horizontal), 47%; Axis 2 (vertical), 36%. A) Spatial predictors; inserts illustrate spatial wave length expressed by MEM score distributions; large white squares, low values; large black squares, high values; small squares, intermediate values. "d" indicates the grid scale.

3.3. Unexplained water quality variation and spatial patterns

Only part of variance in the WQ data is explained by the upstream land use indicators in section 3.1. The residual variance from the winter analysis was not significantly spatialized ($p > 0.05$). In summer 15% of residual variance was explained by space (Table 3); again, no AEM was significant. The pattern was predominantly explained by MEMs expressing scales of a few kilometres. The structures identified in the axis scores clearly represent smaller scale variation compared to the axis scores of the previous analysis. While the clusters of WQ parameters are mostly similar to those found in the results for summer in analysis 3.3. Axis 1 is characterized by oxygen demanding parameters such as NH_4, Ptot, oPO_4 and KjN which are opposed by oxygen itself. Axis 2 is mainly composed out of Na, Cl, Cond, NO_3, and NO_2.

Again MEM2 and MEM7 were found to be significantly related. MEM2, as in analysis 3.3 - summer, covaries with most of the WQ parameters along both axes, except for oxygen and pH and additionally Ca and CO_2 along axis 2. MEM7 covaries, as in analysis 3.3 - summer, with Ca and CO_2 and additionally with oxygen and pH. PCAIVs plot of the analysis can be found in the supplementary materials (Fig. S7).

Table 3: Results of spatial modelling displaying the significant spatial predictors retained in PCAIV and their contributions to the residuals from the land uses – water qualities summer relationships.

Spatial predictor	R^2	Adjusted R^2	Cummulated explained variance	F	p-value
MEM7	0.033	0.033	0.019	2.39	0.015
MEM20	0.030	0.063	0.036	2.27	0.016
MEM51	0.029	0.092	0.053	2.23	0.024
MEM8	0.029	0.121	0.070	2.25	0.017
MEM55	0.027	0.148	0.085	2.11	0.026
MEM59	0.026	0.175	0.099	2.11	0.027
MEM44	0.025	0.200	0.114	2.06	0.027
MEM49	0.025	0.224	0.128	2.03	0.027
MEM2	0.024	0.249	0.141	2.03	0.031
MEM18	0.024	0.272	0.155	2.01	0.034

Discussion

Upstream land uses appear to be a relatively strong predictor for WQ variation, which is in line with previous results (Allan, 2004; Baker, 2003). Increases in most parameters covary in first instance along a gradient of increasing urbanization. However, there is a clear distinction between RWZI connected and not-connected houses mostly, which confirms earlier findings within the catchment (Vrebos et al., 2015). Land uses were more distinctly covariant in summer (Fig. 3C), with possibly similar impact on water qualities among land uses. Only oxygen is negatively impacted because of break down oxygen demanding nutrients related with the anthropogenic land uses (de la Crétaz and Barten, 2007).

While many studies only assess a limited number of parameters, our results signify that the entire chemistry balance is affected by human activities.

The WQ in the catchment appears to be highly variable: both between winter and the rest of the year and between sample points. WQ changes take place along different gradients of different sizes. When land use was included, other large and small MEMs were found to be significant in both periods. The increase in selected MEMs is most likely a result of the fragmented land use. Different processes and pollution sources might counteract each other, obscuring the patterns of the different processes. This can result in an underestimation of the actual complexity of the system. Selection of general and additional, large and small scale structures between both periods illustrate both land use impacts that are relatively stable throughout the year, as well as impacts that differ between seasons. Our results suggest that WQ varies on several scales, underpinning the catchment's complexity. Only two different spatial structures were found to be significant in all different steps of the analysis, signifying that some processes do remain constant throughout the year, working at stable scales.

The impact of land uses and space in winter seems to take place along three gradients. A first gradient is related to increases in urbanization, which takes place on larger scales, the second gradient relates to different types of urbanization and a third to different types of agriculture. Urbanization changes on larger scales with alternating areas of cities, smaller villages and open land. While types of urbanization and agriculture differ on smaller scales. Neighborhoods or houses that are connected to a WWTP or not, alternate on a small scale within the catchment due to complex spatial planning and urban sprawl. In summer these effects between land use, WQ and space are more diffuse and complex. This can be an effect of the biological processes which can differ strongly within the catchment and within the streams, Decreases in flow rate in summer can also increase the, sometimes local, impact of pollution sources with a relatively stable load discharge. The combination of both biological processes and local pollution sources results in a more complex WQ pattern, a less pronounced impact of land use across the catchment and the selection of smaller MEMs in summer.

The origin of medium and small scale structures within the unexplained water quality variation is difficult to uncover. Medium and small MEMs range within several kilometers and encompass several independent sample points that are situated on neighboring tributaries, but are fed by the same ground water system. This indicates that vertical vectors, related to seepage, can have an important impact on a smaller scale. Considering the sandy soil and groundwater fed river system, water table exchanges likely occur within the catchment (Anibas et al., 2011). The impact of local variation in ground water quality, due to seepage location and pollution sources is estimated to increase in summer as runoff and dilution effects decrease and deeper groundwater becomes more important in feeding the tributaries. These small MEMs are however still logically structured, creating a distinct pattern across the catchment. Yet using these structures to identify other specific properties or processes within the catchment remains difficult because of their low explanatory strength and the absence of relevant information. Why these small scale patterns are only found in summer and not in winter remains questionable.

An important result was the absence of significance of the isotropic structures in the analyses. Potential upstream-downstream effects cannot be incorporated within land use predictors and should therefore be retained within the remaining variation. As a result, we expected to find isotropic structures within the unexplained variance. Especially given the high density of sampling stations,

which could have captured upstream-downstream trends in WQ characteristics. In-stream processes should after all have longitudinal isotropic effects within a stream and therefore be represented by isotropic structures in the analysis. AEMs were designed for spatial modelling in lotic systems, outcompete MEMs in such conditions (Blanchet et al., 2011) and have been successfully applied in river ecology (e.g. Wan et al., 2015). However, within our catchment, they appeared to be inadequate to explain any WQ variation. The total absence of significant unidirectional predictors raises crucial questions. Our results suggest that the upstream-downstream pattern, as described in the RCC, is not directly applicable to our catchment. Whether this is because the upstream–downstream pattern was never there or because the anthropogenic impact and cumulative effects on the river system has overruled its initial state, is impossible to answer (MacDonald, 2000). Legacy effects such as past agricultural land uses, not incorporated in our analysis, can effect WQ (Maloney and Weller, 2011). Also, some of the variability might be due to the diurnal cycle of many parameters, which was not incorporated fully within the analysis.

Managing WQ in heavily altered river systems is challenging. Despite large efforts during the past two decades, only a few streams in the Kleine Nete reach the European 'Good Ecological Health' status. Our results indicate that WQ if affected by both land use and complex mixes of spatial scales. As different sources and processes can obscure and interact with each other, it is generally difficult to understand the correct impact of different pollution sources and their predominant pathways. The intricacy of the river system makes the management of it a daunting challenge, requiring significant amounts of investment in both time and effort.

4. Conclusion

Advances in spatial statistics now give us tools to analyze different pathways in ecological studies and help us understand the complexity of rivers systems. The interaction between the natural characteristics of the catchment and human activities has created a river system of which the WQ variation and its sources are difficult to analyze and understand. Our results advocate for continuous small scale monitoring to better understand these local variations across the catchment and the impact of pathways such as ground water flows on the river WQ. Although parts of the WQ variation can be attributed to land uses, more research related to impact of ground water and other potential pathways is complementary needed.

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5. References

AGIV. Digitale bodemkaart van het Vlaams Gewest. AGIV, Gent, België, 2006.

Allan JD. Landscapes and riverscapes: The influence of land use on stream ecosystems. Annual Review of Ecology Evolution and Systematics 2004; 35: 257-284.

Anibas C, Buis K, Verhoeven R, Meire P, Batelaan O. A simple thermal mapping method for seasonal spatial patterns of groundwater-surface water interaction. Journal of Hydrology 2011; 397: 93-104.

Baker A. Land use and water quality. Hydrological Processes 2003; 17: 2499-2501.

Baker ME, Weller DE, Jordan TE. Effects of stream map resolution on measures of riparian buffer distribution and nutrient retention potential. Landscape Ecology 2007; 22: 973-992.
Bertolo A, Blanchet FG, Magnan P, Brodeur P, Mingelbier M, Legendre P. Inferring Processes from Spatial Patterns: The Role of Directional and Non-Directional Forces in Shaping Fish Larvae Distribution in a Freshwater Lake System. PLoS ONE 2012; 7.
Blanchet FG, Legendre P, Borcard D. Forward selection of explanatory variables. Ecology 2008a; 89: 2623-2632.
Blanchet FG, Legendre P, Borcard D. Modelling directional spatial processes in ecological data. Ecological Modelling 2008b; 215: 325-336.
Blanchet FG, Legendre P, Maranger R, Monti D, Pepin P. Modelling the effect of directional spatial ecological processes at different scales. Oecologia 2011; 166: 357-368.
Bourgeois B, Gonzalez E, Vanasse A, Aubin I, Poulin M. Spatial processes structuring riparian plant communities in agroecosystems: implications for restoration. Ecological Applications 2016; 26: 2103-2115.
Caissie D. The thermal regime of rivers: a review. Freshwater Biology 2006; 51: 1389-1406.
Chessel D, Dufour AB, Thioulouse J. The ade4 package- I - One-table methods. R News. 4, 2004, pp. 5-10.
De Decker P. Understanding housing sprawl: the case of Flanders, Belgium. Environment and Planning A 2011; 43: 1634-1654.
De Doncker L, Troch P, Verhoeven R, Bal K, Desmet N, Meire P. Relation between resistance characteristics due to aquatic weed growth and the hydraulic capacity of the river Aa. River Research and Applications 2009; 25: 1287-1303.
de la Crétaz A, Barten P. Land use effects on streamflow and water quality in the Northeastern United States. Boca Raton, Florida: CRC PRess, 2007.
Dray S, Dufour AB, Chessel D. The ade4 package - II: Two-table and K-table methods. R News. 7, 2007, pp. 47–54.
Dray S, Pelissier R, Couteron P, Fortin MJ, Legendre P, Peres-Neto PR, et al. Community ecology in the age of multivariate multiscale spatial analysis. Ecological Monographs 2012; 82: 257-275.
ESRI Inc. ArcGIS 9.3. ESRI Inc., Redlands, CA, 2009.
FEA. Digital Elevation Model Flanders, raster, 5 m. AGIV, Erembodegem, Belgium, 2006.
Gergel SE, Turner MG, Miller JR, Melack JM, Stanley EH. Landscape indicators of human impacts to riverine systems. Aquatic Sciences 2002; 64: 118-128.
Griffith DA, Peres-Neto PR. Spatial modeling in ecology: The flexibility of eigenfunction spatial analyses. Ecology 2006; 87: 2603-2613.
Humphries P, Keckeis H, Finlayson B. The River Wave Concept: Integrating River Ecosystem Models. Bioscience 2014; 64: 870-882.
Jenson SK, Domingue JO. Extracting topographic structure from digital elevation data for geographic information system analysis. Photogrammetric Engineering and Remote Sensing 1988; 54: 1593-1600.
Jones KB, Neale AC, Nash MS, Van Remortel RD, Wickham JD, Riitters KH, et al. Predicting nutrient and sediment loadings to streams from landscape metrics: A multiple watershed study from the United States Mid-Atlantic Region. Landscape Ecology 2001; 16: 301-312.
Kaushal SS, Belt KT. The urban watershed continuum: evolving spatial and temporal dimensions. Urban Ecosystems 2012; 15: 409-435.
Kaushal SS, Mayer PM, Vidon PG, Smith RM, Pennino MJ, Newcomer TA, et al. Land use and climate variability amplify carbon, nutrient and contaniment pulses: a review with management implications. Journal of the American Water Resources Association 2014; 50: 585-614.
Landeiro VL, Magnusson WE, Melo AS, Espirito-Santo HMV, Bini LM. Spatial eigenfunction analyses in stream networks: do watercourse and overland distances produce different results? Freshwater Biology 2011; 56: 1184-1192.

Lebreton J, Sabatier R, Banco G, Bacou AM. Principal component and correspondence analyses with respect to instrumental variables: an overview of their role in studies of structure-activity and species-environment relationships. In: Devillers J, Karcher W, editors. Applied Multivariate Analysis in SAR and Environmental Studies. Kluwer Academic Publishers, Dordrecht, 1991, pp. 85–114.
Legendre P. Spatial autocorrelation - trouble or new paradigm? Ecology 1993; 74: 1659-1673.
Levin SA. The problem of pattern and scale in ecology. Ecology 1992; 73: 1943-1967.
Liu J, Soininen J, Han BP, Declerck SAJ. Effects of connectivity, dispersal directionality and functional traits on the metacommunity structure of river benthic diatoms. Journal of Biogeography 2013; 40: 2238-2248.
MacDonald LH. Evaluating and managing cumulative effects: Process and constraints. Environmental Management 2000; 26: 299-315.
Maloney KO, Weller DE. Anthropogenic disturbance and streams: land use and land-use change affect stream ecosystems via multiple pathways. Freshwater Biology 2011; 56: 611-626.
Manly B. Randomization and Monte Carlo Methods in Biology. London: Chapman and Hall, 1991.
Massicotte P, Frenette JJ. Spatial connectivity in a large river system: resolving the sources and fate of dissolved organic matter. Ecological Applications 2011; 21: 2600-2617.
Melles SJ, Jones NE, Schmidt B. Review of theoretical developments in stream ecology and their influence on stream classification and conservation planning. Freshwater Biology 2012; 57: 415-434.
Moran PA. Notes on continuous stochastic phenomena. Biometrika 1950; 37: 17-23.
Mortillaro JM, Rigal F, Rybarczyk H, Bernardes M, Abril G, Meziane T. Particulate Organic Matter Distribution along the Lower Amazon River: Addressing Aquatic Ecology Concepts Using Fatty Acids. PLoS ONE 2012; 7.
NGI. Top10Vector. Nationaal Geografisch Instituut, Brussel, Belgium, 2007.
Peralta-Tapia A, Sponseller RA, Aring;gren A, Tetzlaff D, Soulsby C, Laudon H. Scale-dependent groundwater contributions influence patterns of winter baseflow stream chemistry in boreal catchments. Journal of Geophysical Research-Biogeosciences 2015; 120: 847-858.
Poole GC. Fluvial landscape ecology: addressing uniqueness within the river discontinuum. Freshwater Biology 2002; 47: 641-660.
Poole GC. Stream hydrogeomorphology as a physical science basis for advances in stream ecology. Journal of the North American Benthological Society 2010; 29: 12-25.
R Core Team. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria, 2015.
Sabatier R, Lebreton J, Chessel D. Principal component analysis with instrumental variables as a tool for modelling composition data. Multiway Data Analysis. Elsevier Science Publishers B.V, 1989, pp. 341–352.
Sharma S, Legendre P, De Caceres M, Boisclair D. The role of environmental and spatial processes in structuring native and non-native fish communities across thousands of lakes. Ecography 2011; 34: 762-771.
Stanfield LW, Kilgour B, Todd K, Holysh S, Piggott A, Baker M. Estimating Summer Low-Flow in Streams in a Morainal Landscape using Spatial Hydrologic Models. Canadian Water Resources Journal 2009; 34: 269-284.
Stanford JA, Ward JV. An ecosystem perspective of alluvial rivers - connectivity and the hyporheic corridor. Journal of the North American Benthological Society 1993; 12: 48-60.
Statzner B, Higler B. Stream hydraulics as a major determinant of benthic invertebrate zonation patterns. Freshwater Biology 1986; 16: 127-139.
Steele MK, Aitkenhead-Peterson JA. Long-term sodium and chloride surface water exports from the Dallas/Fort Worth region. Science of the Total Environment 2011; 409: 3021-3032.
Thorp JH, Thoms MC, Delong MD. The riverine ecosystem synthesis: Biocomplexity in river networks across space and time. River Research and Applications 2006; 22: 123-147.

Townsend CR. The patch dynamics concept of stream community ecology. Journal of the North American Benthological Society 1989; 8: 36-50.
Townsend CR. Concepts in river ecology: Pattern and process in the catchment hierarchy Archiv für Hydrobiologie 1996; 113 (Suppl.): 3-21.
Townsend CR, Doledec S, Norris R, Peacock K, Arbuckle C. The influence of scale and geography on relationships between stream community composition and landscape variables: description and prediction. Freshwater Biology 2003; 48: 768-785.
Van Sickle J, Johnson CB. Parametric distance weighting of landscape influence on streams. Landscape Ecology 2008; 23: 427-438.
Vandenberghe V, Goethals PLM, Van Griensven A, Meirlaen J, De Pauw N, Vanrolleghem P, et al. Application of automated measurement stations for continuous water quality monitoring of the Dender River in Flanders, Belgium. Environmental Monitoring and Assessment 2005; 108: 85-98.
Vannote RL, Minshall GW, Cummins KW, Sedell JR, Cushing CE. The river continuum concept. Canadian Journal of Fisheries and Aquatic Sciences 1980; 37: 130-137.
Vrebos D, Staes J, Struyf E, Van Der Biest K, Meire P. Water displacement by sewer infrastructure and its effect on the water quality in rivers. Ecological Indicators 2015; 48: 22-30.
Walsh CJ, Roy AH, Feminella JW, Cottingham PD, Groffman PM, Morgan RP. The urban stream syndrome: current knowledge and the search for a cure. Journal of the North American Benthological Society 2005; 24: 706-723.
Wan Y, Xu LL, Hu J, Xu C, Wan A, An SQ, et al. The Role of Environmental and Spatial Processes in Structuring Stream Macroinvertebrates Communities in a Large River Basin. Clean-Soil Air Water 2015; 43: 1633-1639.
Ward JV. The four-dimensional nature of lotic ecosystems. Journal of the North American Benthological Society 1989; 8: 2-8.
Wards JV, Stanford JA. The serial discontinuity concept of lotic ecosystems. In: Fontaines TD, Bartells SM, editors. Dynamics of Lotic Ecosystems. Ann Arbor Science Publishers, Michigan, 1983, pp. 494.
Webster JRB, Patten BC. Effects of Watershed Perturbation on Stream Potassium and Calcium Dynamics. Ecological Monographs 1979; 49: 51-72.
Withers PJA, Jarvie HP. Delivery and cycling of phosphorus in rivers: A review. Science of the Total Environment 2008; 400: 379-395.