Professur für Umwelthydrosysteme

Albert-Ludwigs-Universität Freiburg

Higher floods, stronger droughts? On the impact of land use change on streamflow extremes in the Weser-Ems region

Master Thesis
of

Marc Djahangard

Supervisor: Dr. Manuela Brunner

Reviewer: Prof. Dr. Markus Weiler

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Abstract

Land use change (LUC) potentially intensifies streamflow extremes. However, there still exists a lack of knowledge about the influence of LUC on high and low flows because a valid assessment is difficult. That is mainly due to the need of isolating the impact of LUC on streamflow from other influences e.g., climate or other human interferences. Therefore, it is important to use reliable methods in order to investigate the effect of LUC on streamflow extremes. This thesis focuses on the influence of four LUC classes (agriculture, pasture, urban, green area) on high and low flows. To examine the influences, I applied two different methodologies (regional-scale comparison and panel regression model) and evaluated their performance. The study was conducted on 30 catchments over the period 1986 – 2017 in the Weser-Ems Region in Northwestern Germany. To address the streamflow extremes, I represented them by indices of their most important characteristics (discharge magnitude, duration and volume). The regional-scale comparison showed no pattern of LUC influencing streamflow extremes in the region. In contrary, the panel regression model resulted in a significant effect of change in green area on the high flows. Hereby, a 1% increase in green area (relative to catchment area) reduced the maximum peak discharge by over 3%. Furthermore, there was a mitigating effect on the excess volume. I related the differences in results to the methodologies' inherent calculation. Evaluating the methodologies, I conclude that the regional-scale comparison is a straightforward approach with minor limitations. The panel regression model is complex and requires an elaborate comprehension. However, if correctly applied it can lead to valuable results.

Keywords: streamflow extremes; floods; droughts; land use change; catchment hydrology; lowland; regional-scale comparison; panel regression model; methodology assessment

Zusammenfassung

Landnutzungsänderungen können zur Erhöhung von Extremereignissen in Fließgewässern beitragen. In Bezug auf den genauen Wirkungsgrad von Landnutzungsänderungen auf das Abflussgeschehen besteht jedoch Unklarheit, da die Abschätzung der Auswirkungen schwierig sein kann. Das liegt vor allem daran, dass der Einfluss von Landnutzungsänderungen von anderen Faktoren (Klima oder anderen menschlichen Einflüssen) isoliert werden muss. Für eine Untersuchung sind daher verlässliche Methoden von besonderer Wichtigkeit. Diese Masterarbeit untersucht den Einfluss von vier Landnutzungsänderungen (Landwirtschaft, Weide, Urban sowie Natur- und Grünfläche) auf Hoch- und Niedrigwasser. Hierbei wurden zwei verschiedene Methoden angewendet: ein regionaler Vergleich sowie ein Panel Regression Modell. Die Methoden wurden im Weitern auf deren Anwendbarkeit und Verlässlichkeit evaluiert. Die Studie wurde an 30 Einzugsgebieten in der Weser-Ems Region in Nordwestdeutschland durchgeführt. Dabei wurden Hoch- und Niedrigwasser durch Indizes repräsentiert, welche deren wichtigste Eigenschaften abbilden (Abflusshöhe, Dauer und Volumen). Der regionale Vergleich konnte kein Muster zwischen Landnutzungsänderungen und deren Auswirkung auf extremes Abflussgeschehen feststellen. Im Gegensatz dazu zeigte das Panel Regression Modell einen signifikanten Einfluss von Grünfläche auf Hochwasser. Dabei verringerte die Zunahme von 1% Grünfläche die Abflussspitzen um mehr als 3%. Zusätzlich hatten Grünflächen auch einen vermindernden Effekt auf das Hochwasservolumen. Die Unterschiede zwischen den Methoden werden der einzelnen Methodik inhärenten Berechnung zugeordnet. Die Beurteilung der Methoden kam zu dem Schluss, dass der regionale Vergleich ein leicht anwendbarer und verlässlicher Ansatz ist, dessen Fehlerquellen gering sind. Hingegen ist das Panel Regression Modell komplex und benötigt viel tiefgehendes Verständnis, was zeitaufwendig ist und zu Problemen führen kann. Bei richtiger Anwendung kann das Panel Regression Modell jedoch wertvolle Ergebnisse liefern.

1. Introduction

River dynamics have changed globally with major implications for hydrological extremes including high and low flows (Berghuijs et al., 2017; Gudmundsson et al., 2019; Hall et al., 2014; Stahl et al., 2010). This development will, in all likelihood, be intensified even more: Streamflow extremes are predicted to increase in frequency and severity with climate change being the main driver (Asadieh and Krakauer, 2017; Görgen et al., 2010; Hirabayashi et al., 2013; IPCC 2021: Seneviratne et al., In Press; Nilson et al., 2014; Prudhomme et al., 2014). However, climate change is not the only reason. Alterations in streamflow extremes are also caused by anthropogenic interventions like constructions of water reservoirs or hydropower regulations (Arheimer et al., 2017; Batalla et al., 2004; Zhang et al., 2014).

The intensification of floods and droughts poses a great challenge due to the socio-economical as well as ecological damage which they can cause (Messner and Meyer, 2006; Naumann et al., 2015; Winsemius et al., 2016). Therefore, it is important to understand the nexus of drivers of change and their impact on streamflow. This comprehension is the main requirement to ensure necessary measures and mitigate the consequences of an increase in streamflow extremes. Besides meteorological factors and highly alterations of river dynamics, land use change (LUC) potentially has a major impact on streamflow extremes (section 1.1 and 1.2). For example, urban growth as well as deforestation can increase flood peaks and afforestation can reduce low flows (Bradshaw et al., 2007; Rogger et al., 2017; Calder, 1992; Cheng et al., 2017; Ochoa-Tocachi et al., 2016a; Diem et al., 2018; Brown et al., 2005)

However, there still exists a lack of knowledge about the influence of LUC on hydrological extremes because a valid assessment is difficult: One challenge is related to the decreasing effect of LUC on streamflow with increasing scale where an effect may be great on the hillslope scale but decreases with increasing catchment size (Blöschl et al., 2007). Another challenge is the estimation of the effect size that LUC has on the streamflow because other factors like climate change or additional human interferences (e.g., dams, reservoirs) may cause an alteration in flow as well. Therefore, an investigation requires the isolation of the exclusive LUC effect on streamflow extremes apart from other influences. If the isolation is not correctly applied, changes can be wrongly assigned to LUC. Thus, the choice of the method is central in order to gain insights into the effects of LUC on streamflow extremes.

Moreover, most research has focused on one LUC direction (e.g., urban development or forestry) whereas looking at various LUC classes can give a more general impression on the impact of LUC on hydrological processes in a catchment area. Furthermore, only limited studies exist that analyze both streamflow extremes, droughts and floods.

Therefore, this thesis investigates how four important LUC – agriculture, pasture, urban and green area – affected both streamflow extremes, high and low flows, in various catchments in Northwestern Germany. In order to examine this research question, I apply two different methodologies (regional-scale comparison and panel regression model) and evaluate (1) their performance in isolating the LUC effect from other factors, (2) the plausibility and reliability of the outcome and (3) the complexity of application. The aim of this assessment is to make a recommendation for the more appropriate methodology. Nevertheless, the results of the LUC impact on streamflow extremes will be valid for the study region only because hydrological processes are highly context-dependent i.e., LUC affects the region's intrinsic dynamics (Blöschl et al., 2007). These effects can even be opposing depending on the region (Wang and Hejazi, 2011).

1.1. LUC and hydrological processes

Mainly, LUC refers to changes between agriculture, forest or other natural vegetation as well as urban area presenting a complex coupling with hydrological processes. The most important implications for streamflow extremes are (1) changes in runoff generation and overland flow as well as (2) changes in soil water processes (Blöschl et al., 2007; Calder, 1992; Chang and Franczyk, 2008; Rogger et al., 2017).

Both have an effect on the high flow generation. The alteration of the land surface and its cover (e.g., changes in imperviousness, compaction, and vegetation cover) affects the infiltration as well as the surface roughness. Less infiltration capacity increases infiltration excess runoff and reduced surface roughness scales up the overland flow velocity. Furthermore, the soil's water content is influenced by changes in infiltration. Moreover, these alterations can be intensified by changes in evapotranspiration e.g., through the transpiration demand of different plants. Thereby, increases in soil water content can lead to higher antecedent soil moisture that causes excess saturation runoff and is an important flood driver (Berghuijs et al., 2019; Brunner et al., 2020). In addition, flooding caused by high antecedent soil moisture can be further intensified by reduction of the soil's water storage capacity e.g., because of drainage of wetlands (Wingfield et al., 2019).

For the low flow dynamics, the soil water processes play the major role. Less infiltration and higher evapotranspiration demand can cause a reduction in the soil water content. The decrease of the soil's storage capacity can further shrink the water storage. On the long-term, these effects decrease the baseflow as well as the groundwater recharge.

In summary, increasing infiltration excess runoff and saturation excess runoff can influence flooding. Reduction in soil water can decrease low flows through impacts on baseflow. However, LUC can also have more elusive consequences like changes in preferential flow pathways through roads or artificial drainage, yet even indirect ones e.g., through irrigation water or groundwater abstraction (Döll et al., 2009; Jones and Grant, 1996).

1.2. Literature overview

As the method of choice is crucial to the outcome, the results of studies have to be critically examined taking into consideration the methodology used. Most applied methodologies comprise hydrological modelling, case study, paired-catchment approach, large-scale comparison and panel regression model.

Hydrological modelling is a widely applied approach and compares different modelling scenarios (e.g., natural and urbanized) to evaluate the impact of LUC. Mostly, LUC influences are integrated in the model as changes in infiltration and runoff coefficients. However, simulated results are only as accurate as the model itself and furthermore models are often large scaled (e.g., SWAT or VIC model) which causes uncertainty. Simulations showed that for urban development, reaching 10 – 20% impervious cover in the catchment area affects streamflow extremes (Chang and Franczyk, 2008; Oudin et al., 2018), however others reported a 3 – 5% threshold (Booth and Jackson, 1997; Yang et al., 2010). High urban expand of more than 40% catchment area increased peak flow by 13% (Shi et al., 2007), yet effects were observed by way smaller increases in urban area (Choi et al., 2003; Hurkmans et al., 2009; Lei et al., 2021; Petchprayoon et al., 2010). High agriculture increase above 30% of catchment area with losses of pasture, forests and other natural areas caused small increases in droughts and floods (Huisman et al., 2008; Qi et al., 2020). Deforestation of 20% of catchment area increased peak flows up to a third (Seibert and McDonnell, 2010). However, very high afforestation of 40% catchment area only caused a slight decrease in peak flow (Wegehenkel, 2002). Yet, including climate change into the model setup led to a minimization of the LUC contribution (Chawla and Mujumdar, 2015; Frans et al., 2013).

The case study approach compares streamflow of a pre-LUC period to a post-LUC period to investigate alterations in streamflow between the two periods. However, other factors (e.g., climate, other interferences) can have a greater impact on discharge change. Therefore, climate data is often included in the analysis that makes the approach more valuable. Yet, the data collection is time consuming and excluding all possible confounders can be difficult. Furthermore, changes in streamflow are not detected if they appear with a time lag. Studies including climate confounders, showed that agricultural expansion of 20 – 30% catchment area, high urban increase up to 60% catchment area or grassland reduction up to 13% catchment area altered streamflow and streamflow extremes (Costa et al., 2003; Debbage and Shepherd, 2018; Rientjes et al., 2011; Zheng et al., 2009). However, other studies reported streamflow changes were driven by climate change rather than LUC (Gupta et al., 2015; Krajewski et al., 2021; Richey et al., 1989; Sullivan et al., 2004; Tu et al., 2005).

The paired-catchment approach is a classic method that compares the streamflow of two catchments with similar characteristics (e.g., precipitation, temperature, hydrogeology, soil) but with differences in LUC – a catchment with LUC and a control catchment without LUC. There is no need to control for changes in climate because discharge data of the same observation period is compared which makes the approach safer to bias. However, there can be problems if there have been unobserved interferences in the catchments. Furthermore, the search for pairs can be challenging and time consuming. Deforestations of 20%, 50% and 100% catchment area accounted for increases in groundwater and baseflow (Cheng et al., 2017; Brown et al., 2005). Clearcutting was reported to have a high impact on peak discharge yet another statistical analysis with the same data attributed only a smaller influence (Beschta et al., 2000; Jones and Grant, 1996). Afforestation as well as agricultural expansion decreased low flows and increased high flows (Ochoa-Tocachi et al., 2016a, b). Urban expansion of 10% and 20% caused upward trends in runoff and thus influenced flooding (Putro et al., 2016). Other studies of human interferences attributed increases in droughts to groundwater abstraction and dam constructions (Rangecroft et al., 2019; Van Loon et al., 2019).

Another method, yet closely related to the paired-catchment approach, is the large-scale or regional-scale comparison. Instead of searching for similar pairs, a large sample of catchments with variation in LUC is compared. Therefore, streamflow changes are related to LUC only if the major proportion of catchments with LUC – in contrast to those without – showed an alteration in streamflow. The sheer number of catchments thus achieves robustness for the statistical analysis as well as makes the control for other changes (e.g., climate, human interferences) less important (Gupta et al., 2014). This approach can be effective and reliable yet it needs a larger number of catchments. Studies showed that imperviousness reaching levels of 10 – 20% catchment area could not be related to flood or drought dynamics yet an urban expansion of 30% catchment area due to decrease in forests caused an increase in high flow days (Brandes et al., 2005; Diem et al., 2018). Moreover, another study showed that human influences (e.g., reservoirs, groundwater abstractions) are not consistent in their impact on drought characteristics and can vary between catchments (Tijdeman et al., 2018).

The panel regression model is a relatively new approach in hydrology with interest on the rise, originating from economics and social science. By making use of the panel structure (time and space) of a large data set with various catchments, the average effect of LUC on streamflow is estimated through regression modelling. Hereby, the panel regression model can control for unobserved influences (e.g., climate changes) through time dummies and other modifiers. However, the right model setup can be complex yet is crucial and therefore can cause bias. A study showed that a 1%-point increase of impervious cover in catchment area slightly increased flood peak discharge (Blum et al., 2020). Deforestation of 10% catchment area caused an increase in flood frequency and duration (Bradshaw et al., 2007) and agricultural expansion due to deforestation of over 10% catchment area slightly reduced low flows (Levy et al., 2018). However, another study could not draw a connection between urban expansion and flood dynamics (Steinschneider et al., 2013).

The literature overview points out the high variability in results depending on the applied methodology. Out of the various methodologies, I choose the regional-scale comparison and the panel regression model because both are considered state-of-the-art methodologies in order to gain reliable results with a low risk of bias. Furthermore, they are the most suitable approaches to investigate a large sample of catchments, which is the case in my thesis.

1.3. Study region

The area of study is the Weser-Ems region in northwestern Germany. It is delimited by the North Sea in the north, the Weser in the east, North Rhine-Westphalia in the south and the Netherlands in the west (Fig. 1). I selected this region because a study reported that Northern Germany including the Weser-Ems region experienced high agricultural expansion form 1990 – 2006 (Kuemmerle et al., 2016). However, the LUC data that I used (section 2.1.5) did not support this statement of high agricultural expansion, showing expansions of less than 1% catchment area (Copernicus, 2021). Nevertheless, the area experienced LUC and appeared of interest because of its specific hydrology being part of the Northern Lowland.

The Northern Lowland, also called the North German Plain, is part of the glacial series formed by glaciation in the Pleistocene. Its main characteristics are a flat relief and grounds of glacial sediments with high vertical extent (Semmel, 1996). Yet, there are differences of relief and hydrogeology within the region that can be separated in two groups: the lowlands and the moraine area with the latter being the major landscape form. The lowlands were shaped through glacial meltwater and are characterized by a very flat relief, shallow water tables and thus groundwater influenced soils like gley and moors. Furthermore, a special landscape form within the lowlands is the marsh that later was formed through tide processes and relocation of silt. The moraine areas, also called Geest, are moderately higher elevated zones. Characteristics are high groundwater levels (yet lower than in the lowlands) and mostly sandy soils with partwise wetlands and moors. In the south, the relief becomes slightly mountainous due to outliers of the Teutoburger forest and the Wiehen Hills.

Agriculture has played a big role and still does today with more than two third of area in agricultural use. This reflects in the soil structure as well as in the highly altered channel network (e.g., by irrigation channels and artificial drainages) (Tetzlaff et al., 2009; Elfert and Bormann, 2010). Natural vegetation is in the form of shrubs, heath and small forests. The climate of the region is temperate oceanic thus characterized by mild winter and summer temperatures. Precipitation falls continuously throughout the year and mostly in the form of rain.

Due to the high infiltration capacity of the soils and shallow water tables, streamflow is foremost shaped by baseflow and groundwater interaction (Gauger, 2007; Elfert and Bormann, 2010). Therefore, infiltration excess runoff plays a minor role for flooding. However, saturation excess runoff can contribute because the general high water tables and long-lasting precipitations can exceed the soil's storage capacity. Furthermore, increasing groundwater can also contribute to flooding. Floodplains play an important role due to the flat relief of the area. Low rainfall and thus less infiltration and groundwater recharge reduces the baseflow and leads to decrease in low flows. In the Weser-Ems region, floods and droughts potentially intensify in the future (Huang et al., 2014). Therefore, investigating the historical contribution of LUC on alterations in streamflow is of interest in order to develop planning strategies for the future.

2. Material and methods

2.1. Material

For this study, I collected hydrological data of the Weser-Ems region (long-term discharge data and catchment information) and further processed it to select the catchments of interest. I processed the discharge data of the catchments of interest to calculate streamflow extremes indices (SEI) representing flood and drought characteristics on the event-scale. Additionally, I collected and processed climate data for catchment information as well as to control for trends in precipitation and temperature. At last, I collected and processed LUC data to assign the LUC to each catchment.

2.1.1. Hydrological and catchment data

The Niedersächsische Landesbetrieb für Wasserwirtschaft, Küsten- und Naturschutz (NLWKN) provided the hydrological data for the Weser-Ems region. This dataset included average daily discharge data ($m^3 \times s^{-1}$) measured at a large number of gauging stations over the period 1986 – 2017. Moreover, it included catchment boundaries of small basins and the river network of the Weser-Ems region. I assigned the upstream catchment area to each corresponding station by using the metadata of the catchment boundaries and the river network. It was not possible to identify the catchment area with the help of a digital elevation model (DEM) because of the almost flat relief and the highly altered channel network. However, I used an open-source DEM with 20-m resolution to calculate the average slope of each catchment (Sonny, 2021). From the set of stations, I excluded all gauging stations with no continuous time series as well as with parts of the upstream area outside of my study region. Moreover, I excluded stations with highly interfered catchment area (e.g., canal crossing) or flow regulations (e.g., regulation of inflow or outflow). I did not exclude catchments with minor interferences (e.g., channel structures, groundwater or surface water withdrawals or water feed) because there was no accurate data on these interferences. In total, I selected 30 catchments of interest that consisted of 28 upstream or tributary catchments and 2 downstream catchments with majority of catchments contributing to the major streams (Ems, Hunte, Hase, Oeste, Weser) of the area (Fig. 1).

Overall, the streams of the 30 catchments are of smaller size with mean annual discharge of 0.77 $m^3 \times s^{-1}$ (min.: 0.17 $m^3 \times s^{-1}$, max.: 2.04 $m^3 \times s^{-1}$), mean annual low flow 0.21 $m^3 \times s^{-1}$ (0.004 $m^3 \times s^{-1}$, 0.66 $m^3 \times s^{-1}$) and mean annual high flow 4.55 $m^3 \times s^{-1}$ (0.8 $m^3 \times s^{-1}$, 13.2 $m^3 \times s^{-1}$) over the observation period. The relief of most catchments is nearly level with exceptions of catchments in the south of the Weser-Ems region (ID: 27, 28, 29, 30) having a slight slope due to the Wiehen Hills and outliers of the Teutoburg Forest. Information about geology (GÜK250) and soils (BÜK250), I obtained from the Landesamt für Bergbau, Energie und Geologie Niedersachsen (LBEG). The geology of the catchments is typical for the North German Plain, being mostly sand and silt as well as partly peat. Soils are groundwater-influenced soils being mostly gley or podsol yet luvisol in more elevated areas. The region's annual precipitation for the observation period was around 800 mm and mean annual daily temperature 9.8°C (CDC, 2021). In the reference year of 1990, the main land use was overall agriculture (70%) with smaller parts of pasture (below 10%) followed by natural areas of e.g., heath or forests (15%). Urban area played a minor role (3%) (Copernicus, 2021). I provide a table with detailed information for each catchment in the appendix (Appendix 1).

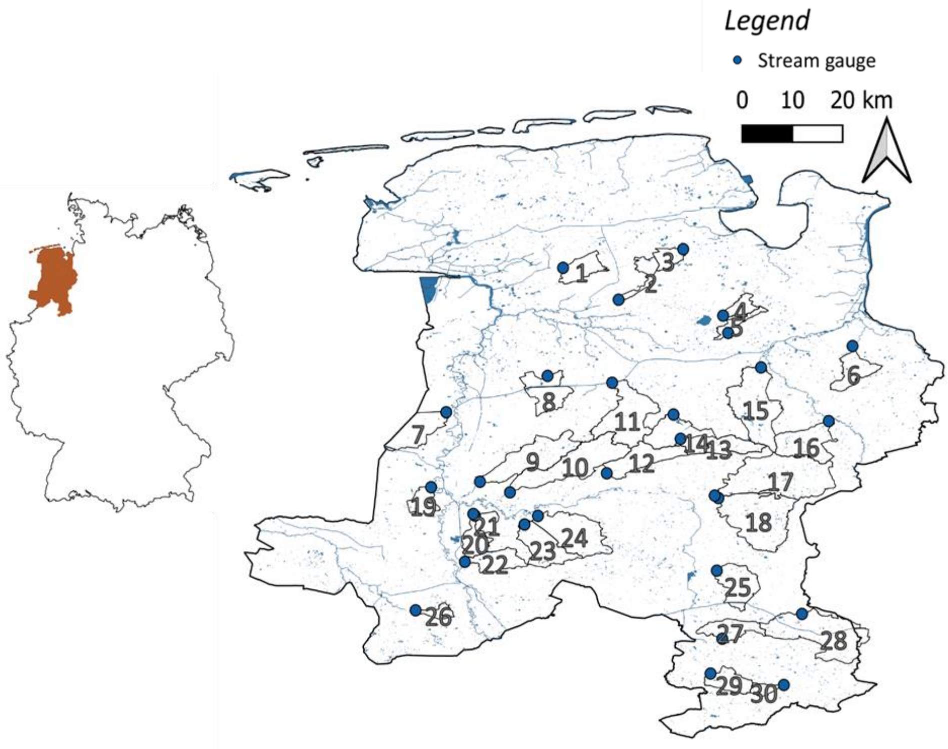

Figure 1. The Weser-Ems Region in Northwestern Germany with its main river network and the locations of the 30 catchments of interest indicated by their ID.

2.1.2. Climate data

I derived gridded daily precipitation data over the period 1985 – 2017 from Deutscher Wetter Dienst Climate Data Center (CDC) and assigned it to each catchment. I used REGNIE-Deutschland precipitation data based on interpolation of observed precipitation with grid resolution of 1-km (CDC, 2021; Rauthe et al., 2013). I used this data to calculate precipitation indices with the daily precipitation data to represent different precipitation conditions before the streamflow extreme events. In order to get an overview of trends in high temperatures, I used two datasets representing annual days with maximum air temperature above 25°C ('summer days') and above 30°C ('hot days') (CDC, 2021). This temperature data is gridded and based on interpolation of observed temperatures with 1-km resolution. However, I did not calculate temperature indices for each catchment and event because I assumed precipitation rather playing the major role for high and low flows in the study region.

2.1.3. Streamflow extremes indices (SEI)

The intention of the streamflow extremes indices (SEI) is to represent the most important characteristics of streamflow extremes on the event-scale. I applied the peak-over-threshold approach (POT) for high flows and the threshold-level approach (TLA) for low flows, where event identification functions by discharge exceeding or falling below a set threshold respectively (Fig. 2) (Brunner et al., 2021).

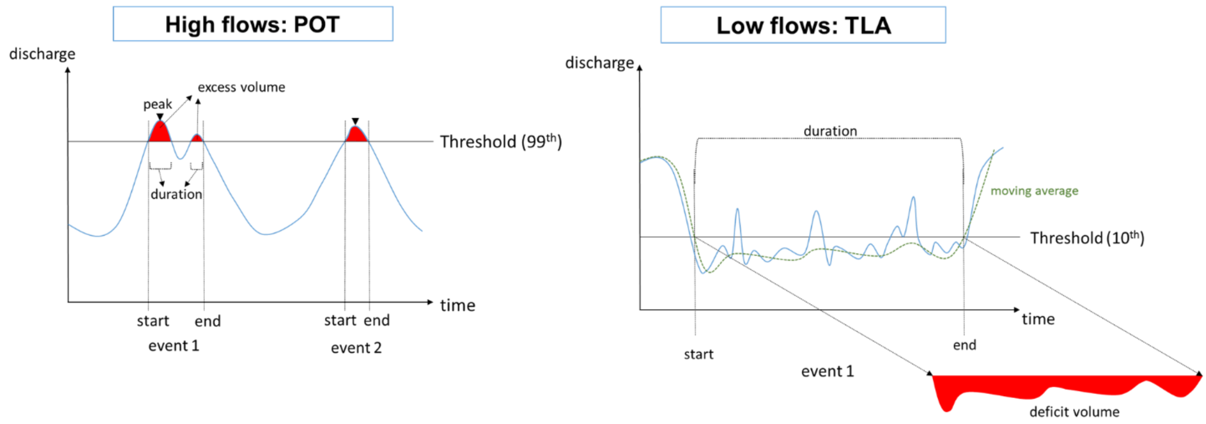

Figure 2. Schematic overview of the POT and TLA for the streamflow extremes indices.

For the POT, I set the threshold to the 99th-precentile of discharge over the whole observation period to get on average two events per year. I calculated it for each catchment separately. I pooled the events when the time gap in-between events was less than 6 days (Brunner et al., 2021). For each event, I calculated the three most important flood characteristics: the maximum discharge peak of the event ($m^3 \times s^{-1}$), the duration being days above the threshold (days) and the excess volume being volume above the threshold (m^3) (Fig. 2, table 1.1). Furthermore, I calculated the events per year to know if the number of exceedances per year had changed.

A threshold between the 5th- and 20th-percentile of discharge data is advised to represent low flows (Asadieh and Krakauer, 2017; van Huijgevoort et al., 2012). I choose the 10th-percentile because this threshold depicted my low flow data well by giving on average two drought events per year. Furthermore, I used a 10-day moving average for time series smoothing and pooled the events within 3 days range (Brunner et al., 2021; Tallaksen et al., 1997). For each event, I calculated the three most important low flow conditions: the average low flow over the event ($m^3 \times s^{-1}$), the duration being days beneath the threshold (days) and the deficit volume below the threshold (m^3) (Fig. 1, table 1.2). In addition, I calculated the drought events per year to check for changes in event number. A visualization of all SEI with normalized values is in the appendix (Appendix 2).

Table 1.1. High flow indices: Mean value of all catchments, minimum and maximum value.

maximum peak [$m^3 \times s^{-1}$]	duration [days]	excess volume [m^3]
5.0 (0.59, 31.1)	2.7 (1, 31)	2.5e+5 (0*, 7.7e+6)

*1 value at threshold (without: min.: 145 m^3)

Table 1.2. Low flow indices: Mean value of all catchments, minimum and maximum value.

mean low flow [$m^3 \times s^{-1}$]	duration [days]	deficit volume [m^3]
0.24 (0.001, 0.086)	22.8 (1, 144)	9.3e+4 (0*, 2.7e+6)

*12 values at threshold (without: min.: 4.3 m^3)

2.1.4. Precipitation indices

The purpose of the precipitation indices is to control for changes in precipitation conditions before each streamflow extreme event. For both high and low flows, I calculated the precipitation sum of the year and 30 days before an event to check for long- and short-term changes in water storage. Additionally, I calculated the mean precipitation over the event to check for drivers of duration and volume. For the high flows, I summed the precipitation of 10 days and 3 days before each event to check for antecedent soil moisture and heavy precipitation respectively. For the low flows, I summed the precipitation 90 days before an event to check for further changes in water storage as well as 10 days before to see short-term deficits in precipitation. A compilation of the precipitation indices is in the appendix (Appendix 3).

2.1.5. Land use change data

Accurate LUC data is crucial for performing an analysis on the LUC effect on streamflow extremes. Therefore, I used the widely applied and accurate (above 85% accuracy) CORINE Land Cover Changes (CLC-CHA) dataset by Copernicus Land Monitoring Service (Büttner, 2014; Copernicus, 2021). The CLC-CHA displays changes spatially with a resolution of 5-ha being more detailed than the CORINE Land Cover dataset (25-ha). CLC-CHA is available for four periods of change: 1990 to 2000, 2000 to 2006, 2006 to 2012 and 2012 to 2018 covering a time series from 1986 – 2018. CLC-CHA consists of 44 classes, which I aggregated according to my research question in agriculture, pasture, urban and green area.

The class agriculture included all agriculture types (CLC-CHA class 2) except pasture (CLC-CHA class 2.3.1). I assigned pasture (e.g., grassland, humid meadows or peatlands) as a separate class because of its better infiltration and storage capacities compared to cropland or arable land (Fohrer et al., 2001). The class urban consisted of all urban fabric, industrial and commercial area as well as transport units (CLC-CHA class 1.1 – 1.2) representing conglomerates of developed area. The green class, I assigned as artificial, non-agricultural vegetated areas, forests and wetlands as well as semi natural areas excluding non-vegetated spaces (CLC-CHA class 1.4, 3.1, 3.2, 4.1). Furthermore, I checked for changes in the excluded classes (e.g., water bodies) but could not detect a considerable change. I processed the LUC data for each catchment as absolute LUC (km^2) and relative to catchment area (%). I considered all LUC in the catchment area and not only in the riparian zone because I wanted to see how LUC is affecting the whole catchment. Moreover, the river networks densely covered the catchment areas.

Figure 3 depicts the accumulated LUC (relative to catchment area) of each class over the observation period 1986 – 2018 in the 30 catchments. There was a clear pattern of LUC from agriculture to urban area. However, agriculture also increased in four catchments, yet one of these catchment (marked by *) experienced a LUC within the agriculture class from a non-irrigated cropland to potentially irrigate and heterogeneous agriculture. I did not exclude this catchment to see if the within agriculture change caused an alteration in streamflow. Moreover, there were small decreases in pasture and some changes in green area which either were an increase due to decrease in agriculture or a decrease due to increase in urban area. The maximum increase and decrease in agriculture was 3.4% (the within agriculture change: 26%) and -12.7%, pasture 0.2% and -2%, urban 14% and no decrease, and in green area 1.7% and -6.2%. Further information about the LUC of each catchment is in the appendix (Appendix 1, table A2).

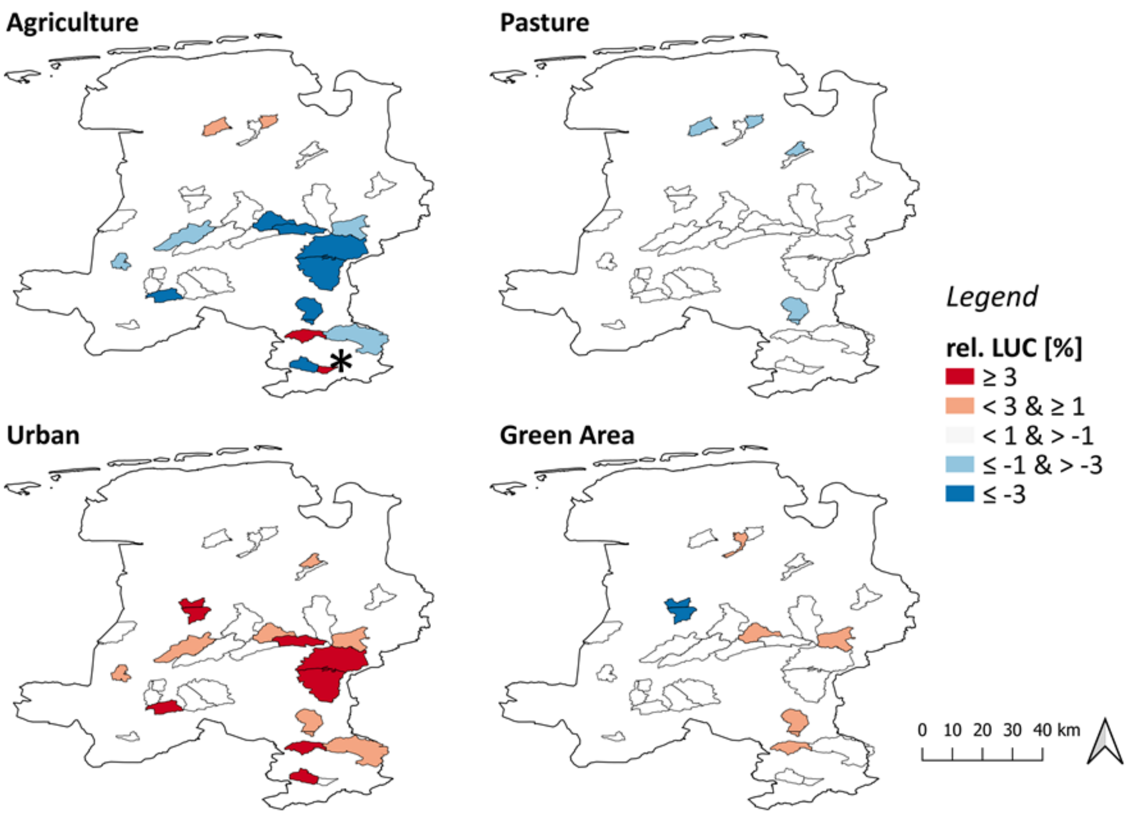

Figure 3. Accumulated LUC relative to catchment area over the observation period (1986 - 2018) for each class. The *-marked catchment represents a LUC within agriculture.

Nevertheless, I wanted to get another source of LUC data to validate the results that I obtained with CLC-CHA. I got in contact with different administrations of the Land Niedersachsen but there was no digital version of historical topographical maps or other remote sensing data available. The only available information on historical LUC was in form of cadastral data, which I derived from the Landesamt für Statistik Niedersachsen's (LSN) online database.

The data, defined as land survey according to actual use, is available for the period 1979 – 2019 and accurate to 1-ha. However, the spatial information is limited to the municipality level. It consists of 17 different land use classes, which I grouped in the four classes similar to the CLC-CHA data. Yet, the data showed unrealistic high LUC which I related to changes in classification rather than actual change in land use. This assumption is supported by the LSN, which reported unrealistic changes being caused due to changes in classification. I considered these errors and excluded the false values. However, a further and even greater problem was that catchment area and municipalities did not match i.e., mostly very small parts of multiple municipalities were located in one catchment area. I tried to control the mismatching by two conditions: (1) at least 60% of the municipality area had to be inside the catchment area and (2) at least 60% of the catchment area had to be covered by the municipalities fulfilling (1) as well as all showing a similar LUC. In case of fulfilling all conditions, I assumed data being accurate. This yielded in total LUC data for nine catchments of which six showed similar results as CLC-CHA (Appendix 4). However, three catchments (ID: 7, 23, 24) indicated LUC where CLC-CHA did not detect any. The LUC of these three catchments were increases in urban area (4.3%, 4.1%, 2.2%) and decreases in agriculture (-5.4%, -5.4%, -2.5%). Nevertheless, I did not base the analysis on this LUC data but I considered it in the later discussion.

2.2. Methods

2.2.1. Regional-scale comparison

The first methodology is referred to as the regional-scale comparison because it applies a large-scale comparison on the regional level. This method makes use of the relatively large sample size of catchments. Hereby, the idea is to compare alterations in SEI between catchments without or minor LUC and catchments that experienced moderate or high LUC. Generally, the hypothesis is that SEI have changed with increasing LUC. Therefore, I divided the catchments in three groups depending on the magnitude of their LUC in order to compare changes in SEI between the three groups and not consider each catchment separately. I set the thresholds for partition to have (1) a control group with no or minor LUC, (2) a group with relatively small to intermediate LUC compared to the other catchments and (3) a group with higher LUC compared to the other catchments:

(1) Group 1 (G1) with LUC of -1 – 1%
(2) Group 2 (G2) with LUC 1 – 3% and -3 – -1%
(3) Group 3 (G3) above 3% and below -3%

Hereby, the percentage is accumulated LUC over the whole period relative to catchment area. G1 consisted of 12, G2 and G3 of nine catchments respectively. My hypothesis for each group respectively was that G1 experienced no change in SEI, G2 a slight change in SEI and G3 a change higher than G2. I defined a change in SEI as a significant, monotonic trend over the observation period. Analyzing the impact in form of a trend made the approach easier because catchment specific characteristics that stayed stationary over the period (e.g., geology, soil or slope) required no control. Furthermore, through the catchment selection excluding highly interfered catchments, I assumed that except LUC, there was no other interference. However, the regional-scale comparison can minimize a confounding effect caused by other interferences through the large sample of catchments. Moreover, I assumed that within the Weser-Ems region there was no spatial difference in climate changes. Nevertheless, I checked for trends in precipitation indices and temperature for each catchment. The time series for the trend analysis was between 29 – 30 years, which I assumed necessary due to shorter time series potentially causing periodicity being mistaken for a trend. Furthermore, to compare the trend slopes between the three groups, I rescaled the SEI by min-max normalization (Appendix 5).

With the catchments subdivided into groups and the SEI normalized, I estimated the trends by using *zyp.trend.vector* function from the R-package *zyp* (Bronaugh and Werner, 2019), which computes a non-linear monotonic trend with slope estimation by Theil-Sen estimator (Sen, 1968; Yue et al., 2002). I applied this trend analysis, because I assumed trends potentially being non-linear as well as to control for outliers by the Theil-Sen estimator. I tested for trend significance with the Mann-Kendall test and set the level for rejection to $\alpha = 5\%$ (*p-value*=0.05). Moreover, I chose the order of firstly assigning the LUC groups and then calculating the trends to avoid a potential selection bias. In addition, I calculated the trends in climate data (precipitation indices and temperature) by the same method.

2.2.2. Panel regression model

The panel regression model comprises of two important parts: the transformation of the data into a panel structure and the setup of the model. Here, the latter is crucially important in order to achieve reliable results.

I reorganized the SEI by catchment and event to transform the data into a panel structure with a time and space dimension. Each catchment-event identification had to be unique to compare the catchments at concurrent events. However, events did not start on the same date. Therefore, I aggregated events with less than 5 days difference in-between. Yet, there were some concurrent events taking place in only one or very few catchments. Therefore, I excluded the events with less than six catchments to have a sufficient number for comparison. This approach resulted in 67 events for the high flows with an average of 14 catchments per event. For the low flows, it resulted in 64 events with an average of 10 catchments per event.

However, I wanted to further validate the outcome of the panel regression model on the event-scale, which required a higher number of catchments per event. Therefore, I annually mean-aggregated the SEI by the season which either was summer (May until October) or winter (November until April). This aggregation resulted in 27 season events (23 winter, 4 summer) for the high flows with an average of 20 catchments per event. For the low flows, it resulted in 29 season events (1 winter, 28 summer) with an average of 19 catchments per event.

Furthermore, I had to transform the CLC-CHA data in order to evaluate the influence of the event specific LUC on the SEI. I linearly interpolated within the time periods covered by each of the four CLC-CHA dataset (1986 – 2001, 1999 – 2007, 2005 – 2013, 2011 – 2018). I assumed that LUC gradually increased over the time periods. By this interpolation, I received an annual value of LUC over the period 1986 – 2017 for each catchment. I accumulated the obtained LUC values over time to get the total changed area since the year 1986. This was necessary because my aim was to estimate the effect on the SEI events depending on the total changed area before an event. At last, I excluded the two downstream catchments because I assumed that they might cause a bias due to a strong correlation between upstream and downstream discharge.

The setup of the panel regression model requires guidance by a clear definition of the analysis' aim. In my case, the aim was to investigate the influence of LUC on SEI within a catchment over the observation period. With this definition, I chose the within-model or also called fixed-effect-model (FEM) because it estimates the influence within a catchment and not compares between catchments. Furthermore, I assumed that only one spatial level (catchment) and no higher level (e.g., sub-regions in the Weser-Ems region) existed. Another remark of the FEM is that – in contrast to other models – it allows for the unobserved influences within a catchment being correlated with the LUC e.g., unobserved flood measures being constructed in catchments that undergone urban growth. These assumptions made the FEM the right model for my analysis (Bell et al., 2019; Bell and Jones, 2015; Clark and Linzer, 2015; Steinschneider et al., 2013; Wooldridge, 2010). However, there are two further important notes on the usage and interpretation of the FEM: (1) that the results are only of explanatory nature thus just account for the observed LUC in the catchments over the period and cannot be generalized. (2) That the causal relationship between LUC and SEI has to be explained because otherwise simple correlation can be confused for causality (Bell et al., 2019; Shmueli, 2011; Wooldridge, 2010).

Model 1 (M1) represents the first model setup of the FEM:

$$ln\left(y_{i,t}\right) = \alpha_i + \beta_k * x_{k,i,t} + \gamma_t * D_t + \varepsilon_{i,t} \tag{M1}$$

y: SEI	α: fixed effect	β_{1-4}, x_{1-4}: effect size, LUC classes	*γ, D:* effect size, time dummy	*ε:* unobserved heterogeneity

with *i* catchment ID, *t* event and *k* (= 1, 2, 3, 4) the LUC classes.

In M1, *y* represents the SEI of each catchment and event being maximum peak discharge ($m^3 \times s^{-1}$) and excess volume (m^3) as well as mean low flow ($m^3 \times s^{-1}$) and deficit volume (m^3). For both high and low flows, the event duration as well as the number of events per year was not possible to model due to the discreteness of values and thus the insufficient model fit. I applied the natural logarithm (ln) because the ln made the effect of LUC on SEI interpretable in a percentage change. Moreover, the ln transformed the SEI data to a more normal distribution because the data distribution was generally very left skewed. α represents the fixed effects for each catchment being the stationary catchment specific characteristics (e.g., size, geology, soil, average SEI magnitudes, stationary climate) that did not change over time. The LUC classes (agriculture, pasture, urban, green area) are the regressors of the FEM respectively and are represented by x_1 to x_4. Hereby, β_k is the average effect size the specific LUC class has on the SEI. The effects of each LUC class had to be estimated separately because of their strong correlation. I tested for multicollinearity between them by calculating the variance inflation factor (VIF) which was highly above the advised maximum of VIF = 10 (Hair et al., 2010). Furthermore, I included time dummies to control for other influences that changed over time and affected SEI in all catchments at the same event (e.g., large precipitation events, regional high temperatures). However, I did not include them as time fixed effects for each event but only for specific events to avoid overfitting i.e., if the regional effect was significant the time effect was included. In M1, D represents the dummy variable, which is binary for the significance of an event (0, 1), and γ is the concurrent effect size of the dummy.

In summary, the model controlled for time independent spatial variation (fixed effects) and temporal variation over all catchments (time dummies). However, M1 did not control for time and space varying confounders e.g., catchment specific changing climate conditions or other interferences in a catchment. This unobserved heterogeneity could not be estimated and therefore is represented by the event and catchment varying error, ε.

To improve M1, I included spatial as well as temporal variable parameters. These parameters are the precipitation indices (PI) and presented in model 2 (M2):

$$ln\left(y_{i,t}\right) = M1 + \delta_5 * x_{5,i,t} + \cdots + \delta_l * x_{l,i,t} \qquad \text{(M2)}$$

y: SEI	M1: Model 1	δ_{5-9}, x_{5-9}: effect size, precipitation indices

with i catchment ID, t event and l (= 5, 6, 7, 8, 9) the PI.

In M2, x_5 to x_9 represent the PI for high flows and low flows respectively with δ_l being the estimator for each PI. I included all PI in the model at the same time even though they were correlated and multicollinearity existed because (1) they were not the variables of interest thus their actual estimators were of no importance to this research and (2) because VIF test showed values below the advised maximum value of VIF = 10 (Hair et al., 2010).

I estimated the panel regression models M1 and M2 with the R-package *plm* (Croissant and Millo, 2008) and tested the hypothesis that a LUC classes had a significant influence with a two-tailed test setting rejection level to $\alpha = 5\%$ (*p-value* = 0.05).

Another important remark while using panel regression models is the treatment of the error term because the wrong estimation of standard errors (SE) can lead to biased significance of the predictors (Cameron and Miller, 2015; Hoechle, 2007). Regular SE are calculated by the ordinary least square (OLS) method, which does not account for heteroscedasticity nor serial or cross-sectional correlation of the residuals (Vogelsang, 2012). In hydrological modelling, each may be the case because residuals tend to have higher variance with increasing values (e.g., discharge) or are correlated across catchments or within catchments across time (Schoups and Vrugt, 2010; Steinschneider et al., 2013). In order to allow for heteroscedasticity or serial as well as cross-sectional correlation, I used robust SE (Cameron and Miller, 2015; Vogelsang, 2012; Zeileis et al., 2020). I tested for heteroscedasticity with the studentized Breusch-Pagan test, for serial correlation with Breusch–Godfrey test and for cross-sectional correlation with Breusch–Pagan's LM test with the R-packages *lmtest* and *plm* (Baltagi et al., 2012; Breusch, 1978; Breusch and Pagan, 1979; Croissant and Millo, 2008; Godfrey, 1978). I applied different robust SE depending on the case. For heteroscedasticity, I applied a heteroscedasticity-consistent covariance matrix with R-function *vcovHC* by R-package *sandwich* (Millo, 2017; Zeileis, 2006). In case of serial correlation (or cross-sectional correlation) I clustered residuals on the catchment level (or time level) with Arellano method using *vcovHC* by R-package *sandwich* (Zeileis et al., 2020; Arellano, 1987). In case of serial as well as cross-sectional correlation, I calculated robust SE by Driscoll and Kraay method with *vcovSCC* of the R-package *plm* (Croissant and Millo, 2008; Driscoll and Kraay, 1998; Millo, 2017). However, the treatment of SE in panel data modelling is still at issue because if SE are diverging depending on the treatment it can also indicate a misspecification of the model itself (King and Roberts, 2015). Therefore, I evaluated both regular SE and robust SE treatments in order to compare and make an elaborate choice.

For the model diagnostics, I checked the overall fit by visually analyzing the observed and fitted values as well as by the FEM goodness of fit (R^2) being calculated on the mean de-trended data i.e., without including the fixed effects making R^2 therefore generally low. Moreover, I calculated the mean absolute error (MAE) for further comparison purposes (Appendix 6). I analyzed the leverage of observations to check for influential data. High leverage observations have a strong influence thus excluding them could change the effect size of a LUC significantly. In case of high leverage, I excluded the high leverage observations or an entire catchments (in case the entire catchment had high leverage) and estimated the model again to check for changes in significance and effect size. I interpreted the results as reliable in case of the LUC influence becoming insignificant (*p-value* > 0.05) but without a greater change in the estimator. I accepted the result because there was already high tendency of an influence of the LUC on streamflow extreme, which became significant by a certain high influential observations. In contrary, I rejected the results for the opposing case of LUC becoming insignificant and the estimator changing highly.

3. Results

3.1. Regional-scale comparison

The results of the regional-scale comparison are presented in figure 4. The scatterplot shows the results of the trend analysis for each SEI. Here, the y-axis depicts the normalized slope (except events per year) of each SEI over the whole observation period. Positive values are an upward and negative a downward trend. The big dots indicate catchments that had a significant trend in the specific SEI and the small points represent catchments with an insignificant trend. The numbers indicate the catchment ID. The three colors identify the three groups, G1 (grey) with the hypothesis of no trend in SEI, G2 (light yellow) with the hypothesis of a slight trend in SEI and G3 (orange) with the hypothesis of a trend higher than G2.

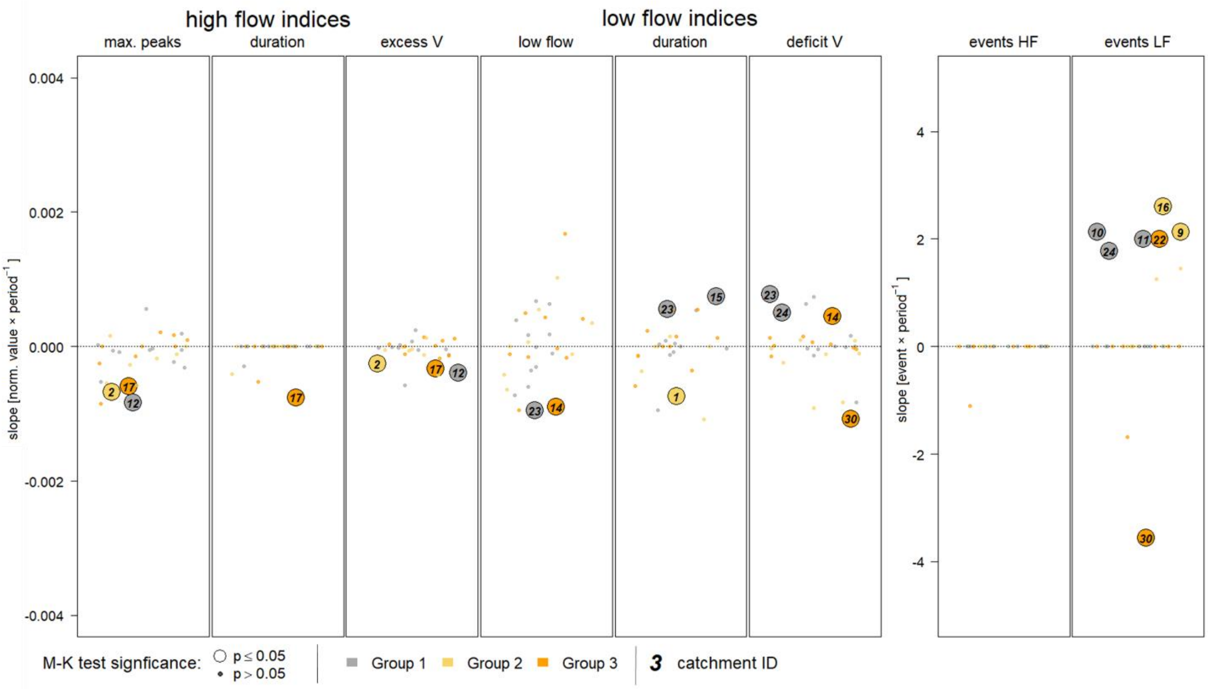

Figure 4. Scatterplot of the trends in SEI (maximum peak discharge, high flow duration, excess volume, mean low flow, low flow duration, deficit volume, number of high flow events per year, number of low flow events per year). Big dots indicating catchments with significant trend and small points insignificant. Colors represent the three groups.

Only three catchments (ID = 2, 12, 17), one of each group, had a significant trend in the high flow indices. All three catchments experienced a downward trend in maximum peak discharge as well as excess volume with catchment 12 (G1) having the most decrease in both indices. However, the magnitude of the normalized slope between the three did not vary strongly. Furthermore, catchment 17 showed a significant downward trend in the high flow duration. There was no significant trend in the high flow events per year in any catchment.

Trends in the low flow indices showed different results with 11 catchments (ID = 1, 9, 10, 11, 14, 15, 16, 22, 23, 24, 30) having a significant trend. Catchment 23 (G1) and catchment 14 (G3) had a significant downward trend in the mean low flow with catchment 23 having a slightly higher trend. Furthermore, catchment 23 and catchment 14 (both G1), experienced a significant increase in low flow duration whereas catchment 1 (G2) had a significant decrease in duration. In addition, catchment 23 and catchment 24 (both G1) as well as catchment 14 (G3) had a significant increase in deficit volume with the G1 catchments having a slightly higher increase. There was a significant downward trend in deficit volume in catchment 30 (G3). The number of low flow events per year showed a significant increase in three catchments of G1 (ID = 10, 11, 24), in two of G2 (ID = 9, 16) as well as one of G3 (ID = 22) and a decrease in catchment 30 (G3). In summary, only one out of nine catchments of G2 and G3 respectively showed a significant trend in the high flows without a high difference in slope magnitude yet even smaller than the slope of the G1 catchment. Only three out of nine catchments of G2 and G3 respectively experienced a significant trend in the low flows. The slope magnitudes of these catchments did not differentiate as hypothesized and furthermore was partwise lower than that of the G1 catchments.

However, it is important to consider the specific LUC values of each catchment apart from the groups. The aim of this consideration is to check if (1) G3 catchments with a trend experienced an especially high LUC relative to catchment area and (2) to investigate if the absolute LUC values (km^2) might give an explanation. Therefore, I visually compared the absolute LUC values and the LUC values relative to catchment area (Appendix 7). Catchment 17 (G3) experienced high LUC from agriculture to urban area with absolute values being especially high compared to the other catchments. Furthermore, this catchment had the highest absolute reduction in pasture. However, three more catchments of G3 experienced similar high LUC patterns (except pasture) yet did not show a significant trend in high flow indices (Appendix 7, fig. A6). Considering the low flows, catchment 14 (G3) experienced the highest change from agriculture to urban in both absolute and relative values. Moreover, it had the highest increase in green area (Appendix 7, fig. A7). Nevertheless, three more catchments of G3 experienced a similar high LUC (except green area) yet did not show a significant trend in low flows (Appendix 7, fig. A7). Moreover, catchment 30 (G3) experienced an increase in agriculture far more than any other catchment; however this change was within the agriculture land use.

3.2. Panel regression model

The panel regression model estimated a significant influence of the green area on the two high flow indices maximum discharge peak and excess volume at the event and seasonal scale. All other LUC classes showed no significant influence on the high flow indices. Furthermore, the panel regression model showed no significant effect of LUC on the low flow indices whatsoever.

One percentage catchment area changed to green area caused on average a decrease in maximum peak discharge of -3.85% with confidence interval (CI) (CI: -6.15 – -1.5%) on the event scale and on the seasonal of -3.28% (CI: -5.54 – -0.75%). The effect size of one percentage catchment area changed to green area on the excess volume was -28.37% (CI: -39.57 – -15.1%) for the event scale and -19.23% (CI: -32.27 – -3.66%) for the season scale. The estimated effect sizes account vice versa i.e., changes from green area to another land use form caused an increase in high flows. However, the results only account for the catchments that experienced a LUC in green area. The results originate from the estimation with model 2 (M2) including time dummies and precipitation indices. Overall, M2 showed the best fit (R^2 and MAE) for all four SEI on both event and seasonal scale (Appendix 8). However, the goodness of fit of maximum peak discharge and mean low flow is highly better than that of excess volume and deficit volume (Appendix 8). Therefore, I reconsider the meaningfulness of the results for the excess volume in the discussion.

However, adding the precipitation indices only slightly enhanced the model performance. The fixed effects and time dummies had the largest impact on the model performance. The effect size of green area changed only minimally by integrating precipitation indices thus; they did not function as moderators or confounding variables but as simple modifiers. Residuals were mostly serially and cross-sectionally correlated. Therefore, I used robust SE. However, the different SE treatments did not change the significance of LUC influence except for the mean low flow. Here, regular SE estimated an effect (decrease) of the mean low flow due to an increase in pasture. However, using robust SE – because residuals were serially and cross-sectionally correlated – made it insignificant. The analysis of influential stations for maximum peak discharge and excess volume pointed out that one station (ID: 8, highest decrease in green area: -6.2%) had a high leverage and excluding it made the influence insignificant. However, the effect size only changed minimally (by 0.1%). In addition, I excluded two stations (ID: 2, 25) with the highest increase in green area (1.6%, 1.7%). The exclusion changed the significance yet the effect size only minimally. Therefore, I accept the result that the influence of green area on high flows was significant because there was already a tendency, which became significant by certain high influential catchments.

4. Discussion

4.1. Impact of land use change

Based upon the regional-scale comparison, I conclude that there was no pattern of LUC causing trends in streamflow extremes in the Weser-Ems region over the observation period from 1986 – 2017. There were catchments that experienced relatively high LUC as well as a trend in streamflow extremes. However, other catchments with similar magnitudes of LUC showed no trend. Therefore, I reject the hypothesis that the observed LUC caused an alteration in streamflow extremes. This result coincides with other studies where LUC of small size in neighboring regions over partly similar periods had no effect on streamflow (Ashagrie et al., 2006; Bronstert et al., 2007; De Roo et al., 2001; Elfert and Bormann, 2010). Even though some of the investigated catchments experienced LUC from agriculture to urban area of around 10% catchment area, the results do not object the literature of imperviousness thresholds (3 – 20%, section 1.2) because urban area in this study was a conglomerate of urban associated areas and does not indicate impervious cover. However, effects on streamflow caused by LUC could have balanced each other out e.g., by an increase in both urban and natural area (De Roo et al., 2003) or even counteract streamflow alterations caused by climate change and thus equilibrate .

Nevertheless, I discuss some results of the regional-scale comparison. I do not assume that the relatively high decrease in pasture of catchment 17 contributed to the decrease in high flow indices. Even though the value was the highest among the catchments, it was generally low. Furthermore, I rather assume an increase in high flows due to a change from pasture to urban area because of the increased surface runoff (Chang and Franczyk, 2008; Fohrer et al., 2001; Rogger et al., 2017). Apart from the decrease in agriculture and increase in urban area, the relatively high increase of green area in catchment 14 might have contributed to the low flow reduction. The reduction may have been caused by impacts on baseflow due to higher evapotranspiration demand of changed vegetation (Brown et al., 2005; Zhang et al., 2001). Catchment 30 (the within agriculture change) was the only catchment where drought conditions improved what I relate to the change from non-irrigated arable land to a heterogeneous, potentially irrigated agriculture form. Furthermore, the other LUC data source (section 2.1.5) indicated a change opposing the CLC-CHA data in three catchments. Two of these catchments (ID: 23, 24) had a trend in streamflow extremes. However, six other catchments with similar magnitudes and LUC directions (decrease in agriculture and increase in urban area) had no trend. Therefore, the consideration of the other LUC data does not change the rejection of the hypothesis.

The trends in climate data can give some explanation on trends. Catchment 12 experienced a decrease in the precipitation sum 10 days and 365 days before an event, that may have decreased high flows. Catchment 23 had a downward trend in precipitation sum 30 days and 365 days before an event, which may have increased the drought indices. Moreover, catchment 14, 16 and 22 had an upward trend in summer days thus potentially causing the increase in low flows. Furthermore, all catchments had an upward trend in mean annual temperature. However, aside from meteorological and LUC influences, I make two assumptions for the source of trends in low flows. I conceived these two hypotheses after analyzing the spatial distribution of the catchments that experienced a trend in low flows (Fig. 5).

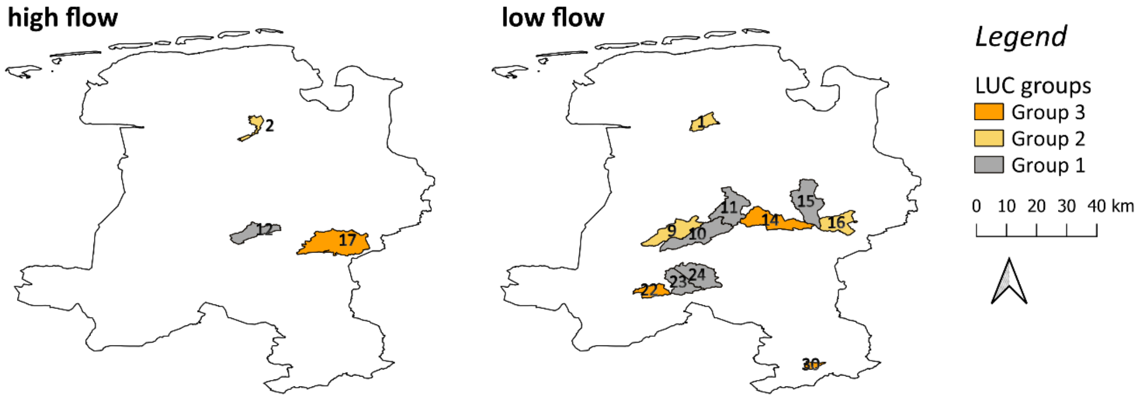

Figure 5. Location of catchments with trends in high and low flows in the Weser-Ems region over the observation period.

Catchments 9 – 16 and 22 – 24 are located in the same natural area called the Ems-Hunte-Weser-Geest having a hydrogeology of mostly glacial deposits. A report on groundwater dynamics from the NLWKN stated that this area experienced groundwater droughts every year since 2008 (NLWKN, 2021). Therefore, my first hypothesis is that these groundwater droughts caused decreases in streamflow by baseflow reduction. The second hypothesis is, that artificial drainages had an effect on the low flow reduction because artificial drainage is widespread in the area (Tetzlaff et al., 2009). This assumption is not contrary to the first one but can even contribute. On one side, it could have been the case that yet existing drainages aggravated the situation of low groundwater thus causing a trend. On the other, that newly build drainage systems caused a decrease. However, information about drainage systems in the region since the end of the 1980s does not exist yet artificially drained area was constantly increasing until the end of the 1980s in the Weser-Ems region (Tetzlaff et al., 2009).

The second method, the panel regression model, showed that the change in green area had a significant impact on high flows in the observed catchments over the observation period. Increases in green area had a mitigating effect on the high flows and vice versa. In order to accept the result, it requires causally explanation. In this study, the land use class green area included vegetation cover (e.g., forests, shrubs or heath) as well as wetlands and artificial green area (e.g., urban green space). Vegetation cover and natural area has a mitigating effect on high flows interception and reduction of surface roughness as well as by potentially decreasing antecedent soil moisture (Calder, 1992; Kittredge, 1948; Rogger et al., 2017; Chang and Franczyk, 2008). Wetlands can have an especially high impact due to the high infiltration and storage capacity making them natural flood measures (Wingfield et al., 2019). This causally explains the significant influence of green area on high flows estimated by the panel regression model. Therefore, I accept the result that changes in green area had an impact on high flows mitigating the peak discharge. However, I assume the very high effect size of green area on excess volume as not reliable. The large confidence interval reflects the inaccuracy and furthermore the model performance was overall poor (Appendix 8, fig. A10 & A11). Therefore, I reject the effect size of the influence on excess volume. However, I accept the effect size of green area on the maximum peak discharge due to the good model fit (Appendix 8, fig. A8 & A9).

Looking at the model performance once again, I relate the cross-sectional correlation to clusters on the sub-regional level e.g., groundwater processes affecting a group of neighboring catchments with the same hydrogeology. However, climate events on a sub-regional level could have also affected the streamflow extremes. Furthermore, including just the precipitation indices in the model could not explain temporal variation in the streamflow extremes indicated by the relatively low R^2 and high MAE

(Appendix 8). My hypothesis for an explanation of the residuals is that complex groundwater dynamics had an influence on the streamflow in the catchments over the observation period.

4.2. Methodologies assessment

The two applied methodologies lead to different results demonstrating the necessity of an evaluation. The two applied methods represent two different approaches to isolate the LUC effect on streamflow extremes from other influences: (1) by directly integrating other influences (e.g., climate changes) or (2) an indirect control. The regional-scale approach applies the indirect control through the large number of catchments. That means, the approach concludes that LUC had an impact on streamflow extremes only if a major share of catchments with LUC showed a significant alteration in streamflow extremes in contrast to the opposing case of catchments without LUC having no alteration.

On the contrary, the panel regression model directly integrates other influences into the model by either more data (in my case the precipitation indices) or by time dummies. Moreover, unobserved effects on streamflow extremes that appeared on the catchment level and changed in time are controlled by the error term. This control is efficient because the significance of the LUC effect on streamflow extremes depends on the magnitude of the error term.

Assessing the plausibility and reliability of the methodologies depends on understanding their intrinsic processes. Generally, the regional-scale comparison is a statistical analysis and the panel regression model a statistical model. The regional-scale comparison bases the results reliability on the large number of catchments that give statistical robustness (Gupta et al., 2014). This approach is reliable if it is assumed that there is no strong correlation between LUC and other confounding changes (e.g. climate or other interferences). A change in streamflow is evaluated by trend analysis, which is an established approach in hydrological time series analysis. The results are easily comprehensible: there either existed a trend or not. However, in this thesis it was only possible to investigate monotonic changes over the whole observation period because I applied the trend analysis on the whole observation period. This approach therefore may have led to overlook changes in streamflow extremes caused by LUC. If LUC occurred non-monotonic over the observation period (e.g., increase and decrease in the land use class) and caused a non-monotonic change in streamflow extremes overlooking might have been the case.

In contrary, the panel regression model can identify non-monotonic changes due to calculating the effect of LUC on streamflow indices at a specific event and catchment. However, when it comes to the reliability of the results, the panel regression model can be ambiguous. That is because the model itself requires many controls in order to function correctly therefore making it prone to bias. The choice of the model (e.g., fixed effect or random effect model), the right model structure (e.g., dummies, confounding variables) as well as the standard error treatment (e.g., regular or robust SE) can give different or even opposing results depending on the application. Furthermore, the model diagnostics can highly change the results e.g., excluding influential catchments can change the significance as well as the effect size of a variable of interest. Moreover, it is also important to check for the overall model fit (e.g., R^2, residuals) to decide if the goodness of fit is sufficient to accept its results. Nevertheless, if the panel regression model is correctly applied it can be reliable.

Furthermore, the panel regression model investigated the effect size of each LUC class separately giving information about the influence on streamflow extremes of each specific LUC class. In contrary, the regional-scale model could only assess the impact of the catchments specific LUC signature. Moreover, the reliability of both methodologies strongly depends on the accuracy of the LUC data. Therefore, the source of the LUC data requires elaborate examination.

The last important point of evaluating the two methodologies is their applicability because complex and time-consuming approaches are less favorable. The regional-scale comparison is a straightforward and easily interpretable approach. The only time-consuming factor can be gathering a sufficiently large number of catchments as well as long-term hydrological data. However, the panel regression model not only needs a large data set but also intensive data preparation for the panel structure. Moreover, if it is the first time of application, the panel regression model requires a profound examination and comprehension of the model structure and its controls. Therefore, the panel regression model is a complex and time-consuming approach. However, if once comprehended, the panel regression model can be valuable.

I hypothesize that the opposing results of the two methodologies – no impact and an impact of LUC on streamflow extremes – were caused by the different definitions and calculations of a change in streamflow extremes. I defined and calculated a change in streamflow extremes as a monotonic trend over the whole observation period with the regional-scale comparison. In contrast, the panel regression model estimated the impact of LUC on the streamflow extremes at a certain event thus non-monotonic. However, other methodology specific controls (section 2.2.2) can also have caused the difference in the results.

5. Conclusions

A better understanding about the effects of land use change (LUC) on streamflow extremes can help mitigating an intensification in floods and droughts. Yet, the impact varies because it is strongly dependent on the hydrological context and scale. Therefore, a deeper comprehension demands more research of different hydrological regions at various scales. Thus, it is important to use reliable and applicable methods for an investigation. To examine the effect of LUC on streamflow extremes, I applied two different methodologies – regional-scale comparison and panel regression model – and discussed their benefits and limitations.

The two applied methods resulted in different conclusions for the influence of LUC on streamflow extremes in the Weser-Ems region. The regional-scale comparison did not connect changes in streamflow extremes to LUC. However, the panel regression model showed that an increase in green area mitigated the high flows (1% increase in green area relative to catchment area caused a decrease in maximum peak discharge of around 3% and vice versa). Since I correctly applied the methodologies, I attribute the difference in outcome to the methods' inherent calculations (monotonic and non-monotonic).

The regional-scale comparison is a straightforward statistical analysis giving robust results yet it requires a large catchment set with long-term discharge data. It may pose difficulties to isolate the LUC effects on streamflow extremes from other influences (e.g., climate changes). The panel regression model is a statistical model that requires intensive control and thus can be complex, time-consuming and prone to bias. However, if correctly applied it can give valuable results. Giving a recommendation, I advise the usage of the regional-scale comparison because it is straightforward, not time consuming and results are robust.

Concluding, the gained knowledge about the contribution of LUC on streamflow extremes can give a better understanding of the hydrological processes in the Weser-Ems region. Furthermore, the results can be used to develop strategies to mitigate streamflow extremes in the Weser-Ems region. The assessment of the two methodologies is generalizable and can help choosing the right method for investigating LUC influences on streamflow.

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References

Arellano, M.: Computing Robust Standard Errors for Within-Groups Estimators, 49, 431–434, 1987.

Arheimer, B., Donnelly, C., and Lindström, G.: Regulation of snow-fed rivers affects flow regimes more than climate change, Nat Commun, 8, 62, https://doi.org/10.1038/s41467-017-00092-8, 2017.

Asadieh, B. and Krakauer, N. Y.: Global change in streamflow extremes under climate change over the 21st century, Hydrol. Earth Syst. Sci., 21, 5863–5874, https://doi.org/10.5194/hess-21-5863-2017, 2017.

Ashagrie, A. G., de Laat, P. J., de Wit, M. J., Tu, M., and Uhlenbrook, S.: Detecting the influence of land use changes on discharges and floods in the Meuse River Basin – the predictive power of a ninety-year rainfall-runoff relation?, Hydrol. Earth Syst. Sci., 10, 691–701, https://doi.org/10.5194/hess-10-691-2006, 2006.

Baltagi, B. H., Feng, Q., and Kao, C.: A Lagrange Multiplier test for cross-sectional dependence in a fixed effects panel data model, J. Econom., 170, 164–177, https://doi.org/10.1016/j.jeconom.2012.04.004, 2012.

Batalla, R. J., Gómez, C. M., and Kondolf, G. M.: Reservoir-induced hydrological changes in the Ebro River basin (NE Spain), J. Hydrol., 290, 117–136, https://doi.org/10.1016/j.jhydrol.2003.12.002, 2004.

Bell, A. and Jones, K.: Explaining Fixed Effects: Random Effects Modeling of Time-Series Cross-Sectional and Panel Data, Political Science Research and Methods, 3, 133–153, https://doi.org/10.1017/psrm.2014.7, 2015.

Bell, A., Fairbrother, M., and Jones, K.: Fixed and Random effects models: making an informed choice, Quality and Quantity, 53, 1051–1074, https://doi.org/10.1007/s11135-018-0802-x, 2019.

Berghuijs, W. R., Aalbers, E. E., Larsen, J. R., Trancoso, R., and Woods, R. A.: Recent changes in extreme floods across multiple continents, Environ. Res. Lett., 12, 114035, https://doi.org/10.1088/1748-9326/aa8847, 2017.

Berghuijs, W. R., Harrigan, S., Molnar, P., Slater, L. J., and Kirchner, J. W.: The Relative Importance of Different Flood-Generating Mechanisms Across Europe, Water Resour. Res., 55, 4582–4593, https://doi.org/10.1029/2019WR024841, 2019.

Beschta, R. L., Pyles, M. R., Skaugset, A. E., and Surfleet, C.: Peakflow Responses to Forest Practices in the Western Cascades of Oregon, USA, J. Hydrol., 233, 102–120, https://doi.org/10.1016/S0022-1694(00)00231-6, 2000.

Blöschl, G., Ardoin-Bardin, S., Bonell, M., Dorninger, M., Goodrich, D., Gutknecht, D., Matamoros, D., Merz, B., Shand, P., and Szolgay, J.: At what scales do climate variability and land cover change impact on flooding and low flows?, Hydrol. Process, 21, 1241–1247, https://doi.org/10.1002/hyp.6669, 2007.

Blum, A. G., Ferraro, P. J., Archfield, S. A., and Ryberg, K. R.: Causal Effect of Impervious Cover on Annual Flood Magnitude for the United States, Geophys. Res. Lett., 47, e2019GL086480, https://doi.org/10.1029/2019GL086480, 2020.

Booth, D. B. and Jackson, C. R.: Urbanization of Aquatic Systems: Degradation Thresholds, Stormwater Detection, and the Limits of Mitigation1, JAWRA, 33, 1077–1090, https://doi.org/10.1111/j.1752-1688.1997.tb04126.x, 1997.

Bradshaw, C. J. A., Sodhi, N. S., Peh, K. S.-H., and Brook, B. W.: Global evidence that deforestation amplifies flood risk and severity in the developing world, Glob. Change Biol., 13, 2379–2395, https://doi.org/10.1111/j.1365-2486.2007.01446.x, 2007.

Brandes, D., Cavallo, G. J., and Nilson, M. L.: Base Flow Trends in Urbanizing Watersheds of the Delaware River Basin1, JAWRA, 41, 1377–1391, https://doi.org/10.1111/j.1752-1688.2005.tb03806.x, 2005.

Breusch, T. S.: Testing for Autocorrelation in Dynamic Linear Models*, Australian Economic Papers, 17, 334–355, https://doi.org/10.1111/j.1467-8454.1978.tb00635.x, 1978.

Breusch, T. S. and Pagan, A. R.: A Simple Test for Heteroscedasticity and Random Coefficient Variation, Econometrica, 47, 1287–1294, https://doi.org/10.2307/1911963, 1979.

Bronaugh, D. and Werner, A.: Package "zyp," 2019.

Bronstert, A., Bárdossy, A., Bismuth, C., Buiteveld, H., Disse, M., Engel, H., Fritsch, U., Hundecha, Y., Lammersen, R., Niehoff, D., and Ritter, N.: Multi-scale modelling of land-use change and river training effects on floods in the Rhine basin, River Res. Appl., 23, 1102–1125, https://doi.org/10.1002/rra.1036, 2007.

Brown, A. E., Zhang, L., McMahon, T. A., Western, A. W., and Vertessy, R. A.: A review of paired catchment studies for determining changes in water yield resulting from alterations in vegetation, J. Hydrol., 310, 28–61, https://doi.org/10.1016/j.jhydrol.2004.12.010, 2005.

Brunner, M. I., Gilleland, E., Wood, A., Swain, D. L., and Clark, M.: Spatial Dependence of Floods Shaped by Spatiotemporal Variations in Meteorological and Land-Surface Processes, Geophys. Res. Lett., 47, e2020GL088000, https://doi.org/10.1029/2020GL088000, 2020.

Brunner, M. I., Slater, L., Tallaksen, L. M., and Clark, M.: Challenges in modeling and predicting floods and droughts: A review, WIREs Water, 8, e1520, https://doi.org/10.1002/wat2.1520, 2021.

Büttner, G.: CORINE Land Cover and Land Cover Change Products, in: Land Use and Land Cover Mapping in Europe: Practices & Trends, edited by: Manakos, I. and Braun, M., Springer Netherlands, Dordrecht, 55–74, https://doi.org/10.1007/978-94-007-7969-3_5, 2014.

Calder, I. R.: Hydrologic effects of land-use change., McGraw-Hill Inc, New York, USA, 1992.

Cameron, A. C. and Miller, D. L.: A Practitioner's Guide to Cluster-Robust Inference, J. Human Resources, 50, 317–372, https://doi.org/10.3368/jhr.50.2.317, 2015.

CDC: DWD Climate Data Center (CDC): REGNIE grids of daily precipitation; Annual grids of number of summer days over Germany, version v1.0; Annual grids of number of hot days over Germany, version v1.0.; Annual grids of monthly averaged daily air temperature (2m) over Germany, version v1.0., 2021.

Chang, H. and Franczyk, J.: Climate Change, Land-Use Change, and Floods: Toward an Integrated Assessment, Geogr. Compass, 2, 1549–1579, https://doi.org/10.1111/j.1749-8198.2008.00136.x, 2008.

Chawla, I. and Mujumdar, P. P.: Isolating the impacts of land use and climate change on streamflow, Hydrol. Earth Syst. Sci., 19, 3633–3651, https://doi.org/10.5194/hess-19-3633-2015, 2015.

Cheng, L., Zhang, L., Chiew, F. H. S., Canadell, J. G., Zhao, F., Wang, Y.-P., Hu, X., and Lin, K.: Quantifying the impacts of vegetation changes on catchment storage-discharge dynamics using paired-catchment data, Water Resour. Res., 53, 5963–5979, https://doi.org/10.1002/2017WR020600, 2017.

Choi, J.-Y., Engel, B. A., Muthukrishnan, S., and Harbor, J.: Gis Based Long Term Hydrologic Impact Evaluation for Watershed Urbanization1, JAWRA, 39, 623–635, https://doi.org/10.1111/j.1752-1688.2003.tb03680.x, 2003.

Clark, T. S. and Linzer, D. A.: Should I Use Fixed or Random Effects?, Political Science Research and Methods, 3, 399–408, https://doi.org/10.1017/psrm.2014.32, 2015.

Copernicus: European Union, Copernicus Land Monitoring Service, 2021.

Costa, M. H., Botta, A., and Cardille, J. A.: Effects of large-scale changes in land cover on the discharge of the Tocantins River, Southeastern Amazonia, J. Hydrol., 283, 206–217, https://doi.org/10.1016/S0022-1694(03)00267-1, 2003.

Croissant, Y. and Millo, G.: Panel Data Econometrics in R: The plm Package, 27, 1–43, https://doi.org/10.18637/jss.v027.i02, 2008.

De Roo, A., Odijk, M., Schmuck, G., Koster, E., and Lucieer, A.: Assessing the effects of land use changes on floods in the meuse and oder catchment, Physics and Chemistry of the Earth, Part B: Hydrology, Oceans and Atmosphere, 26, 593–599, https://doi.org/10.1016/S1464-1909(01)00054-5, 2001.

De Roo, A., Schmuck, G., Perdigao, V., and Thielen, J.: The influence of historic land use changes and future planned land use scenarios on floods in the Oder catchment, Physics and Chemistry of the Earth, Parts A/B/C, 28, 1291–1300, https://doi.org/10.1016/j.pce.2003.09.005, 2003.

Debbage, N. and Shepherd, J. M.: The Influence of Urban Development Patterns on Streamflow Characteristics in the Charlanta Megaregion, Water Resour. Res., 54, 3728–3747, https://doi.org/10.1029/2017WR021594, 2018.

Diem, J. E., Hill, T. C., and Milligan, R. A.: Diverse multi-decadal changes in streamflow within a rapidly urbanizing region, J. Hydrol., 556, 61–71, https://doi.org/10.1016/j.jhydrol.2017.10.026, 2018.

Döll, P., Fiedler, K., and Zhang, J.: Global-scale analysis of river flow alterations due to water withdrawals and reservoirs, Hydrol. Earth Syst. Sci., 13, 2413–2432, https://doi.org/10.5194/hess-13-2413-2009, 2009.

Driscoll, J. C. and Kraay, A. C.: Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data, Rev Econ Stat REV ECON STAT, 80, 549–560, https://doi.org/10.1162/003465398557825, 1998.

Elfert, S. and Bormann, H.: Simulated impact of past and possible future land use changes on the hydrological response of the Northern German lowland 'Hunte' catchment, J. Hydrol., 383, 245–255, https://doi.org/10.1016/j.jhydrol.2009.12.040, 2010.

Fohrer, N., Haverkamp, S., Eckhardt, K., and Frede, H.-G.: Hydrologic Response to land use changes on the catchment scale, Physics and Chemistry of the Earth, Part B: Hydrology, Oceans and Atmosphere, 26, 577–582, https://doi.org/10.1016/S1464-1909(01)00052-1, 2001.

Frans, C., Istanbulluoglu, E., Mishra, V., Munoz-Arriola, F., and Lettenmaier, D.: Are Climatic or Land Cover Changes the Dominant Cause of Runoff Trends in the Upper Mississippi River Basin?, Geophys. Res. Lett., 40, 1104–1110, https://doi.org/10.1002/grl.50262, 2013.

Gauger, C.: Wasserhaushaltsmodellierung in Flachlandeinzugsgebieten der Weser unter spezieller Berücksichtigung der Oberfächen-Grundwasser-Interaktion, Diplomarbeit, Institut für Hydrologie Universität Freiburg, Freiburg, 2007.

Godfrey, L.: Testing against General Autoregressive and Moving Average Error Models When the Regressors Include Lagged Dependent Variables, Econometrica, 46, 1293–1301, 1978.

Görgen, K., Beersma, J., Brahmer, G., Buiteveld, H., Carambia, M., Keizer, O. de, Krahe, P., Nilson, E., Lammersen, R., Perrin, C., and Volken, D.: Assessment of climate change impacts on discharge in the Rhine River Bassin: Results of the RheinBlick2050 project, report, irstea, 2010.

Gudmundsson, L., Leonard, M., Do, H. X., Westra, S., and Seneviratne, S. I.: Observed Trends in Global Indicators of Mean and Extreme Streamflow, Geophys. Res. Lett., 46, 756–766, https://doi.org/10.1029/2018GL079725, 2019.

Gupta, H. V., Perrin, C., Blöschl, G., Montanari, A., Kumar, R., Clark, M., and Andréassian, V.: Large-sample hydrology: a need to balance depth with breadth, Hydrol. Earth Syst. Sci., 18, 463–477, https://doi.org/10.5194/hess-18-463-2014, 2014.

Gupta, S. C., Kessler, A. C., Brown, M. K., and Zvomuya, F.: Climate and agricultural land use change impacts on streamflow in the upper midwestern United States, Water Resour. Res., 51, 5301–5317, https://doi.org/10.1002/2015WR017323, 2015.

Hair, J., Black, W., Babin, B., and Anderson, R.: Multivariate Data Analysis: A Global Perspective, 2010.

Hall, J., Arheimer, B., Borga, M., Brázdil, R., Claps, P., Kiss, A., Kjeldsen, T. R., Kriaučiūnienė, J., Kundzewicz, Z. W., Lang, M., Llasat, M. C., Macdonald, N., McIntyre, N., Mediero, L., Merz, B., Merz, R., Molnar, P., Montanari, A., Neuhold, C., Parajka, J., Perdigão, R. a. P., Plavcová, L., Rogger, M., Salinas, J. L., Sauquet, E., Schär, C., Szolgay, J., Viglione, A., and Blöschl, G.: Understanding flood regime changes in Europe: a state-of-the-art assessment, Hydrol. Earth Syst. Sci., 18, 2735–2772, https://doi.org/10.5194/hess-18-2735-2014, 2014.

Hirabayashi, Y., Mahendran, R., Koirala, S., Konoshima, L., Yamazaki, D., Watanabe, S., Kim, H., and Kanae, S.: Global flood risk under climate change, Nature Clim Change, 3, 816–821, https://doi.org/10.1038/nclimate1911, 2013.

Hoechle, D.: Robust Standard Errors for Panel Regressions with Cross-Sectional Dependence, The Stata Journal, 7, 281–312, https://doi.org/10.1177/1536867X0700700301, 2007.

Huang, S., Krysanova, V., and Hattermann, F.: Projections of climate change impacts on floods and droughts in Germany using an ensemble of climate change scenarios, Reg. Environ. Change, 15, https://doi.org/10.1007/s10113-014-0606-z, 2014.

van Huijgevoort, M. H. J., Hazenberg, P., van Lanen, H. a. J., and Uijlenhoet, R.: A generic method for hydrological drought identification across different climate regions, Hydrol. Earth Syst. Sci., 16, 2437–2451, https://doi.org/10.5194/hess-16-2437-2012, 2012.

Huisman, J., Breuer, L., Bormann, H., Bronstert, A., Croke, B., Frede, H.-G., Graeff, T., Hubrechts, L., Jakeman, A. J., Kite, G., Lanini, J., Leavesley, G., Lettenmaier, D., Lindstroem, G., Seibert, J., Sivapalan, M., Viney, N., and Willems, P.: Assessing the Impact of Land Use Change on Hydrology by Ensemble Modeling (LUCHEM) III: Scenario Analysis, Adv. Water Resour., 32, 159–170, https://doi.org/10.1016/j.advwatres.2008.06.009, 2008.

Hurkmans, R. T. W. L., Terink, W., Uijlenhoet, R., Moors, E. J., Troch, P. A., and Verburg, P. H.: Effects of land use changes on streamflow generation in the Rhine basin, Water Resour. Res., 45, https://doi.org/10.1029/2008WR007574, 2009.

Jones, J. and Grant, G.: Peak Flow Responses to Clear-Cutting and Roads in Small and Large Basins, Western Cascades, Oregon, Water Resour. Res., 32, 959–974, https://doi.org/10.1029/95WR03493, 1996.

King, G. and Roberts, M. E.: How Robust Standard Errors Expose Methodological Problems They Do Not Fix, and What to Do About It, Political Analysis, 23, 159–179, 2015.

Kittredge, J.: Forest influences: The effects of woody vegetation on climate, water, and soil, with applications to the conservation of water and the control of floods and erosion., 1948.

Krajewski, A., Sikorska-Senoner, A. E., Hejduk, L., and Banasik, K.: An Attempt to Decompose the Impact of Land Use and Climate Change on Annual Runoff in a Small Agricultural Catchment, Water Resour. Manage., 35, 881–896, https://doi.org/10.1007/s11269-020-02752-9, 2021.

Kuemmerle, T., Levers, C., Erb, K., Estel, S., Jepsen, M. R., Müller, D., Plutzar, C., Stürck, J., Verkerk, P. J., Verburg, P. H., and Reenberg, A.: Hotspots of land use change in Europe, Environ. Res. Lett., 11, 064020, https://doi.org/10.1088/1748-9326/11/6/064020, 2016.

Lei, C., Wagner, P. D., and Fohrer, N.: Influences of land use changes on the dynamics of water quantity and quality in the German lowland catchment of the Stör, Hydrol. Earth Syst. Sci. Discussion, 1–25, https://doi.org/10.5194/hess-2021-476, 2021.

Levy, M. C., Lopes, A. V., Cohn, A., Larsen, L. G., and Thompson, S. E.: Land Use Change Increases Streamflow Across the Arc of Deforestation in Brazil, Geophys. Res. Lett., 45, 3520–3530, https://doi.org/10.1002/2017GL076526, 2018.

Messner, F. and Meyer, V.: FLOOD DAMAGE, VULNERABILITY AND RISK PERCEPTION – CHALLENGES FOR FLOOD DAMAGE RESEARCH, in: Flood Risk Management: Hazards, Vulnerability and Mitigation Measures, Dordrecht, 149–167, 2006.

Millo, G.: Robust Standard Error Estimators for Panel Models: A Unifying Approach, J. Stat. Softw., 82, 1–27, https://doi.org/10.18637/jss.v082.i03, 2017.

Naumann, G., Spinoni, J., Vogt, J. V., and Barbosa, P.: Assessment of drought damages and their uncertainties in Europe, Environ. Res. Lett., 10, 124013, https://doi.org/10.1088/1748-9326/10/12/124013, 2015.

Nilson, E., Krahe, P., Klein, B., Lingemann, I., Horsten, T., Carambia, M., Larina, M., and Maurer, T.: Auswirkungen des Klimawandels auf das Abflussgeschehen und die Binnenschifffahrt in Deutschland, https://doi.org/10.5675/Kliwas_43/2014_4.01, 2014.

NLWKN: Grundwasserbericht Niedersachsen: Sonderausgabe zur Grundwasserstandsentwicklung im Jahr 2020, 48, 2021.

Ochoa-Tocachi, B. F., Buytaert, W., De Bièvre, B., Célleri, R., Crespo, P., Villacís, M., Llerena, C. A., Acosta, L., Villazón, M., Guallpa, M., Gil-Ríos, J., Fuentes, P., Olaya, D., Viñas, P., Rojas, G., and Arias, S.: Impacts of land use on the hydrological response of tropical Andean catchments, Hydrol. Process., 30, 4074–4089, https://doi.org/10.1002/hyp.10980, 2016a.

Ochoa-Tocachi, B. F., Buytaert, W., and Bièvre, B. D.: Regionalization of land-use impacts on streamflow using a network of paired catchments, Water Resour. Res., 52, 6710–6729, https://doi.org/10.1002/2016WR018596, 2016b.

Oudin, L., Salavati, B., Furusho-Percot, C., Ribstein, P., and Saadi, M.: Hydrological impacts of urbanization at the catchment scale, J. Hydrol., 559, 774–786, https://doi.org/10.1016/j.jhydrol.2018.02.064, 2018.

Petchprayoon, P., Blanken, P. D., Ekkawatpanit, C., and Hussein, K.: Hydrological impacts of land use/land cover change in a large river basin in central–northern Thailand, Int. J. Climatol., 30, 1917–1930, https://doi.org/10.1002/joc.2131, 2010.

Prudhomme, C., Giuntoli, I., Robinson, E. L., Clark, D. B., Arnell, N. W., Dankers, R., Fekete, B. M., Franssen, W., Gerten, D., Gosling, S. N., Hagemann, S., Hannah, D. M., Kim, H., Masaki, Y., Satoh, Y., Stacke, T., Wada, Y., and Wisser, D.: Hydrological droughts in the 21st century, hotspots and uncertainties from a global multimodel ensemble experiment, PNAS, 111, 3262–3267, https://doi.org/10.1073/pnas.1222473110, 2014.

Putro, B., Kjeldsen, T. R., Hutchins, M. G., and Miller, J.: An empirical investigation of climate and land-use effects on water quantity and quality in two urbanising catchments in the southern United Kingdom, Sci. Total Environ., 548–549, 164–172, https://doi.org/10.1016/j.scitotenv.2015.12.132, 2016.

Qi, P., Xu, Y. J., and Wang, G.: Quantifying the Individual Contributions of Climate Change, Dam Construction, and Land Use/Land Cover Change to Hydrological Drought in a Marshy River, Sustainability, 12, 3777, https://doi.org/10.3390/su12093777, 2020.

Rangecroft, S., Van Loon, A. F., Maureira, H., Verbist, K., and Hannah, D. M.: An observation-based method to quantify the human influence on hydrological drought: upstream–downstream comparison, Hydrol. Sci. J., 64, 276–287, https://doi.org/10.1080/02626667.2019.1581365, 2019.

Rauthe, M., Steiner, H., Riediger, U., Mazurkiewicz, A., and Gratzki, A.: A Central European precipitation climatology – Part I: Generation and validation of a high-resolution gridded daily data set (HYRAS), MZ, 235–256, https://doi.org/10.1127/0941-2948/2013/0436, 2013.

Richey, J., Nobre, C., and Deser, C.: Amazon River Discharge and Climate Variability: 1903 to 1985, Science, 246, 101–3, https://doi.org/10.1126/science.246.4926.101, 1989.

Rientjes, T. H. M., Haile, A. T., Kebede, E., Mannaerts, C. M. M., Habib, E., and Steenhuis, T. S.: Changes in land cover, rainfall and stream flow in Upper Gilgel Abbay catchment, Blue Nile basin – Ethiopia, Hydrol. Earth Syst. Sci., 15, 1979–1989, https://doi.org/10.5194/hess-15-1979-2011, 2011.

Rogger, M., Agnoletti, M., Alaoui, A., Bathurst, J. C., Bodner, G., Borga, M., Chaplot, V., Gallart, F., Glatzel, G., Hall, J., Holden, J., Holko, L., Horn, R., Kiss, A., Kohnová, S., Leitinger, G., Lennartz, B., Parajka, J., Perdigão, R., Peth, S., Plavcová, L., Quinton, J. N., Robinson, M., Salinas, J. L., Santoro, A., Szolgay, J., Tron, S., Akker, J. J. H. van den, Viglione, A., and Blöschl, G.: Land use change impacts on floods at the catchment scale: Challenges and opportunities for future research, Water Resour. Res., 53, 5209–5219, 2017.

Schoups, G. and Vrugt, J. A.: A formal likelihood function for parameter and predictive inference of hydrologic models with correlated, heteroscedastic, and non-Gaussian errors, Water Resour. Res., 46, https://doi.org/10.1029/2009WR008933, 2010.

Seibert, J. and McDonnell, J. J.: Land-cover impacts on streamflow: a change-detection modelling approach that incorporates parameter uncertainty, Hydrol. Sci. J., 55, 316–332, https://doi.org/10.1080/02626661003683264, 2010.

Semmel, A.: Geomorphologie der Bundesrepublik Deutschland Grundzüge, Forschungsstand, aktuelle Fragen - erörtert an ausgewählten Landschaften (unter Berücksichtigung der neuen Bundesländer), Franz Steiner Verlag, Stuttgart, 1996.

Sen, P. K.: Estimates of the Regression Coefficient Based on Kendall's Tau, J Am Stat Assoc, 63, 1379–1389, https://doi.org/10.2307/2285891, 1968.

Seneviratne, S. I., Zhang, X., Adnan, M., Badi, W., Dereczynski, C., Di Luca, A., Ghosh, S., Iskandar, I., Kossin, J., Lewis, S., Otto, F., Pinto, I., Satoh, M., Vicente-Serrano, S. M., Wehner, M., and Zhou, B.: IPCC AR6 WGI Chapter 11- Weather and climate extreme events in a changing climate | HimalDoc, Cambridge University Press., In Press.

Shi, P.-J., Yuan, Y., Zheng, J., Wang, J.-A., Ge, Y., and Qiu, G.-Y.: The effect of land use/cover change on surface runoff in Shenzhen region, China, CATENA, 69, 31–35, https://doi.org/10.1016/j.catena.2006.04.015, 2007.

Shmueli, G.: To Explain or to Predict?, Statistical Science, 25, https://doi.org/10.1214/10-STS330, 2011.

Sonny: Digitale LiDAR-Geländemodelle von Deutschland | Digital LiDAR-Terrain Models of Germany, 2021.

Stahl, K., Hisdal, H., Hannaford, J., Tallaksen, L. M., Van Lanen, H., Eric, S., S, D., Fendekova, M., and Jódar, J.: Streamflow trends in Europe: Evidence from a dataset of near-natural catchments, Hydrol. Earth Syst. Sci., 14, 2367–2382, https://doi.org/10.5194/hess-14-2367-2010, 2010.

Steinschneider, S., Yang, Y.-C. E., and Brown, C.: Panel regression techniques for identifying impacts of anthropogenic landscape change on hydrologic response, Water Resour. Res., 49, 7874–7886, https://doi.org/10.1002/2013WR013818, 2013.

Sullivan, A., Ternan, J. L., and Williams, A. G.: Land use change and hydrological response in the Camel catchment, Cornwall, Appl. Geo., 24, 119–137, https://doi.org/10.1016/j.apgeog.2003.11.002, 2004.

Tallaksen, L. M., Madsen, H., and Clasuen, B.: On the definition and modelling of streamflow drought duration and deficit volume, Hydrol. Sci. J., 42, 15–33, https://doi.org/10.1080/02626669709492003, 1997.

Tetzlaff, B., Kuhr, P., and Wendland, F.: A new method for creating maps of artificially drained areas in large river basins based on aerial photographs and geodata, Irrig. Drain., 58, 569–585, https://doi.org/10.1002/ird.426, 2009.

Tijdeman, E., Hannaford, J., and Stahl, K.: Human influences on streamflow drought characteristics in England and Wales, Hydrol. Earth Syst. Sci., 22, 1051–1064, https://doi.org/10.5194/hess-22-1051-2018, 2018.

Tu, M., Hall, M., Laat, P., and Wit, M.: Extreme floods in the Meuse river over the past century, Physics and Chemistry of the Earth, Parts A/B/C, 30, 267–276, https://doi.org/10.1016/j.pce.2004.10.001, 2005.

Van Loon, A. F., Rangecroft, S., Coxon, G., Breña Naranjo, J. A., Van Ogtrop, F., and Van Lanen, H. A. J.: Using paired catchments to quantify the human influence on hydrological droughts, Hydrol. Earth Syst. Sci., 23, 1725–1739, https://doi.org/10.5194/hess-23-1725-2019, 2019.

Vogelsang, T. J.: Heteroskedasticity, autocorrelation, and spatial correlation robust inference in linear panel models with fixed-effects, J. Econom., 166, 303–319, https://doi.org/10.1016/j.jeconom.2011.10.001, 2012.

Wang, D. and Hejazi, M.: Quantifying the relative contribution of the climate and direct human impacts on mean annual streamflow in the contiguous United States, Water Resour. Res., 47, https://doi.org/10.1029/2010WR010283, 2011.

Wegehenkel, M.: Estimating of the impact of land use changes using the conceptual hydrological model THESEUS - A case study, PHYS CHEM EARTH, 27, 631–640, https://doi.org/10.1016/S1474-7065(02)00047-5, 2002.

Wingfield, T., Macdonald, N., Peters, K., Spees, J., and Potter, K.: Natural Flood Management: Beyond the evidence debate, Area, 51, 743–751, https://doi.org/10.1111/area.12535, 2019.

Winsemius, H. C., Aerts, J. C. J. H., van Beek, L. P. H., Bierkens, M. F. P., Bouwman, A., Jongman, B., Kwadijk, J. C. J., Ligtvoet, W., Lucas, P. L., van Vuuren, D. P., and Ward, P. J.: Global drivers of future river flood risk, Nature Clim Change, 6, 381–385, https://doi.org/10.1038/nclimate2893, 2016.

Wooldridge, J. M.: Econometric Analysis of Cross Section and Panel Data, second edition, MIT Press, 1095 pp., 2010.

Yang, G., Bowling, L., Cherkauer, K., Pijanowski, B., and Niyogi, D.: Hydroclimatic Response of Watersheds to Urban Intensity: An Observational and Modeling-Based Analysis for the White River Basin, Indiana, J Hydrometeorol., 11, https://doi.org/10.1175/2009JHM1143.1, 2010.

Yue, S., Pilon, P., Phinney, B., and Cavadias, G.: The influence of autocorrelation on the ability to detect trend in hydrological series, Hydrol. Process., 16, 1807–1829, https://doi.org/10.1002/hyp.1095, 2002.

Zeileis, A.: Object-oriented Computation of Sandwich Estimators, J. Stat. Softw., 16, 1–16, https://doi.org/10.18637/jss.v016.i09, 2006.

Zeileis, A., Köll, S., and Graham, N.: Various Versatile Variances: An Object-Oriented Implementation of Clustered Covariances in R, J. Stat. Softw., 95, 1–36, https://doi.org/10.18637/jss.v095.i01, 2020.

Zhang, L., Dawes, W. R., and Walker, G. R.: Response of mean annual evapotranspiration to vegetation changes at catchment scale, Water Resour. Res., 37, 701–708, https://doi.org/10.1029/2000WR900325, 2001.

Zhang, Q., Singh, V. P., Li, K., and Li, J.: Trend, periodicity and abrupt change in streamflow of the East River, the Pearl River basin, Hydrol. Process., 28, 305–314, https://doi.org/10.1002/hyp.9576, 2014.

Zheng, H., Zhang, L., Zhu, R., Liu, C., Sato, Y., and Fukushima, Y.: Responses of streamflow to climate and land surface change in the headwaters of the Yellow River Basin, Water Resour. Res., 45, https://doi.org/10.1029/2007WR006665, 2009.

Appendix

1. Detailed information of catchment characteristics

Table A1. Characteristics (information, slope, climate, geology, soil) of the 30 catchments of interest.

general Info			area			climate		geology and soil	
ID	gauge	stream	gauge datum [m NHN]	area [km2]	average slope [°]	mean annual precip. [mm x year]	mean annual temp. [°C]	dominant geology	dominant soil
1	Bagband	Bagbander Tief	-5.0	47.4	0.06	776	9.6	silt, sand	gley, podsol
2	Südgeorgsfehn OP	Südgeorgsfehn Kanal	-5.0	30.4	0.04	823	9.6	peat	moor
3	Neuenburg	Zeteler Tief	0	28.7	0.03	832	9.6	sand	gley
4	Aschhausen	Halfsteder Baeke	2.3	27.0	0.00	823	9.7	silt	gley
5	Düwelshoop	Haaren	0	21.6	0.00	831	9.7	silt	gley
6	Hude	Berne	0	55.1	0.30	775	9.7	silt	gley, podsol
7	Walchum	Walchumer Schlot	3.9	78.9	0.02	768	9.8	sand	moor (anthrop.)
8	Neuburlage	Burlage Langholter Tief	0	76.9	0.29	790	9.8	peat, sand	moor, gley
9	Apeldorn	Nordradde	14.0	127.2	0.29	808	9.8	silt, sand	gley
10	Westerlohmühlen I	Mittelradde	15.8	155.5	0.13	803	9.8	silt, sand	gley, podsol
11	Neuscharrel	Marke	2.8	138.5	0.20	800	9.8	sand	gley, podsol
12	Augustenfeld	Südradde	22.1	82.1	0.11	793	9.8	silt, sand	gley
13	Stedingsmühlen	Soeste	25.2	74.0	0.23	802	9.6	silt	gley
14	Thülsfeld	Soeste	0	147.5	0.23	800	9.7	sand, silt	gley, podsol
15	Oberlethe	Lethe	0	160.1	0.21	786	9.6	sand	gley, podsol
16	Wiekau	Visbeker Aue	15.0	94.9	0.45	800	9.6	silt, sand	gley, podsol
17	Addrup	Fladder	19.0	227.5	0.18	765	9.7	silt	gley, podsol
18	Gut Lage	Dinkelager Mühlenbach	19.0	190.6	0.38	742	9.8	sand	gley, podsol
19	Versen	Goldbach	9.3	36.0	0.21	752	10.0	sand	gley, podsol
20	Teglingen 1	Teglinger Beeke	12.4	65.3	0.09	771	10.2	sand	gley, podsol
21	Teglingen II	Kleine Beeke	13.2	23.9	0.04	768	10.1	sand	gley, moor (anthrop.)
22	Lingen Parkstraße 1	Lingener Mühlenbach	19.2	54.5	0.56	779	10.2	sand	gley, podsol
23	Lotten	Lotter Beeke	16.4	86.9	2.62	784	9.7	sand	gley, podsol
24	Andrup-Lage	Lager Bach	15.7	127.3	0.56	795	9.9	sand	gley, podsol
25	Neuenkirchen	Voerdener Aue	30.0	78.6	0.74	773	9.9	sand, silt	gley, podsol
26	Engden I	Engedener Bach	26.1	18.5	0.50	804	10.1	sand	gley
27	Haste	Nette	66.6	54.6	1.80	847	9.7	silt, peat	gley
28	Bohmte	Hunte	40.5	191.5	2.26	769	9.8	silt, sand	gley, plaggenesch
29	Georgsmarienhütte	Duete	74.6	48.0	4.33	938	9.6	silt, claystone	luvisol, gley
30	Auburg	Aubach	82.1	16.8	3.54	856	9.6	silt, claystone	luvisol, gley

Table A2. Land use in the reference year 1990 and sum of LUC relative to catchment area over the observation period.

	land use 1990 (reference year) [%]				rel. Land use change over observation period [%]			
ID	agriculture	pasture	urban	green	agriculture	pasture	urban	green
1	12	74	3	11	1.2	-1.8	0.5	0
2	10	56	1	32	-0.9	-0.7	0	1.6
3	25	57	2	16	1.1	-1.9	0.8	0.3
4	43	35	4	19	0.4	-2.0	2.1	0.0
5	70	27	0	1	-0.5	-0.1	0.6	0.1
6	63	16	2	18	0.4	-0.7	0.1	0.2
7	97	0	1	2	-0.6	0	0.2	-0.1
8	78	2	0	20	-0.4	-0.4	6.7	-6.2
9	75	2	4	19	-1.9	0.1	1.8	0.5
10	72	15	4	8	-0.7	0.0	0.6	0.1
11	68	4	2	25	-0.1	-0.1	0.2	0.2
12	80	12	0	8	0.2	-0.2	0	0
13	75	6	13	6	-12.7	-0.3	13.9	0.2
14	65	5	8	21	-8.0	-0.1	7.6	1.4
15	70	9	2	19	-0.1	-0.3	0.3	-0.1
16	71	0	2	27	-2.2	0.0	2.2	1.2
17	85	3	4	8	-4.2	-1.0	4.9	0.1
18	87	1	6	5	-5.8	-0.4	5.5	0.9
19	89	0	3	9	-1.4	0	1.8	-0.2
20	79	0	2	19	-0.7	0	0.6	0.3
21	54	0	0	46	0	0	0	0.5
22	79	0	7	14	-3.1	0	3.1	0.4
23	87	0	1	12	-0.3	0	0.2	-0.1
24	76	3	1	21	0.3	-0.3	0	0.1
25	82	3	2	14	-3.4	-1.1	2.1	1.7
26	96	0	0	4	0	0	0	0
27	61	0	7	31	3.4	-0.4	5.5	1.1
28	73	1	4	22	-1.4	0.2	1.5	0.9
29	49	0	18	33	-3.5	0	3.5	0.6
30	79	0	0	21	26.2	0	0	0

2. Visualization of streamflow extremes indices

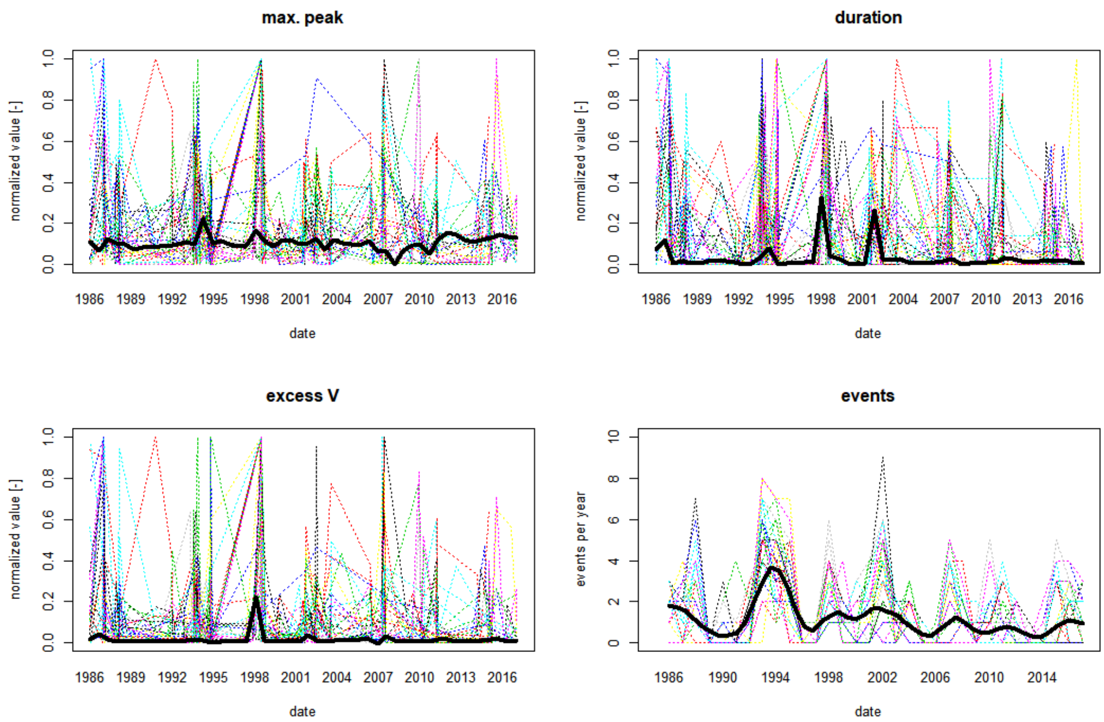

Figure A1. Normalized values of the high flow indices. Black line: moving average.

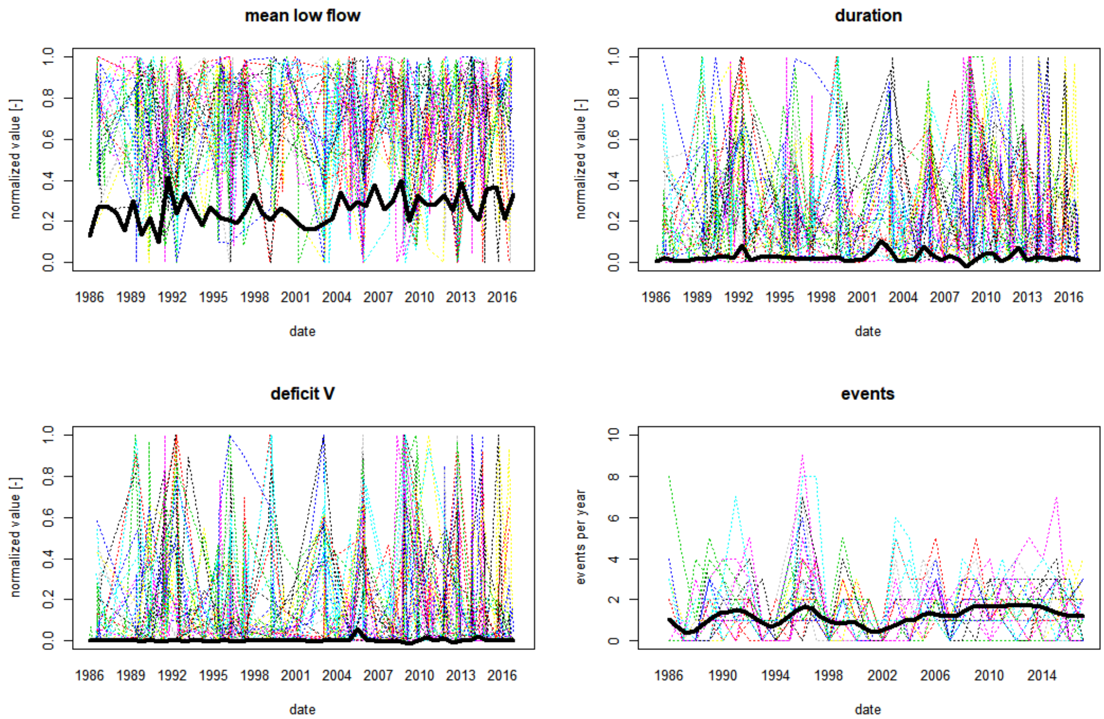

Figure A2. Normalized values of the low flow indices. Black line: moving average.

3. Precipitation indices

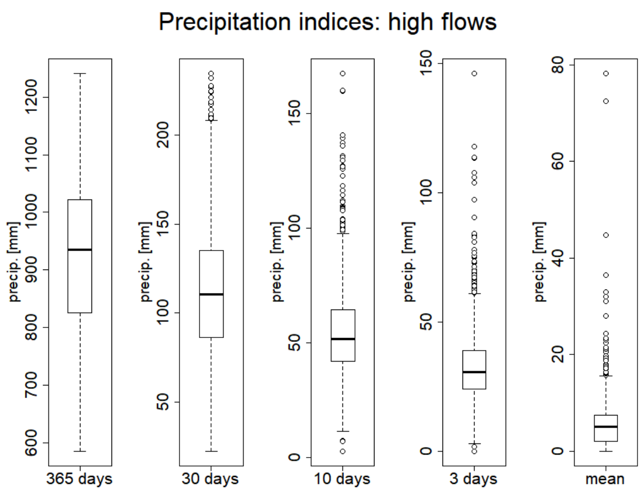

Figure A3. Boxplot of the precipitation indices for the events of high flow. Days being days before an event

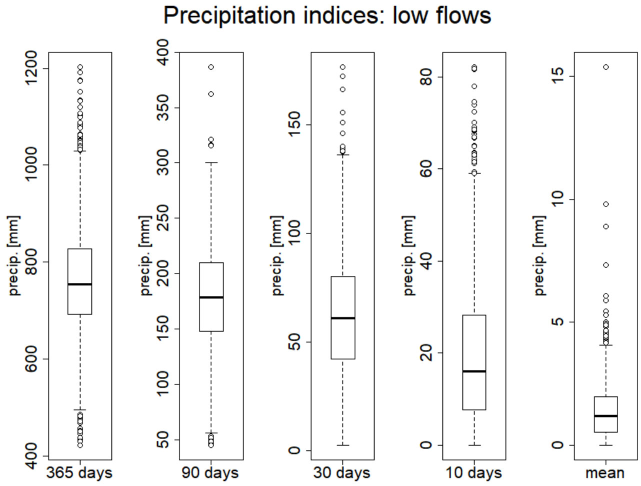

Figure A4. Boxplot of the precipitation indices for the events of low flow. Days being days before an event

4. Catchments with LUC data obtained from LSN

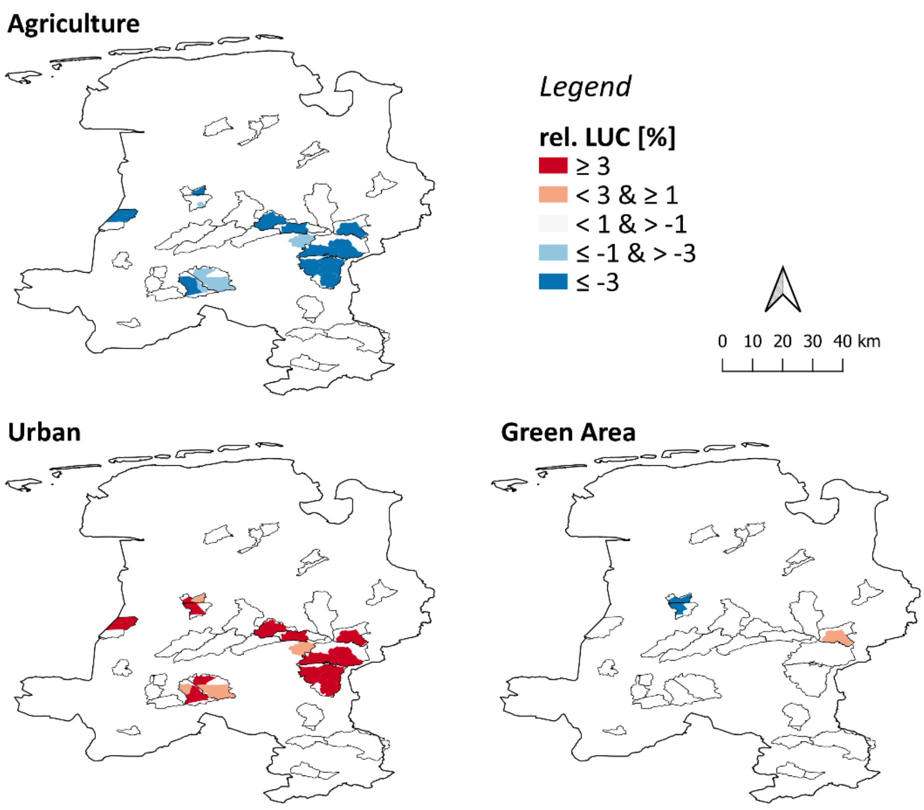

Figure A5. Catchments with LSN data that fulfilled the conditions (section 2.1.5). Seven catchments showed similar LUC as CLC-CHA data (ID: 8, 13, 14, 16, 18, 24). In contrast, three catchments (ID: 7, 23, 24) had changes CLC-CHA did not detect. Catchment 7 (urban: 4.1%, agriculture: - 5.4%), Catchment 23 (urban: 4.3%, agriculture: -5.4%) and catchment 24 (urban: 2.2%, agriculture: -2.5%).

5. Equation min-max normalization

$$x' = \frac{x - min(x)}{max(x) \ - min(x)}$$

Where x is specific SEI and x' the normalized value of each SEI.

6. Equation of the mean absolute error (MAE)

$$MAE = \frac{\sum_{i=1}^{n} |Y_i - \hat{Y}_i|}{n}$$

Where i is the observation number, n the sample size, Y the observed value (unit as SEI) and $\hat{Y}$ the fitted value (unit as SEI).

7. LUC in absolute values vs. LUC relative to catchment area

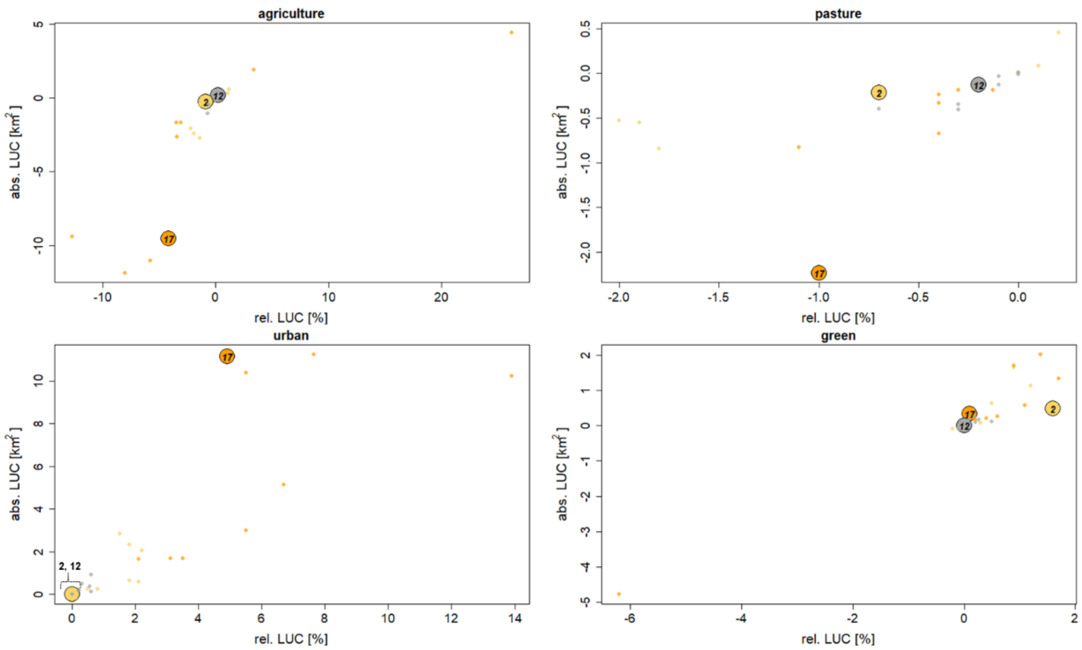

Figure A6. LUC in absolute values and LUC relative to catchment area. Big dots with numbers are catchments with significant trend in high flow indices. Small points catchments without significant trend.

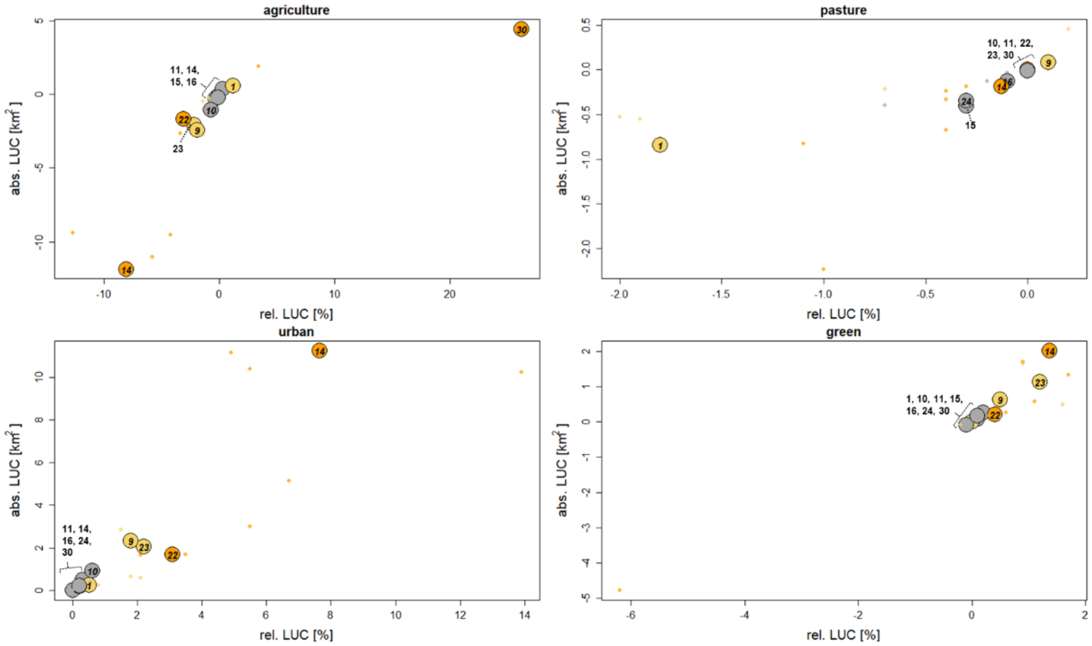

Figure A7. LUC in absolute values and LUC relative to catchment area. Big dots with numbers are catchments with significant trend in low flow indices. Small points are catchments without significant trend.

8. Panel regression model performance

For all following figures, the plots show the fit of the panel regression model with (1) only fixed effects, (2) fixed effects and time dummies – the model 1 (M1), (3) fixed effects and precipitation indices and (4) fixed effects, precipitation indices and time dummies – the model 2 (M2). Furthermore, N is the number of observations.

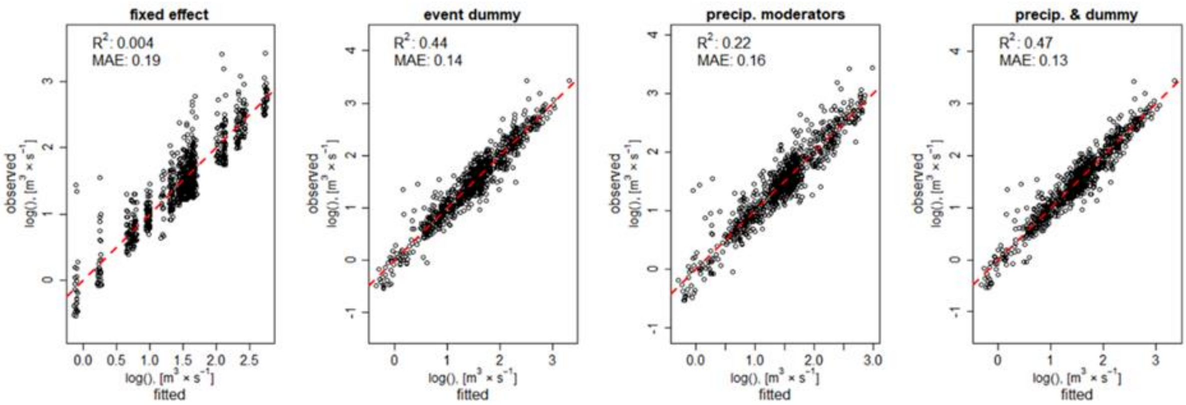

Figure A8. Maximum peak discharge on the event scale (N = 966).

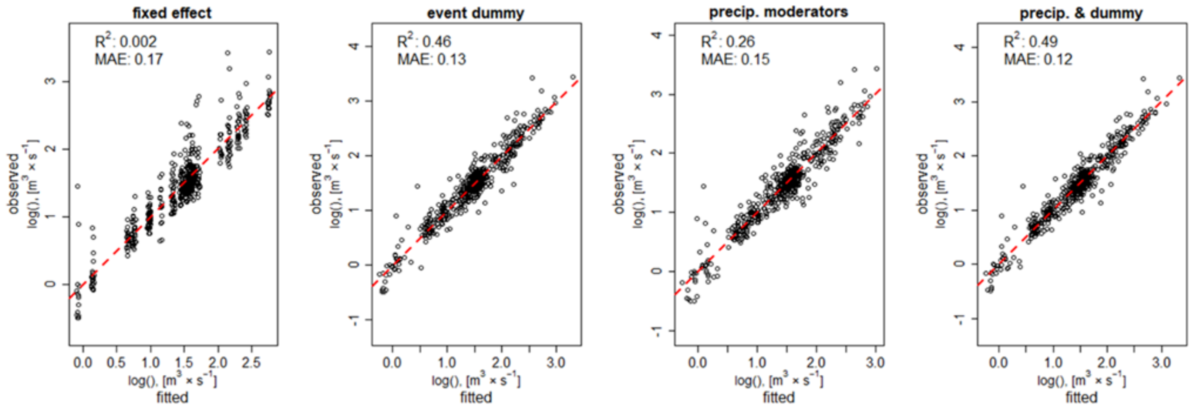

Figure A9. Maximum peak discharge on the seasonal scale (N = 527).

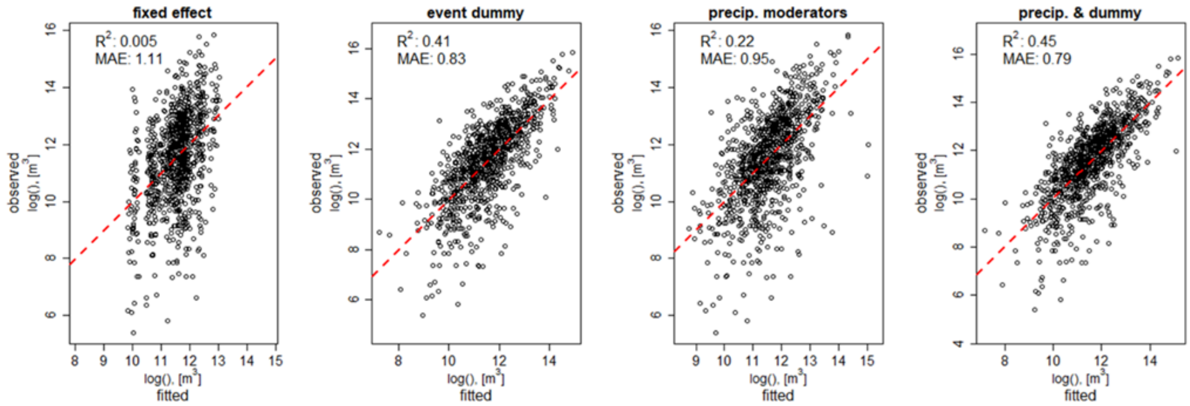

Figure A10. Excess volume on the event scale (N = 962). Smaller N because observations with 0 m^3 excess volume excluded.

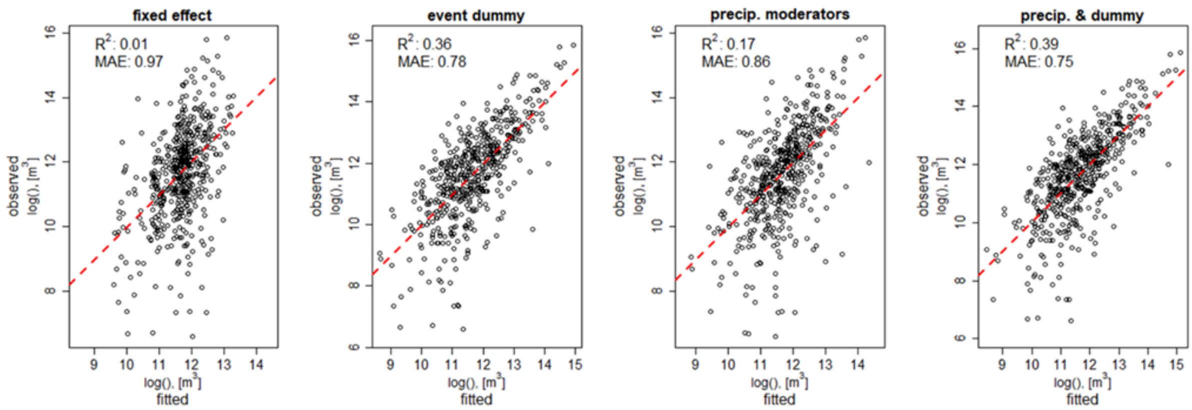

Figure A11. Excess volume on the seasonal scale (N = 526). Smaller N because observations with 0 m^3 excess volume excluded.

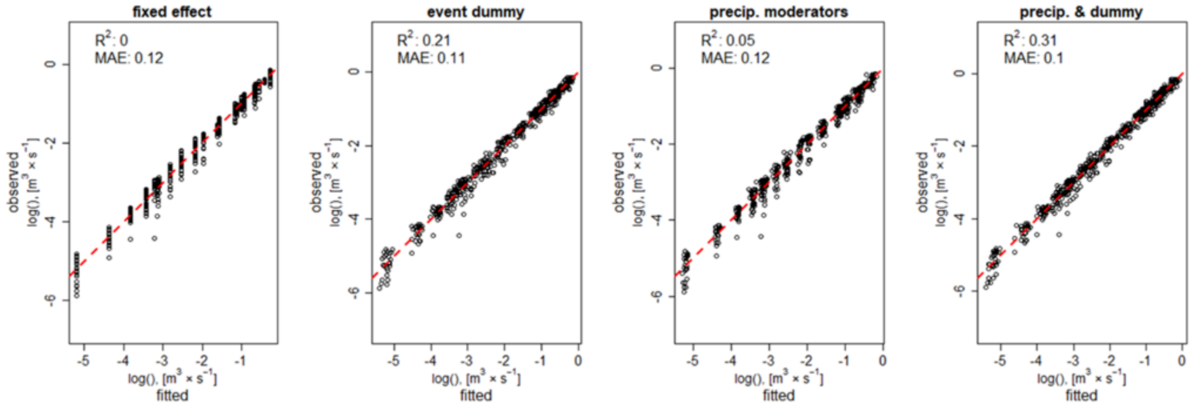

Figure A12. Mean low flow on the event scale (N = 645).

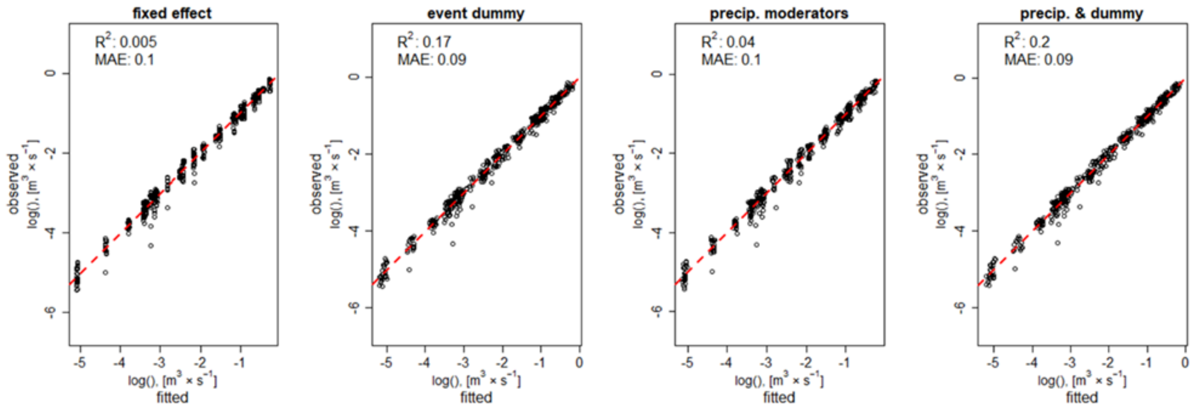

Figure A13. Mean low flow on the seasonal scale (N = 525).

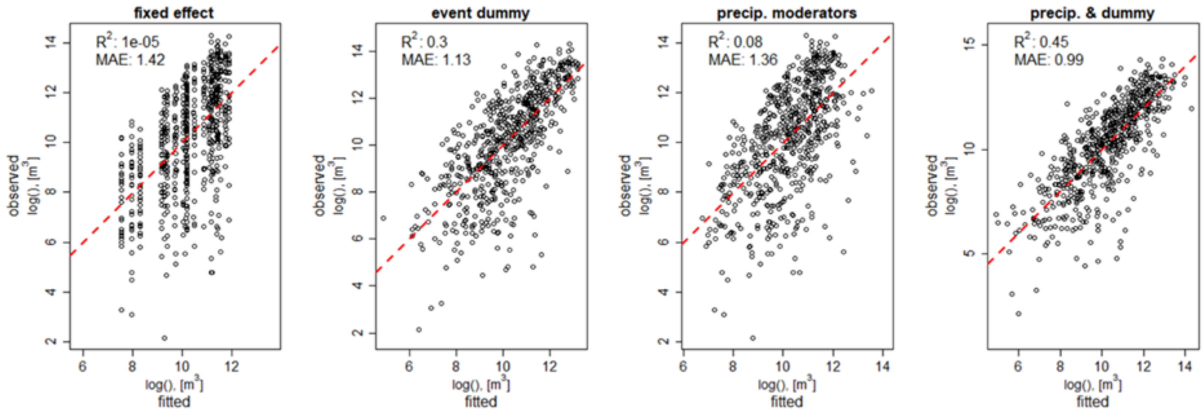

Figure A14. Deficit volume on the event scale (N = 644). Smaller N because observation with 0 m^3 deficit volume excluded.

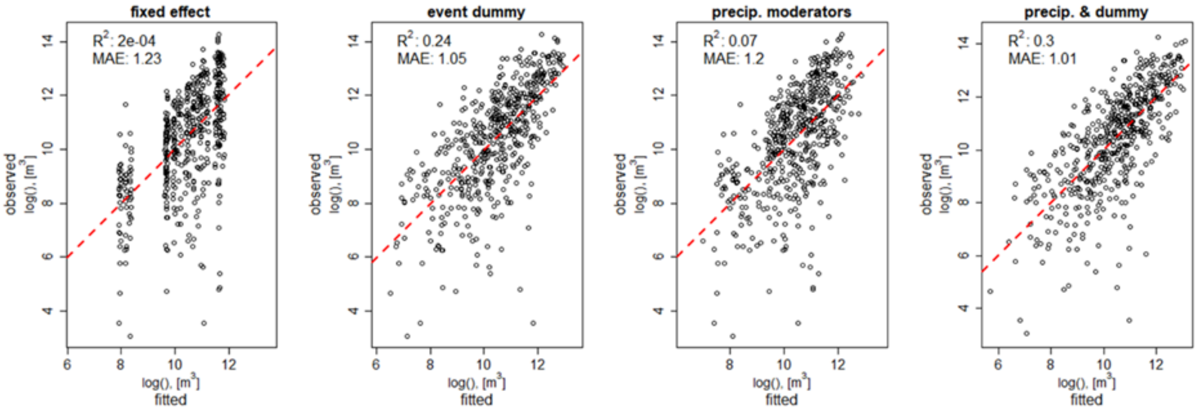

Figure A15. Deficit volume on the seasonal scale (N = 524). Smaller N because observation with 0 m^3 deficit volume excluded.

Statutory Declaration / Ehrenwörtliche Erklärung

I herewith declare that I have composed the present thesis myself and without use of any other than the cited sources and aids. Furthermore, I declare that the thesis has not been or is not the subject of another examination procedure, neither in its entirety nor in substantial parts.

Hiermit erkläre ich, dass die Arbeit selbständig und nur unter Verwendung der angegebenen Hilfsmittel angefertigt wurde. Des weiteren versichere ich, dass die eingereichte Masterarbeit weder vollständig noch in wesentlichen Teilen Gegenstand eines anderen Prüfungsverfahrens war oder ist.

Freiburg, 17.01.2022