Climate or land cover variations: what is driving observed changes in river peak flows? A data-based attribution study

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Abstract. Climate change and land cover changes are influencing the hydrological regime of our rivers. The intensification of the hydrological cycle caused by climate change is projected to cause more flooding in winters and an increased urbanization could amplify these effects by a quicker runoff on paved surfaces. The relative importance of both drivers, however, is still uncertain and interaction effects between both drivers are not yet well understood.

10   In order to better understand the hydrological impact of climate variability and land cover changes, including their interaction effects, we fitted a statistical model to historical data over 3 decades for 29 catchments in Flanders, covering various catchment characteristics. It was found that the catchment characteristics explain up to 18% of changes in river peak flows, climate variability 6% and land cover changes 8%. Interaction terms explain up to 32%. An increase in urban area of +1% might cause increases in river peak flows up to +5%.

15   ## 1   Introduction

Our environment has undergone unprecedented changes over the past decades, and it is very likely that further changes will take place in the coming decades. With respect to the climate system, increases in frequency, intensity and/or amount of heavy precipitation are globally reported for the majority of the land areas (IPCC, 2014); for Flanders (Belgium) in particular, extreme precipitation might increase with +50% in winter and +100% in summer by the late 21st century (Tabari et al., 2015). With

20   respect to the built environment, the world continues to urbanize, with nowadays 55% of the world's population living in urban areas. This is in shear contrast with 1950, where only 30% of the world's population was urban (United Nations, 2018). For Flanders, this is translated into a 300% increase in built-up area over the past four decades (Poelmans, 2010; Ruimte Vlaanderen, 2017).

Changes in climate and urbanization both cause changes in the hydrological regime of catchments in general and changes in

25   flood frequencies in particular. Here, we aim to attribute observed changes in river peak flows to drivers related to the climate and to a changed land use/land cover. Previous attribution studies related to trends in flood hazards faced several challenges. These were, among others, summarized by Merz et al. (2012). The attribution process typically involves two steps: detection of change and attribution of that change to its various drivers. In the first step, the detection of change is often challenging: the signal of flood time series (or river peak flows in general) typically shows a high natural variability, with a low signal-to-noise

ratio. Moreover, floods form part the larger hydrological system and, as such, show a quite complex behavior. With respect to the attribution issue in the second step: in a complex hydrological system, different drivers act in parallel, with interactions between them. The integral response of the system to all these drivers and interactions governs the changed hydrological behavior. And, finally, the power of attribution studies often lies in a deep process knowledge related to the proposed driver-effect mechanisms (Hegerl et al., 2010); unfortunately, knowledge on some driver-effect mechanisms is still limited (Blöschl et al., 2007; Merz et al., 2012).

On the driver-effect mechanism between climate variability and river peak flows, many studies have shown there is a link between weather types and flooding, sometimes through the intermediate variable of precipitation (Brisson et al., 2011; Hirschboek, 1991; Mediero et al., 2015; De Niel et al., 2017; Pattison and Lane, 2012; Pfister et al., 2004; Prudhomme and Genevier, 2011; Santos et al., 2015; Smith et al., 2011; Wilby and Quinn, 2013). For the area of Flanders, westerly atmospheric fluxes would, in general, cause an increased winter precipitation amount and intensity, leading to increased river peak flows (Brisson et al., 2011; De Niel et al., 2017; Willems, 2013).

On the driver-effect mechanism between land use/land cover and river peak flows, most studies hypothesize that deforestation and increased urbanization cause increased surface runoff. (Bronstert et al., 2002; Cheng and Wang, 2002; Cuo et al., 2009; Galster et al., 2006; Hamdi et al., 2011; Hundecha and Bárdossy, 2004; Miller et al., 2014; Misra, 2011; O'Driscoll et al., 2010; Pfister et al., 2004; Poelmans et al., 2011; Reynard et al., 2001; Siriwardena et al., 2006; Trudeau and Richardson, 2016; Zope et al., 2016). However, a lot of uncertainty remains, mainly because of the heterogeneity in catchments globally and the scale of the river basin/catchment considered.

Next to the independent driver-effect mechanisms of climate variability on river peak flows, and land use changes on river peak flows, both drivers should be analyzed jointly in a multiple-driver attribution study (e.g. Hall et al., 2014; Merz et al., 2012). As an example, for the Meuse river, it was concluded that changes in flood frequency and magnitude over the past century could mainly be attributed to climate variability rather than to deforestation and urbanization (Tu et al., 2005). Similarly, for the Rhine and Meuse basins, increased flooding probability was found to be correlated to an observed increase in westerly atmospheric fluxes (causing an increase in winter precipitation amount and intensity) and not to observed land use changes (Pfister et al., 2004). For a smaller catchment such as the Grote Nete (385 km^2, located in the North-East of Flanders), and for the future conditions, both climate change and urban growth are projected to have a considerable impact on river peak flows (Tavakoli et al., 2014; Vansteenkiste et al., 2014).

With this paper, we investigate the (relative) importance of climate variability and land cover changes related to changes in river peak flows, based on 29 catchments throughout Flanders. For the historical dataset covering the past three decades (Sect. 2), a data-based approach is followed where peak flow anomalies are explained based on a set of maximum 24 drivers. These drivers are grouped into three categories: catchments specific drivers, climate variability and land use/land cover changes. A model is built based on panel data regression, with a top-down approach (Sect. 3). Results are presented in Sect. 4 and overall conclusions are given in Sect. 5.

2   Case study and data

For this case study, 29 catchments are selected, evenly spread across Flanders (Figure 1). These catchments were selected based on a minimum of 20 years of available discharge data (www.waterinfo.be). The DTM in Figure 1 was taken from "Digitaal Hoogtemodel Vlaanderen" (https://overheid.vlaanderen.be/producten-diensten/digitaal-hoogtemodel-dhmv). Some

5   of the main characteristics of these catchments are listed in Table 1.

Further, Figure 2 and Figure 3 show details on land cover and soil texture of these catchments, respectively. For land cover, the 30 classes from the ESA CCI Land Cover project (www.esa-landcover-cci.org) were regrouped into the 6 IPCC land categories, i.e. cropland, forest, grassland, wetland, settlement and other land. This was done in order to reduce the total degrees of freedom for this study. For soil texture, taken from www.dov.vlaanderen.be, 3 dominant classes (arenic, loamic and siltic)

10   cover 99.3% of the total area of the selected catchments. Therefore, only these 3 dominant classes were taken into account for this study.

Climatic conditions in the past are based on the NCEP/NCAR reanalysis data, available online through https://www.esrl.noaa.gov/psd/ (Kalnay et al., 1996).

3   Methods

15   ### 3.1   General

The aim of the study is to find the (main) drivers behind changes in river peak flows. Therefore, the daily discharge series of each catchment is first transformed to peak flow anomalies (Sect. 3.2). Then, possible drivers are derived from the data introduced in Sect. 2 and further split into separate categories, see Sect. 3.3. Finally, a regression model is fitted to the data (Sect. 3.4).

20   ### 3.2   Peak flow anomalies

For quantification of peak flow anomalies, the daily discharge data is first split into independent events and extremes are extracted, based on the method proposed by (Willems, 2009). Empirical probabilities (or equivalent return periods) are assigned to these extremes, based on the full time series on the one hand, and based on subsets of extremes in subperiods of 10 years length on the other hand. The quantiles in a particular subperiod are then compared with the corresponding quantiles

25   based on the full timeseries and the ratio of these two empirical quantiles defines an anomaly factor. Finally, per subperiod of 10 years, all anomaly factors corresponding to a return period larger than one year are averaged in order to get one value per subperiod of 10 years. As such, one can plot and/or investigate peak flow anomalies for a given catchment over time.

3.3   Possible drivers

The data introduced in Sect. 2 generally relate to one of the following three categories: catchment characteristics (*CAT*), climate variability (*CLIM*) and land cover changes (*LULC*).

Catchment characteristics are considered time invariant in this study and are derived from following sources: digital terrain model (DTM), river map and soil texture. From the DTM, the river map and locations of the outlet stations, catchment delineations are defined. Further, based on the DTM, the slope at every point in the catchment are calculated, as well as the average slope over the whole catchment. A river density is defined as the ratio of total river length in the catchment over the total area of the catchment. Finally, the relative area of the soil texture classes are being used in the further analysis.

Climate variability is derived from the NCEP/NCAR reanalysis data (Kalnay et al., 1996). Here, weather types are derived based on the daily mean sea level pressure from this reanalysis dataset. Different classification methods exist (Philipp et al., 2010); here, the Jenkinson Collison system (Jenkinson and Collison, 1977), a modified version of the Lamb-weather type classification method (Lamb, 1972) is used to convert sea level pressure into one of 28 weather types. These 28 weather types are reduced to 11 by combining all types with the same directional component (see also e.g. (Demuzere et al., 2009)) and further reduced based on the link between river peak flows and weather types (De Niel et al., 2017). This reduction again aims to limit the degree of freedom in the final model. The remaining weather types are: W; (NW, N), (NE; E; SE), (S; SW); U; C; A, with N, E, S and W referring to wind directions, C and A to cyclonic and anticyclonic atmospheric patterns, respectively, and U to an unclassified weather type. In the further analysis, relative frequencies of these daily weather types are considered, based on a rolling window of 5 years (Figure 4).

Land cover and land cover changes have been described in the past through the ESA CCI project (www.esa-landcover-cci.org): annual global maps of land cover are available between 1992 and 2015. The 22 land cover categories (or 30, when including 'level 2' or 'regional' labels) identified in this project are grouped into the six IPCC land categories, i.e. settlement, agriculture, grassland, forest, wetland and other area.

Table 2 summarizes the possible drivers considered in this attribution study.

3.4   Regression model

3.4.1.   Panel data analysis

A model is built with the techniques and ideas of panel analysis, which is widely used in social sciences, epidemiology, and econometrics where two dimensional data is analysed. Typically, in those sectors data is collected over time and over the same individuals. Here, the data is also collected over time; the individuals should be seen here as the different catchments, with certain heterogeneous characteristics which may also further vary over time. The typical panel data regression model can be described as follows:

$$y_{it} = \alpha + \boldsymbol{\beta}\boldsymbol{X}_{it} + \epsilon_{it}, \tag{1}$$

with y the output of interest, i the individual (or catchment), and t the time; α and $\boldsymbol{\beta}$ are constants, of dimension (1 x 1), and (1 x n) respectively, with n being the number of inputs/observations considered. Note that both α and $\boldsymbol{\beta}$ are catchment independent, as no index i appears here. $\boldsymbol{X}$ represents the input/observations as explanatory variables, with dimension (n x 1) for each individual (or catchment) at a particular time t and ϵ is an error term. In this study, the output of interest is peak

5   flow anomaly, and inputs can be split into three categories: catchment specific characteristics *CAT*, climate variability indicators *CLIM* and land cover *LULC*, as described in Table 2. As such, $\boldsymbol{X}_{it}$ from Eq. (1) becomes:

$$X_{it} = (CAT\ CLIM\ LULC)_{it}^T. \tag{2}$$

Next to the linear model (Eq. (1)), combined effects of (changes in) observed variables might also play a role in explaining the changes in the output of interest.. Therefore, an interaction term is added to the model:

10    $$y_{it} = \alpha + \boldsymbol{\beta}X_{it} + \boldsymbol{\rho}\ X_{it}^T\ X_{it} + \epsilon_{it}. \tag{3}$$

The interaction matrix $\boldsymbol{\rho}$ is of dimension (n x n) and is constant, hence time and catchment independent. This matrix is a strictly upper triangular matrix, meaning all entries on and below the main diagonal are all equal to 0. Furthermore, for our study, we added the restriction that there cannot be any interaction between explanatory variables from within the same category: e.g. $\rho_{area,slope} = 0$.

3.4.2. Model building

Model building happens based on a top down approach. Starting from a simple constant model, with $\boldsymbol{\beta} = \mathbf{0}$ and $\boldsymbol{\rho} = \mathbf{0}$, explanatory variables are added to the model based on changes in the value of the Bayesian information criterion *BIC* (Kass and Raftery, 1995). BIC is a general criterion for model selection, where models with the lowest BIC are preferred. It takes into account the likelihood of a model, the sample size and the number of parameters estimated by the model. In a first step,

20   only the linear model (Eq. (1)) is considered. Once the linear model is fixed, interaction terms are added in a similar way. Note that we only consider interactions between variables present in the linear model. E.g. if β_{arenic} would be equal to 0 in the linear model, then all $\rho_{arenic,X}$ in the model including interaction terms are, a priori, set equal to 0.

In order to build a robust model, 100 linear models are tested based on (100 times) 20 random calibration catchments. Based on this set of 100 models, significant variables are selected, i.e. variables which appear in the majority of the models.

25   ### 4   Results

Prior to the first step of the model building process, a reduction of the number of variables is carried out. With respect to soil texture, it was seen that for all catchments combined, Arenic, Loamic and Siltic describe 99.3% of the total area. Hence, the analysis will further only consider these three dominant soil texture classes. Furthermore, when the class Arenic is seen as the complement of (Loamic + Siltic), this further reduces to only two variables. The absence of an explicit class Arenic is

30   compensated through the constant α in the model. Similarly, with respect to the climate variability, the weather type U is considered as the complement of the other classes. With respect to *LULC*, it was seen that the maximum proportion of Wetland

and Other area in the considered catchments is equal to only 0.2% and 1.5% respectively. Therefore, it is suggested to not take these *LULC*-classes further into account. Similar to the considerations in the soil texture classes, the *LULC* class Grassland is considered as the complement of (Forest + Agriculture + Settlement). Finally, the *LULC* database does not show any significant changes after 2005 (Figure 2), and therefore, the analysis is limited to 1992-2005.

5   After the above reduction in number of variables, 100 models are built, each based on 20 random catchments. Variables are only included in the model if they are found to be significant. The proportion of the models including the various variables are summarized in Figure 5 and, based on this, following variables will further not be considered:

- Catchment characteristics: Area;
- Climate variability: W; (NW, N); (NE,E,SE); A and U;

10   The final model, with 26 terms in 9 predictors, is able to explain 60% of the changes in river peak flows over time (Figure 6). This performance is further broken down into linear effects of the three separate groups and their interactions (Figure 7). Linear effects (28%) are found to be of equal importance as interaction effects (32%). Within the linear effects, catchment characteristics are most important as they explain the highest portion (18%) of the river peak flow changes, followed by land use/land cover (8%) and climate variability (6%). These percentages were obtained by only considering the models that include

15   the variable considered. Note that 18% + 8% + 6% is only slightly larger than 28%, which is due to a small interdependency between land use/land cover and soil texture.

Based on this model, the impact of increased urbanization can further be investigated. This is done by changing, for each catchment, 1% of the total area from settlement to forest, grassland and agriculture, respectively. The resulting changes in river peak flows are summarized for all catchments in Figure 8.

20 **5   Discussion and conclusion**

One of the most interesting findings during the model building and evaluation process, was that the catchment area does not have a significant contribution in explaining observed peak flow changes. Furthermore, when including interaction factors between catchment area and the other variables, the model did not improve (not shown). This might seem surprising at first, since Bloschl et al. (2007), among others, hypothesize that land use impact on hydrological response is depending on the

25   catchment scale. However, all selected case studies are considered to be of the same scale, despite the differences in catchment area and thus, the hypothesized effect of catchment scale on land use impacts is not applicable here.

The regression model is able to explain 60% of the changes in peak flow extremes. For some individual catchments, however, the model is not able to mimic observed step changes, e.g. for catchments L07_289 and L09_145. On the other hand, the direction and the overall trends simulated by the model is found to be accurate. Since the explanatory variables all have a

30   smooth variation over time, it is a priori almost impossible for any simple regression model to mimic these step changes.

The model was built for selected catchments and based on a selected time window. The selected catchments are considered to be a good representation of the spatial heterogeneity within Flanders with respect to land cover and soil texture. For the peak

flow anomalies, the reference period spans the total period where discharge data is available and ranges between 31 and 47 years (depending on the catchment considered). However, due to the lower availability of land cover images, the regression model was fitted based on a shorter time window. Nevertheless, clear changes in peak flow anomalies could be identified for this period and these could be explained for 60% by explanatory variables describing topography, density, soil texture, weather

5   types and land use/land cover.

With respect to the estimation of the regression model, ideally, one would carry out a split-sample test (in space and in time); however, because of data availability and spatial heterogeneity, this approach would fail in this case. Alternatively, the robustness of the model is tested here by fitting multiple models with different calibration data. It is seen from Figure 6 that this approach results in consistent estimations for the peak flow anomalies – only for catchment L11_518 this consistency was

10   not always found.

It was seen that for these case studies, changes in land cover and climate variability play an equally important role in explaining changes in river peak flows. These effects, however, are of a lower importance than catchment specific factors, such as topography and soil texture. Obviously, given the complexity of these environmental systems, the simple linear model will not be able to capture/describe all effects – indeed, it was seen that interaction effects between catchment characteristics, land

15   cover and climate variability are equally important in explaining changes in river peak flows.

The model also showed that, for most of the considered case studies, deforestation indeed leads to increased peak flows. Moreover, 1% increase in urbanization could lead in some cases to a 5% increase in river peak flows.

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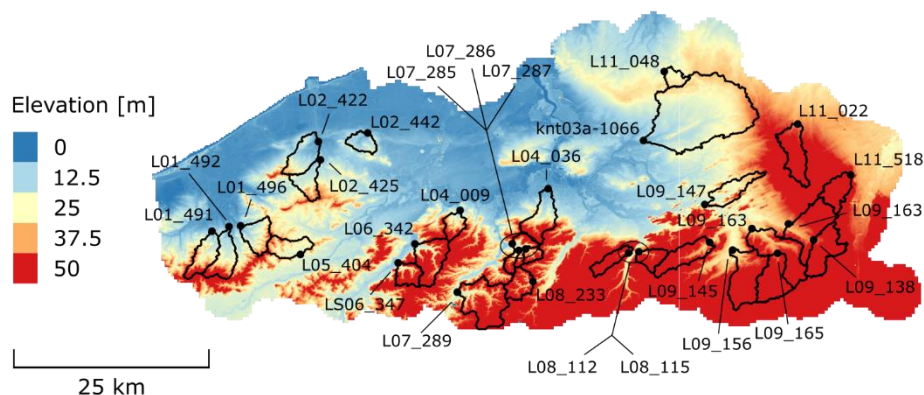
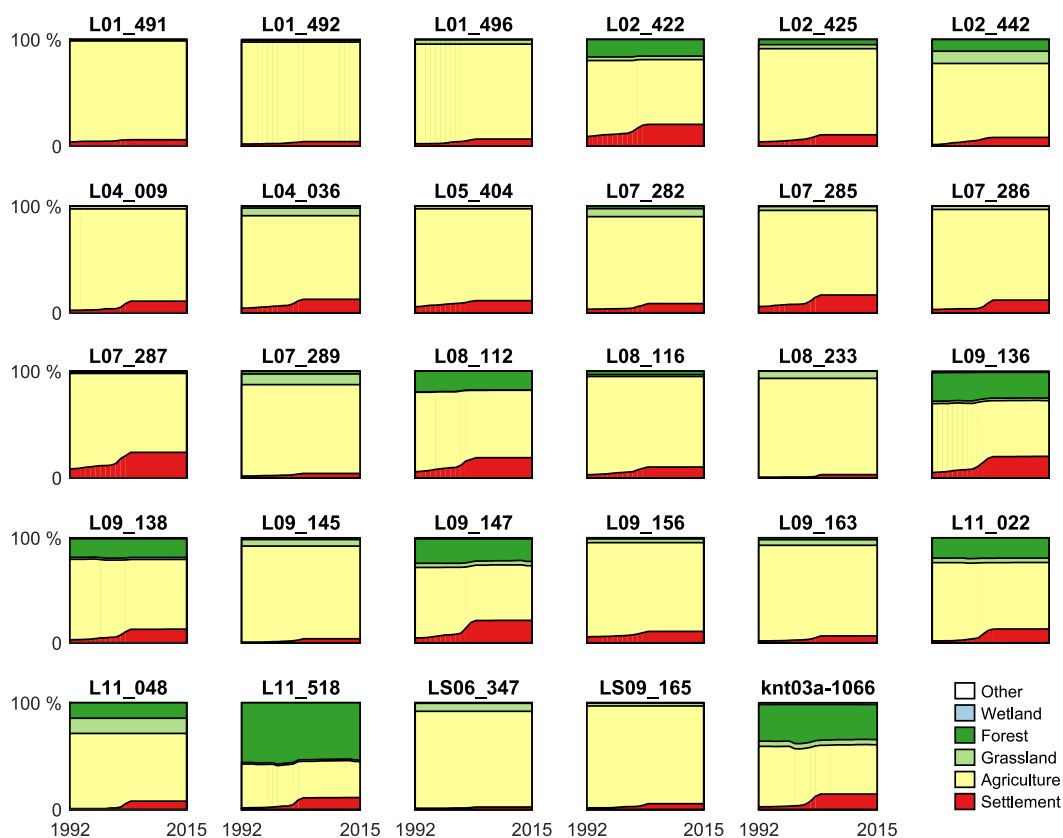


Figure 1. Selected catchments in the Flanders area of Belgium.

5 **Figure 2. Land cover and land cover changes over time (1992 – 2015) for the selected catchments. Data from: www.esa-landcover-cci.org.**

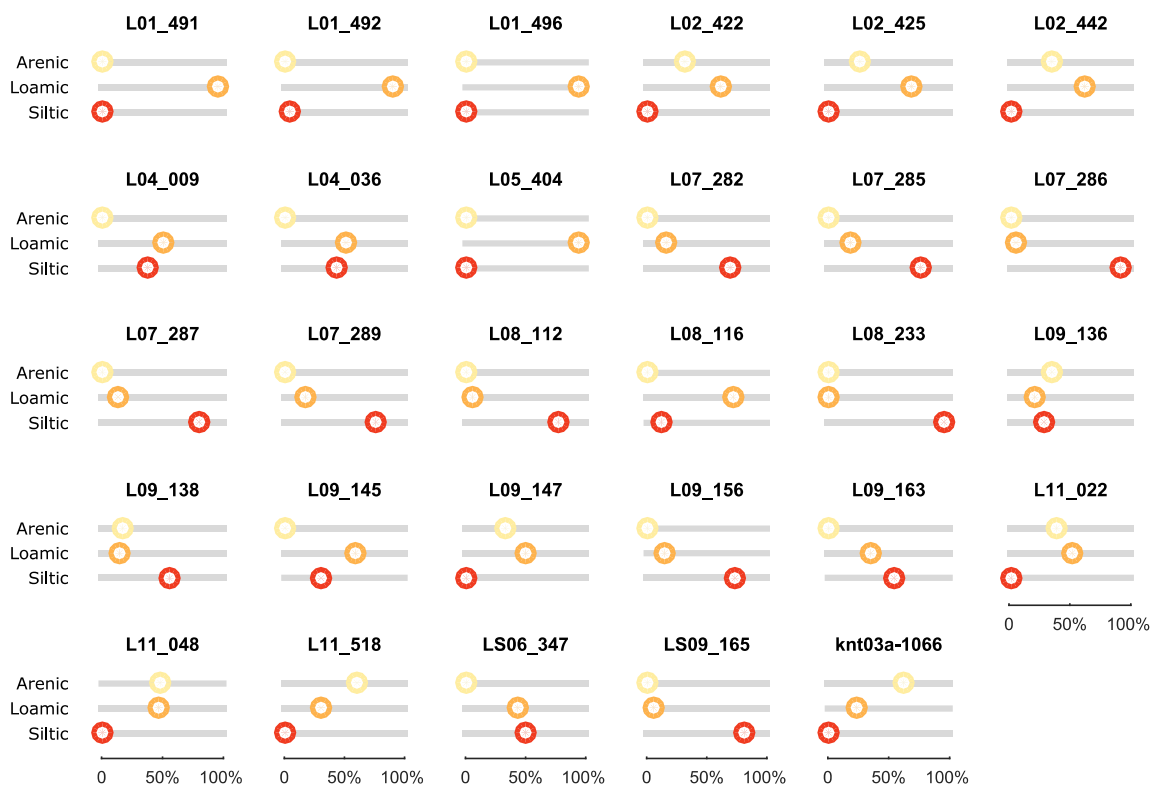



Figure 3. Arenic, loamic and siltic fractions (WRB units) for the selected catchments. Data from: www.dov.vlaanderen.be

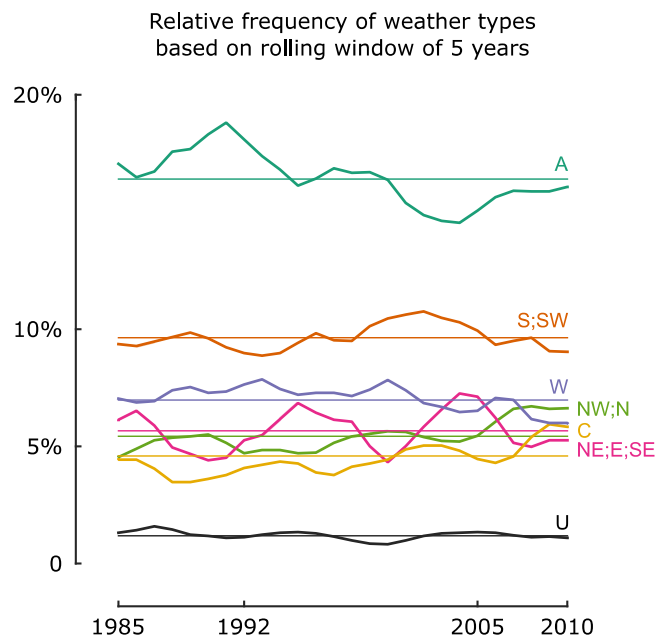



Figure 4. Relative frequency of Lamb weather types over the years.

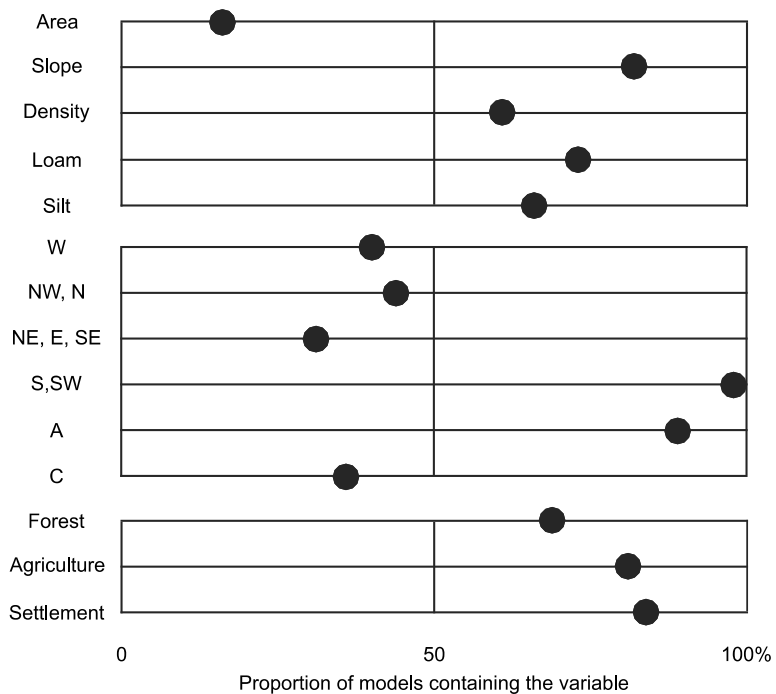



Figure 5. Variables appearing in >50% of the calibrated models are selected to explain changes in river peak flows.

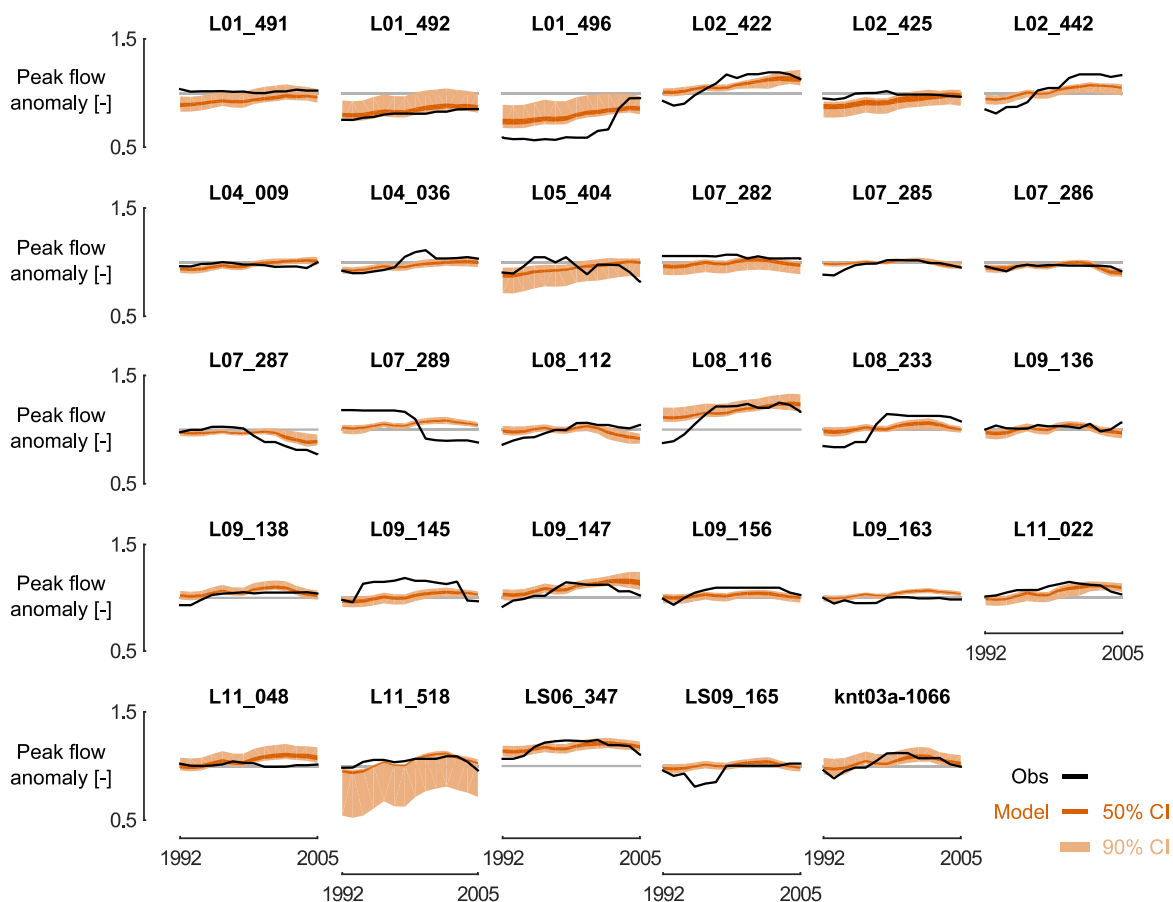



Figure 6. Regression model combining catchment characteristics, climate variability and land cover changes to explain streamflow variability.

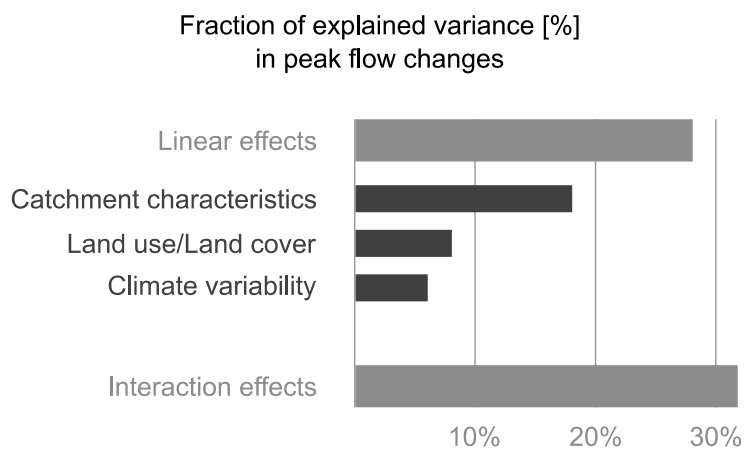



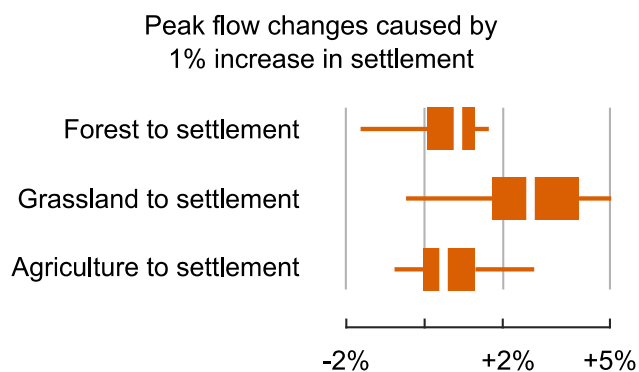
Figure 7. Linear effects and interaction effects between catchment characteristics, climate variability and land cover changes play an equal role in explaining streamflow variability.

5   **Figure 8. Increasing settlement area will, in most cases, lead to increased peak flows.**

Table 1. Main characteristics of the selected catchments.

Id.	Outlet station	River	Area [km^2]	Period		# years
knt03a-1066	Grobbendonk Troon	Kleine Nete	587	1982	2018	36
L01_491	Oostvleteren	Poperingevaart	64	1972	2018	46
L01_492	Reninge	Kemmelbeek	88	1986	2018	32
L01_496	Merkem	Marktjevaart	77	1986	2018	32
L02_422	Sint-Michiels	Kerkebeek	93	1983	2018	35
L02_425	Oostkamp	Rivierbeek	65	1983	2018	35
L02_442	Maldegem	Ede	46	1984	2018	34
L04_009	Massemen	Molenbeek	44	1987	2018	31
L04_036	Liezele	Molenbeek	104	1975	2018	43
L05_404	Moorsele	Heulebeek	73	1985	2018	33
L06_342	Nederzwalm	Zwalmbeek	111	1972	2018	46
L07_285	Essene	Bellebeek	90	1975	2018	43
L07_286	Sint-Katarina-Lombeek	Hunselbeek	22	1983	2018	35
L07_287	Ternat	Steenvoordebeek	26	1983	2018	35
L07_289	Viane	Mark	123	1976	2018	42
L08_112	Heverlee	Voer	49	1986	2018	32
L08_115	Heverlee	Molenbeek	48	1986	2018	32
L08_233	Sint-Pieters-Leeuw	Zuunbeek	65	1978	2016	38
L09_136	Hasselt	Demer	270	1983	2018	35
L09_138	Bilzen	Demer	116	1972	2018	46
L09_145	Ransberg	Velpe	97	1975	2018	43
L09_147	Molenstede	Zwart Water	79	1986	2018	32
L09_156	Rummen	Melsterbeek	153	1983	2018	35
L09_163	Spalbeek	Herk	274	1977	2018	41
L11_022	Overpelt	Dommel	112	1971	2018	47

L11_048	Merksplas	Mark	32	1983	2018	35
L11_518	Opoeteren	Bosbeek	76	1985	2018	33
LS06_347	Etikhove	Molenbeek	51	1972	2018	46
LS09_165	Wellen	Herk	111	1972	2018	46

Table 2. Drivers considered for this study

Catchment specific *CAT*

Topographic	Soil texture [% of total area]
Area [km^2], Slope [%] and Density [m/km^2]	Arenic, Clayic, Loamic, Loamic/Arenic, Loamic/Clayic, Loamic/Siltic, Siltic, Siltic/Clayic, Sitlic/Clayic/Loamic, Sitlic/Loamic

Climate variability *CLIM* – weather types [% of time in a rolling window of 5 years]

W; (NW, N); (NE, E, SE); (S, SW); A; C and U

Land cover *LULC* [% of total area]

Settlement, Agriculture, Grassland, Forest, Wetland and Other area