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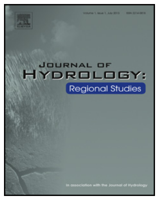

Spatial distribution of groundwater recharge and base flow: Assessment of controlling factors

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ABSTRACT

Study focus: Groundwater is of strategic importance. The accurate estimation of groundwater recharge and assessing the fundamental controlling factors are therefore of utmost importance to protect groundwater systems. We used the spatially-distributed water-balance model WetSpass to estimate long-term average recharge in Flanders. We validated recharge rates with base flow estimates of 67 daily stream flow records using the hydrograph analyses. To this end we performed principal component analysis, multiple linear regression analysis and relative importance analysis to assess the controlling factors of the spatial variation of recharge and base flow with the influencing watershed characteristics.
New hydrological insights for the region: The average resulting recharge is 235 mm/year and occurs mainly in winter. The overall moderate correlation between base flow estimates and modeled recharge rates indicates that base flow is a reasonable proxy of recharge. Groundwater recharge variation was explained in order of importance by precipitation, soil texture and vegetation cover; while base flow variation was strongly controlled by vegetation cover and groundwater depth. The results of this study highlight the important role of spatial variables in estimation of recharge and base flow. In addition, the prominent role of vegetation makes clear the potential importance of land-use changes on recharge and hence the need to include a proper strategy for land-use change in sustainable management of groundwater resources.

1. Introduction

Groundwater is the largest reservoir of liquid freshwater on the planet and is critical for sustaining life on earth, as it is used to satisfy domestic, agricultural, industrial, and environmental water needs (Shiklomanov, 2000; Sophocleous, 2004). Groundwater recharge has a fundamental role in sustainable groundwater resources development and management albeit other hydrologic, social, and economic factors have to be considered (Seiler and Gat, 2007). However, recharge rates are one of the most poorly constrained hydrological parameters in almost all groundwater flow and transport models (Lerner et al., 1990; Anderson and Woessner, 1992), and the least understood, largely because recharge rates vary widely in space and time, and rates are difficult to measure directly (Healy, 2010). In Flanders, Belgium groundwater is the predominant

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source for public water supply, amounting to 48.5% (Dassargues and Walraevens, 2014). Therefore, an accurate estimation of groundwater recharge is of utmost importance for proper management of the groundwater system.

Various methods exist to estimate recharge (Simmers, 1988; Lerner et al., 1990; Scanlon et al., 2002; Healy, 2010). In spite of this variety, uncertainty is still a dominating factor in recharge estimation (Scanlon et al., 2002). There is a conceptual understanding that recharge is highly spatial and temporal variable and a non-linear function of hydrometeorology, land-use, soil texture, slope, and physical properties of aquifers (Sophocleous, 2004; Healy, 2010). Hence, increasingly methods are developed to incorporate the spatial–temporal variation of recharge in groundwater modelling (Jyrkama et al., 2002; Feinstein et al., 2005; Eilers et al., 2007; Jyrkama et al., 2007; Minor et al., 2007; Batelaan and De Smedt, 2007; Markstrom et al., 2008; Hughes et al., 2008; Westenbroek et al., 2010; Best and Lowry, 2014; Moya et al., 2014; Cooper et al., 2015; Hemmings et al., 2015). One of the main advantages of this development is that this will enable to examine impacts of climate and land-use change on water resources at unprecedented levels of temporal and spatial variability (Healy, 2010).

For example, the GSFLOW model (Markstrom et al., 2008) is a coupled watershed/groundwater flow model, which links PRMS (Leavesley et al., 1983) with MODFLOW-2005 (Harbaugh, 2005) to simulate groundwater and surface water resources. Conceptually, GSFLOW divides the coupled system in three compartments. The first compartment is simulated by PRMS and includes the plant canopy, snowpack, impervious storage, and soil zone. The second compartment includes streams and lakes, while the third compartment represents the unsaturated and saturated zones, both are simulated by MODFLOW-2005. Another example is the WetSpass model (Batelaan and De Smedt, 2007), which calculates the long-term recharge by means of a water-balance model coupled to a regional groundwater model. The WetSpass model accounts for the spatial variability of soil texture, land-use, slope and meteorological conditions in recharge estimation. WetSpass can be iteratively connected to a groundwater model, which provides the position of the water table, while WetSpass returns recharge estimates accordingly. The ZOODRM model (Hughes et al., 2008) incorporates the spatial and temporal constraints on the inputs, for instance the length of the daily rainfall time series, the number of rain gauge stations, and spatial distribution of rainfall. Hemmings et al. (2015) evaluated three precipitation distribution scenarios using the ZOODRM model to incorporate the spatial relationships of rainfall with elevation and latitude, to estimate the spatial and temporal recharge rates of Montserrat Island.

Many authors recommend to estimate recharge with multiple methods and to compare the results (Healy and Cook, 2002; Scanlon et al., 2002; Nimmo et al., 2003; Risser et al., 2009). Numerous studies have used base flow from stream gauging stations to estimate groundwater recharge as a means of comparison (Fröhlich et al., 1994; Cey et al., 1998; Arnold et al., 2000; Stewart et al., 2007; Batelaan and De Smedt, 2007; Combalicer et al., 2008; Eckhardt, 2008; Gonzales et al., 2009; Risser et al., 2009). Base flow can be considered as the outflow of the groundwater reservoir feeding the rivers during rainless periods (Fröhlich et al., 1994). The major assumptions in using base flow for estimating recharge are that base flow equals the total groundwater discharge of a catchment and that groundwater discharge is approximately equal to recharge (Piggott et al., 2005; Risser et al., 2005). These assumptions, however, are not entirely accepted by the scientific community as it is difficult to compare base flow and recharge directly because most base flow methods determine some surrogate of the groundwater discharge and therefore of actual recharge (Rutledge, 2005; Risser et al., 2009).

Groundwater recharge simulation requires a wide range of watershed characteristic data (climatic, geologic, hydrologic, and physiographic). The variation in the data reflects different spatial–temporal sources and scales of the data, as well as different hydrologic conditions, making an interpretation of the results in terms of controlling factors difficult. To derive general trends, the complexity of the datasets can be often reduced to a few, more easily interpretable, components (Bücker et al., 2010). Principal component analysis (PCA) is a mathematical algorithm that reduces the dimensionality of the data while retaining most of the variation in the dataset (Suk and Lee, 1999; Jolliffe, 2002; Thyne et al., 2004; Lee et al., 2008; Combalicer et al., 2008; Bücker et al., 2010). In a PCA, the variation in data is projected on new, abstract orthogonal principal components (eigenvectors), with each principal component, or factor, describing a different independent source of variation for the dataset (Bücker et al., 2010). Each component is derived from a set of correlated elements, which are influenced by the same process (recharge) and watershed characteristics (e.g., soil, land-use, climate, hydrology, and geology).

Statistical regression techniques are commonly employed in hydrologic studies for multiple purposes (Helsel and Hirsch, 2002), as e.g., estimation of recharge and/or base flow on basis of watershed characteristics (Holtschlag, 1997; Flynn and Tasker, 2004; Mazvimavi et al., 2005; Delin et al., 2007; Gebert et al., 2007; Longobardi and Villani, 2008; Zhang et al., 2013). However, when the independent variables are correlated with each other, the regression approach can face serious difficulties (Rajab et al., 2012; McAdams et al., 2000). Therefore, PCA is useful for mitigating the problem of multicollinearity (Rajab et al., 2013). Reported significant watershed characteristics that influence recharge and/or base flow variation include topography, slope, catchment drainage area, precipitation, average maximum daily temperature, evapotranspiration, percentage of sand in the soil, and land-use type (Risser et al., 2008; Zhang et al., 2013).

Multiple linear regression analyses (MLR) is particularly useful for addressing issues related to prediction, such as identifying a set of predictors that will maximize the amount of variance explained in the criterion (Tonidandel and LeBreton, 2011). However, this study uses MLR to identify the contribution of each predictor (watershed characteristics) towards explaining the variance in recharge and base flow. On the other hand, the indices produced by MLR analyses may fail to appropriately partition variance to the various predictors when they are correlated (Budescu, 1993; Courville and Thompson, 2001; Tonidandel and LeBreton, 2011; Kraha et al., 2012). Hence, more advanced approaches, such dominance weight analysis (DWA) (Budescu, 1993) and relative weight analysis (RWA) (Johnson, 2000), have been developed to accurately measure the predictor importance among correlated predictors.

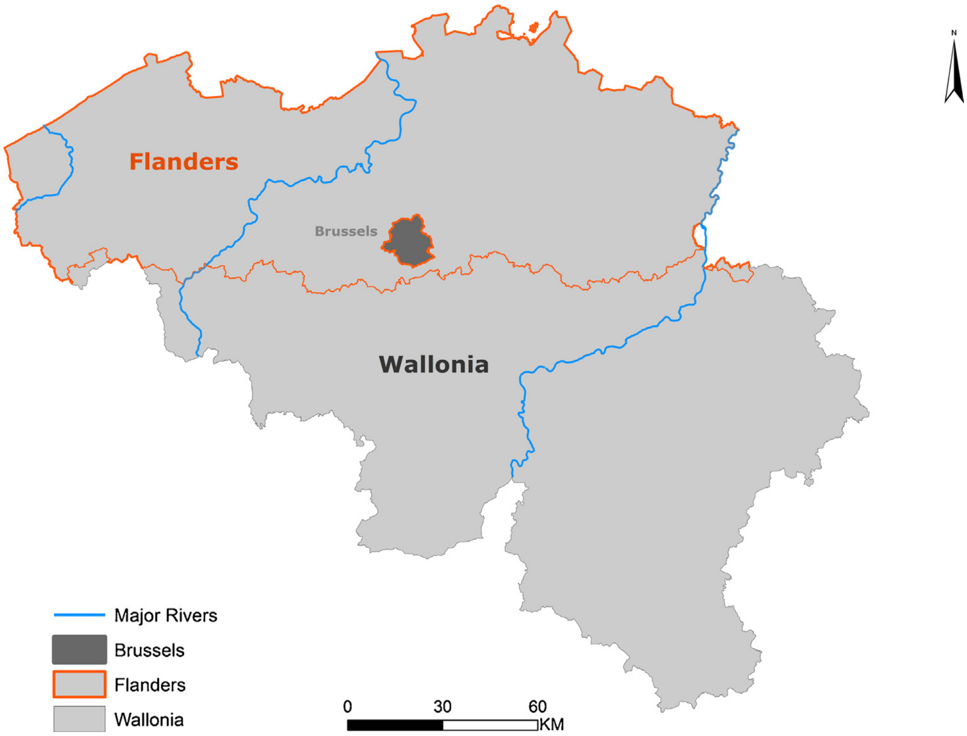

Fig. 1. Location map of Flanders, Belgium.

In this study, we combine PCA, multiple linear regression and relative importance analysis to identify the controlling factors of recharge and base flow. PCA was used to filter the data so that only the significant independent variables (watershed characteristics) that explain most of the variance in recharge and base flow could be determined. Regression equations of principal components are developed to incorporate these controlling factors to predict spatial variation of recharge and base flow. Relative importance analysis DWA and RWA was used to determine the order of importance of the factors resulting from MLR regression of principal components and their contribution to the total variance of the spatial estimation of recharge and base flow.

The objectives of this study are to estimate the spatial variation of groundwater recharge in Flanders, Belgium using the WetSpass model. The hypothesis that will be tested is if the simulated recharge can be confirmed by using base flow estimates derived via the Web-based Hydrograph Analysis Tool (WHAT) (Lim et al., 2005). The controlling factors of recharge and base flow are identified using PCA, multiple linear regression analysis and relative importance analysis.

2. Study area

The study area covers the Flanders region in the northern part of Belgium (Fig. 1). Flanders is a relatively flat region with an average slope of 1%, although the southeastern part shows more elevation variation with slopes above 5%. The mean annual long-term precipitation ranges from 675 to 995 mm/year (1833–1995), while the average yearly, long-term potential open water evaporation ranges from 662 to 675 mm/year (Batelaan et al., 2007). The summer potential evaporation typically constitutes about 85% of the total yearly amount. The long-term average wind speed for the summer and winter season are 3.3 m/s and 3.8 m/s, respectively, while the average temperatures for summer and winter are respectively 14.1 °C and 5.0 °C (Batelaan et al., 2007).

In the study area, nine soil textures occur (Fig. 2), the northern part of Flanders is mainly covered by sand and loamy sand, while in the south silty loam and sandy loam dominates. The coastal area is characterized by the presence of clay, while in the polders heavy clay dominates. The soil textures that are the most common are sand and silty loam respectively 25.9% and 17.8%, followed by loamy sand (17.7%), silt (15.8%), sandy loam (12.5%), clay loam (6.5%), clay (2.5%), sandy clay loam (1.5%), and loam (<0.1%). The land-use map with a resolution of 50 by 50 meter was reclassified from the original land-use map of 10×10 m (Poelmans et al., 2014), the 114 categories were aggregated to 22 classes according to the standard land-use tables of the WetSpass model. The main land-use types (Fig. 3) for 2013 are built-up area (24%), meadow (22%), maize and tuberous (19%), agriculture (11%), forest (11%), and lakes and rivers (2%) (Poelmans et al., 2014).

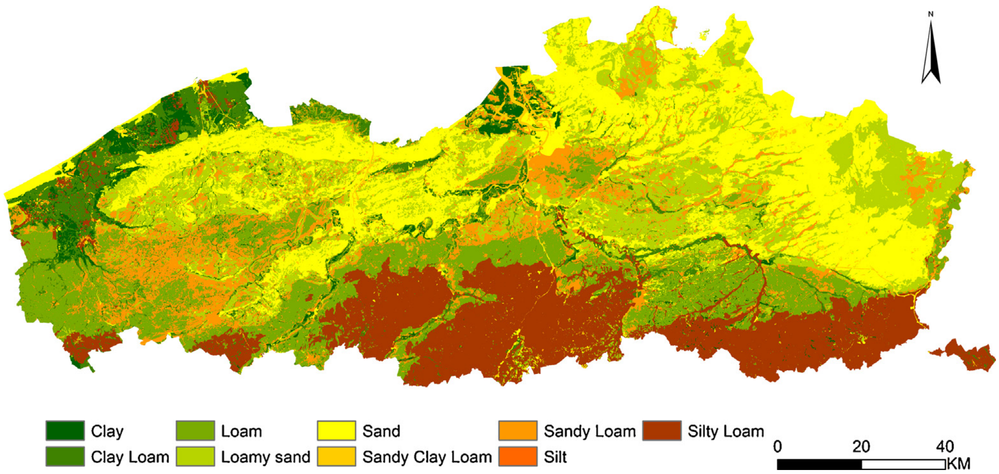

Fig. 2. Soil textures of Flanders, sand, and loamy sandy soils cover more than 50% of the total area.

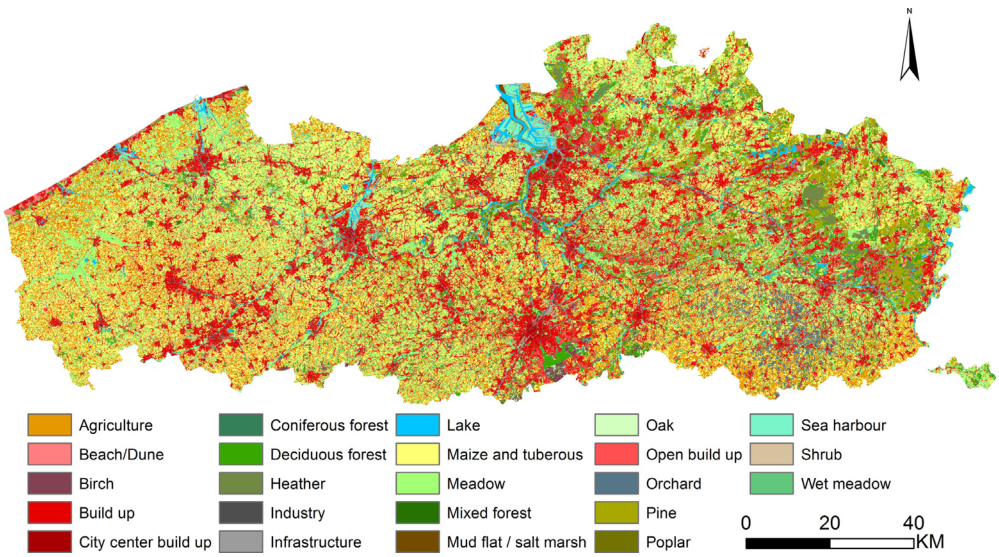

Fig. 3. Land-use types of Flanders for the year 2013, built-up area, meadow, agriculture, and forest are the major land-use types (Poelmans et al., 2014).

3. Methodology

3.1. Overview

The methodology consists of three parts (Fig. 4). In the first part, we have applied the WetSpass model to quantify the groundwater recharge, and to determine the spatial distribution as a function of various factors, such as hydrometeorology, topography, soil texture, and land-use type. Next, base flow for 67 sub-catchments was separated using the Web-based Hydrograph Analysis Tool (WHAT) to compare it with simulated recharge values from the WetSpass model. In the third part, Pearson's correlation coefficients were used to determine the strength of possible relationships between recharge, base flow and watershed characteristics. Next we have used three statistical analysis methods using XL-STAT software to identify the controlling factors affecting recharge and base flow: PCA, MLR, and DWA/RWA. PCA is used to reduce the dimensionality of the data and to identify the controlling factors that explain most of the variance of recharge and base flow. Consequently, regression equations are developed that incorporate these controlling factors to predict spatial variation of recharge and base flow. Finally relative importance analysis (DWA and RWA) was performed to determine the order of importance of each significant variable in explaining the variance of spatial estimation of recharge and base flow.

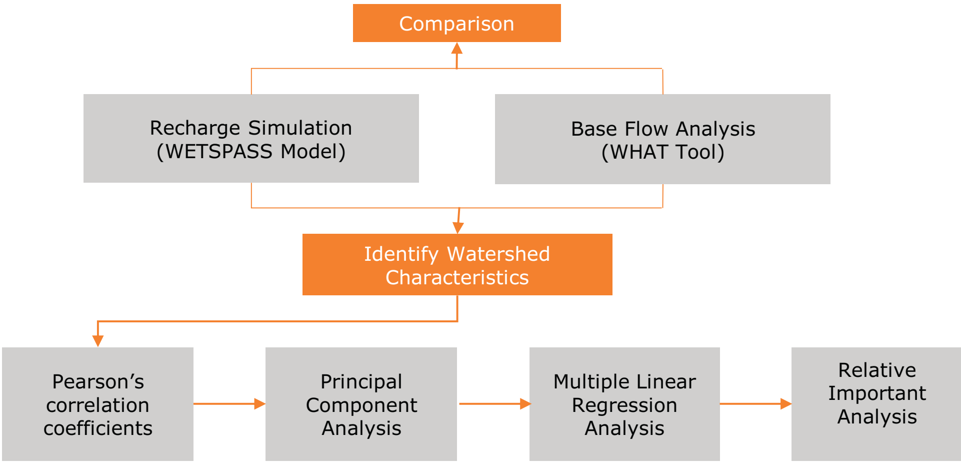

Fig. 4. Overview of the methodology.

3.2. *Recharge estimation*

The WetSpass model is a quasi-steady state, simulation model for water and energy transfer between soil, plants, and atmosphere. It predicts spatial patterns of surface runoff, evapotranspiration, and groundwater recharge on a regional scale (Batelaan and De Smedt, 2007).

The model treats a basin or region as a regular pattern of raster cells. Every raster cell is further sub-divided in a vegetated, bare soil, open water, and impervious surface fraction. The seasonal water balance is calculated for each grid cell. The seasonal water balance for a vegetated fraction of a raster cell is

$$P = \mathrm{Sv} + \mathrm{Tv} + \mathrm{Rv} + I \quad (1)$$

where P is the precipitation (mm), Sv the surface runoff (mm), Tv the actual transpiration (mm), Rv the groundwater recharge (mm), and I the interception (mm). The same procedure is used to calculate the water balance for the bare soil, impervious, and open-water fractions of a cell. Then the water balance of each grid cell can be calculated by summing up the independent water balances for the different fraction per raster cell. The total actual evapotranspiration (ET) is calculated as the sum of the interception, the transpiration (soil and groundwater) and the evaporation from the bare soil in a grid cell. Groundwater recharge is calculated as the residual term from the water balance. A more detailed description, calibration, validation and a case study of the WetSpass model for a part of Flanders can be found in Batelaan and De Smedt (2007).

WetSpass requires spatially distributed land-use, soil texture, slope, long-term average precipitation, potential evapotranspiration, wind speed, and groundwater depth. The required input data with a resolution of 50 × 50 m were available from Batelaan et al. (2007). Only the land-use map has been updated with new 2013 land-use map (Poelmans et al., 2014). The groundwater depth for summer and winter was estimated on basis of topographic elevation and interpolated measured groundwater levels (Meyus et al., 2004). The model parameters were calibrated for Flemish conditions and the uncertainty was estimated by Batelaan and De Smedt (2007) and Batelaan et al. (2007). In the current study, the water balance is calculated for a summer season from April to September and a winter season from October to March. The results are consequently summed to obtain annual values.

3.3. *Base flow estimation*

3.3.1. *Catchment delineation*

The Flanders region consists of the three major river basins of the Scheldt, the Meuse and, the Yser River. These basins are subdivided into 11 regional catchments. Within these regional catchments (see for names Fig. 5) we have selected 67 river gauging stations for hydrograph analysis (see for location Fig. 5), each having at least 10 years of daily discharge data from 1972 to 2008. Discharge data were obtained from the publicly available surface water database of the regional water authority (VMM, 2010). We used the Hydrology Tool in ArcGis to delineate the catchments belonging to each gauging station, based on the Digital Elevation Model and river network map of Flanders (GIS-Vlaanderen, 2001).

3.3.2. *Web-based hydrograph analysis*

The automated Web-Based Hydrograph Analysis Tool (WHAT) is an online freely available tool to separate base flow from stream flow data. The tool includes three separation filters, the local-minimum method (Lim et al., 2004, 2005), the one parameter digital filter method (Lyne and Hollick, 1979; Nathan and McMahon, 1990; Arnold and Allen, 1999; Arnold et al., 2000) and the Eckhardt recursive digital filter (Eckhardt, 2005).

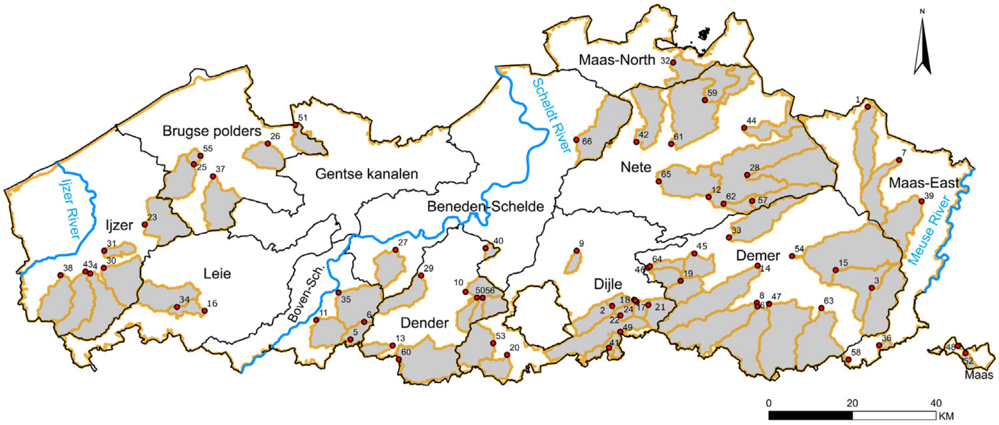

Fig. 5. Delineated sub-catchments (in gray) for the 67 gauging stations (in red) used for base flow analysis within the 11 catchments in Flanders. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The local-minimum method (LMM) connects the lowest points on the hydrograph with straight lines, thereby, mimicking the traditional graphical separation technique. The method checks for every day if the discharge is the lowest value in one half the interval (N) minus 1 day [$0.5(2N^* - 1)$ days] before and after the day being considered. If true, then it is a local minimum and is connected by straight lines to adjacent local minima (Sloto and Crouse, 1996).

The one parameter digital filter method (OPM) is defined as:

$$q_t = \alpha \times q_{t-1} + \frac{1+\alpha}{2} \times (Q_t - Q_{t-1}) \tag{1}$$

where, q_t is the filtered direct runoff at time step t (m^3/s); q_{t-1} is the filtered direct runoff at time step $(t-1)$ (m^3/s); α is the filter parameter; Q_t is the total stream flow at time step t (m^3/s); and Q_{t-1} is the total stream flow at time step $(t-1)$ (m^3/s). A filter parameter of 0.925 was used in this study as recommended by Nathan and McMahon (1990) because they found that it gives realistic results when compared to manual separation results. The advantage of the digital filters is not that it is physically based, but that it is fast, consistent, reproducible and therefore, it removes the subjective aspect from manual separation (Arnold and Allen, 1999).

The general form of the Eckhardt Recursive Digital Filter method (RDF) (Eckhardt, 2005) is:

$$b_t = \frac{(1 - \mathrm{BFI}_{\max}) \times \alpha + b_{t-1} + (1-\alpha) \times \mathrm{BFI}_{\max} \times Q_t}{1 - \alpha \times \mathrm{BFI}_{\max}} \tag{2}$$

where b_t is the filtered base flow at the t time step (m^3/s); b_{t-1} is the filtered base flow at the $t-1$ time step (m^3/s); $\mathrm{BFI}_{\max}$ is the maximum value of long term ratio of base flow to total stream flow; α is the filter parameter; and Q_t is the total stream flow at time step t (m^3/s). This type of digital filter method has been used in signal analysis and processing to separate high frequency signals from low frequency signals (Lyne and Hollick, 1979). High frequency waves can be associated with the direct runoff, and low frequency waves can be associated with base flow (Eckhardt, 2005, 2008). Eckhardt (2005) proposed $\mathrm{BFI}_{\max}$ values of 0.80 for perennial streams with porous aquifers, 0.50 for ephemeral streams with porous aquifers, and 0.25 for perennial streams with hard rock aquifers. These values were obtained through application and validation of this filtering approach on watersheds in Pennsylvania, Maryland, Illinois, and Germany (Lim et al., 2005). Here, the suggested value of 0.98 for the filter parameter and 0.80 for $\mathrm{BFI}_{\max}$ corresponding to the hydrogeological conditions of the area were selected.

3.4. Identification of controlling factors

In a four step procedure, the effects of physical, hydrological, and climatological characteristics of the spatial variation of recharge and base flow are related using multivariate statistical analyses: (1) determination of watershed characteristics that are significant for recharge and base flow using Pearson correlation test; (2) Principal Component Analysis (PCA) to detect the outliers, reduce the number of variables and to identify variables that explain most of the variance; (3) use of multiple linear regression analysis with principal component scores to relate recharge and base flow to independent significant watershed characteristics; (4) relative importance analysis to explain importance of variance for each significant characteristics.

We selected nine parameters, base flow index, simulated recharge, and seven watershed characteristic variables that might be significant for recharge and base flow (Table 1). Mean values of these parameters were derived directly from the input and output raster maps (50 m resolution) of the WetSpass model and prepared by a variety of ArcGIS tools. The base flow index (BFI) is the proportion of base flow to the total stream flow (Bloomfield et al., 2009). We have used BFI as it was widely used in recent literature and shown to be an important variable to detect the influence of watershed characteristics

Table 1
Watershed characteristics selected for multiple linear regression.

Watershed characteristics	Unit
Recharge	mm/year
Base flow index	%
Soil texture	%
Land-use types	%
Catchment slope	degree
Catchment drainage area	km^2
Precipitation	mm/year
Potential evapotranspiration	mm/year
Groundwater depth	m

Table 2
Long-term water balance for Flanders simulated with WetSpass (all values are in mm).

	Parameter	Min	Max	Average	Std. dev
Annual	Precipitation	647	997	756	38
	Evapotranspiration	207	758	450	59
	Groundwater recharge	−109[a]	507	235	93
	Surface runoff	1	605	73	81
Summer	Precipitation	346	511	388	20
	Evapotranspiration	133	626	334	56
	Groundwater recharge	−172[a]	164	18	55
	Surface runoff	0	306	39	38
Winter	Precipitation	328	486	368	19
	Evapotranspiration	72	160	116	7
	Groundwater recharge	0	38	217	56
	Surface runoff	0	364	35	51

[a] Negative recharge should be interpreted as zones where total ET is higher than infiltration (Precipitation–Runoff).

on base flow (Abebe and Foerch, 2006; Price, 2011). We used base flow indices resulting from the RDF method as the method was validated against seven base flow separation techniques (Eckhardt, 2008; Combalicer et al., 2008).

Pearson's correlation coefficients were used to determine the significance of potential relationships between recharge, base flow index, and different watershed characteristics. PCA was carried out only for the variables that were significantly correlated with recharge and/or base flow index (Wang et al., 2013). We used PCA to detect the outliers in the dataset and to identify components that explain most of the variance, only components with an eigenvalue greater than one were retained (Brejda et al., 2000). To maximize the variation among the variables under each component, a varimax rotation was performed. Watershed characteristic variables with a high factor loading (>0.75) were assumed to be the variables that best represent the variation and were selected for regression analysis (Liu et al., 2003).

Subsequently, a new PCA analysis was carried out for the variables with high factor loadings only, followed by a multiple linear regression analysis with the principal component scores with an eigenvalue greater than one.

We used standardized regression coefficients (beta weight) resulting from principal component's regression to evaluate the relative contribution of each variable (predictor) in explaining importance of variance, but these simple measures are recognized as inadequate measure of relative importance when multiple predictors are correlated with one another (which is the case for predictors in MLR for recharge) (Budescu, 1993). Therefore, we performed relative importance analysis, the goal of which is to partition explained variance among multiple predictors to better understand the role played by each predictor in a regression (Tonidandel and LeBreton, 2011). We used dominance analysis (DWA) and relative weight analysis (RWA) (Budescu, 1993; Johnson, 2000), which have been proved as appropriate measures of predictor importance in the context of multiple correlated predictors (Johnson and LeBreton, 2004). Dominance weight analysis determine variable importance based on comparisons of unique variance contributions of all pairs of variables to regression equations involving all possible subsets of predictors (Nathans et al., 2012). While relative weight analysis solves the problem by using principal components analysis to transform the original independent variables into a set of uncorrelated principal components that are highly correlated with the original independent variables (Tonidandel and LeBreton, 2010). Details of DWA and RWA can be found in Azen and Budescu (2003) and Johnson (2000). The DWA excel spreadsheet (LeBreton, 2006) and the web-based RWA tool (Tonidandel and LeBreton, 2014) were used to detect the order of importance of each significant variable in explaining the variance of spatially estimated recharge and base flow.

4. Results and discussion

4.1. Recharge simulation

The long-term average results of the WetSpass modeling for Flanders are summarized in Table 2. The summer season is characterized by a high evapotranspiration (86% of precipitation) and 10% surface runoff, which results often in a net

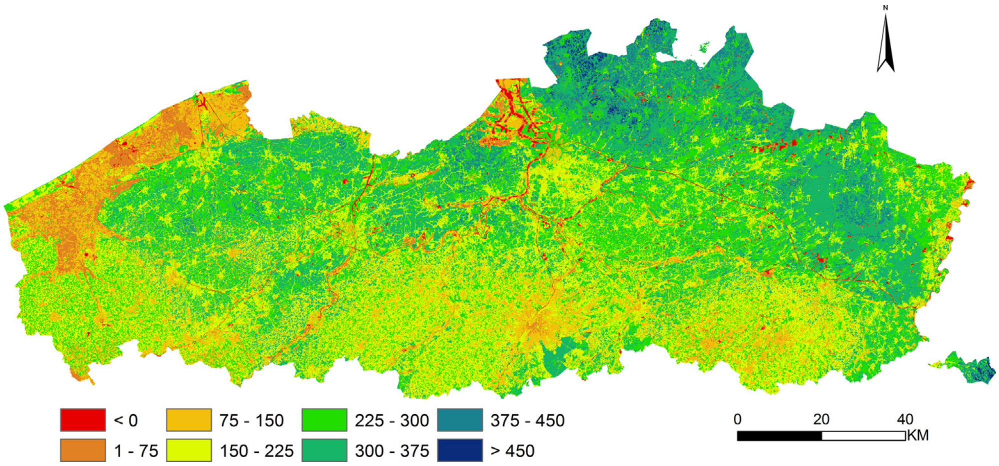

Fig. 6. Simulated long-term average annual groundwater recharge (mm/year) for Flanders.

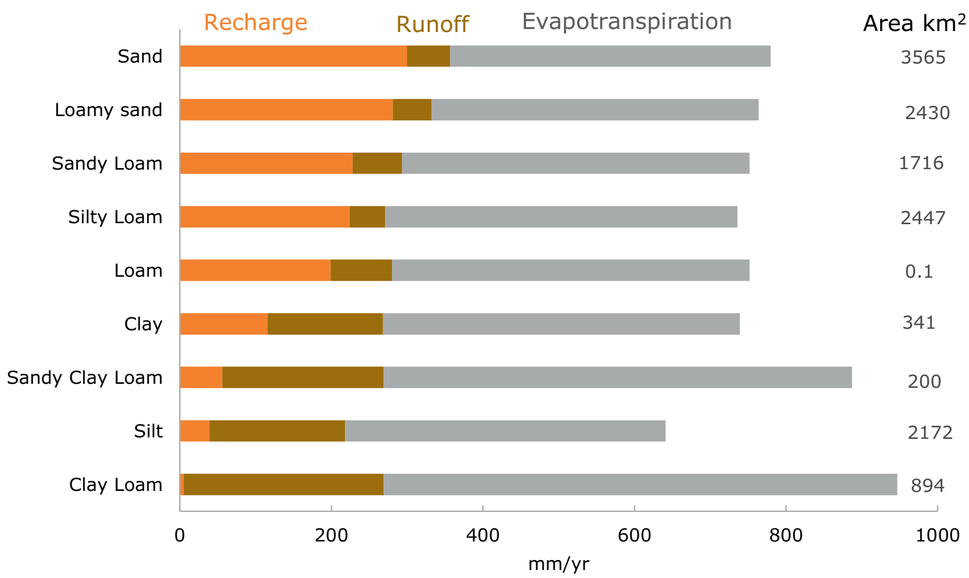

Fig. 7. Average annual groundwater recharge, runoff and evapotranspiration as a function of soil texture. The areal coverage of each soil texture class is given on the right hand side.

negative groundwater recharge under shallow groundwater conditions, i.e., a contribution of the groundwater reservoir to transpiration. In winter, the surface runoff is similar (7%), but the evapotranspiration drops to 32% of rainfall because of lower temperatures. Hence, more water is available for groundwater recharge (59%), which shows that most of the groundwater recharge occurs in winter.

The annual groundwater recharge shows a large spatial variation with values between −109 and 507 mm (Fig. 6). The yearly average value is 235 mm and the standard deviation 93 mm, summer recharge value of 18 mm and winter average recharge of 217 mm. This finding was confirmed by Van Camp et al. (2010) on basis of results from a case study in northern Belgium. They showed that total aquifer recharge calculated with long-term average data is 239 mm/year and mainly occurs in winter. According to our results, the long-term average recharge for the same area is 235 mm/year.

Negative recharge occurs in case the total evapotranspiration is higher than the infiltration (Net Precipitation—Runoff). This only occurs in zones with shallow groundwater. In places where the water table is near the land surface, such as in valleys, polders, areas near to lakes and rivers, plant roots can penetrate into the saturated zone, allowing the plants to transpire water directly from the groundwater system.

We calculated the average groundwater recharge for each sub-catchment by overlaying the annual recharge map of Flanders (Fig. 6) with the sub-catchments map (Fig. 5). The sub-catchment Pulle/Molenbeek (see for location Fig. 5, No. 42) has the highest recharge rate (336 mm/year). Pulle/Molenbeek is dominated by sandy soils and covered by agriculture 35%, forest 26%, and meadow 24%. On the other hand the Budingen/Gete sub-catchment (see for location Fig. 5, No. 8) has the

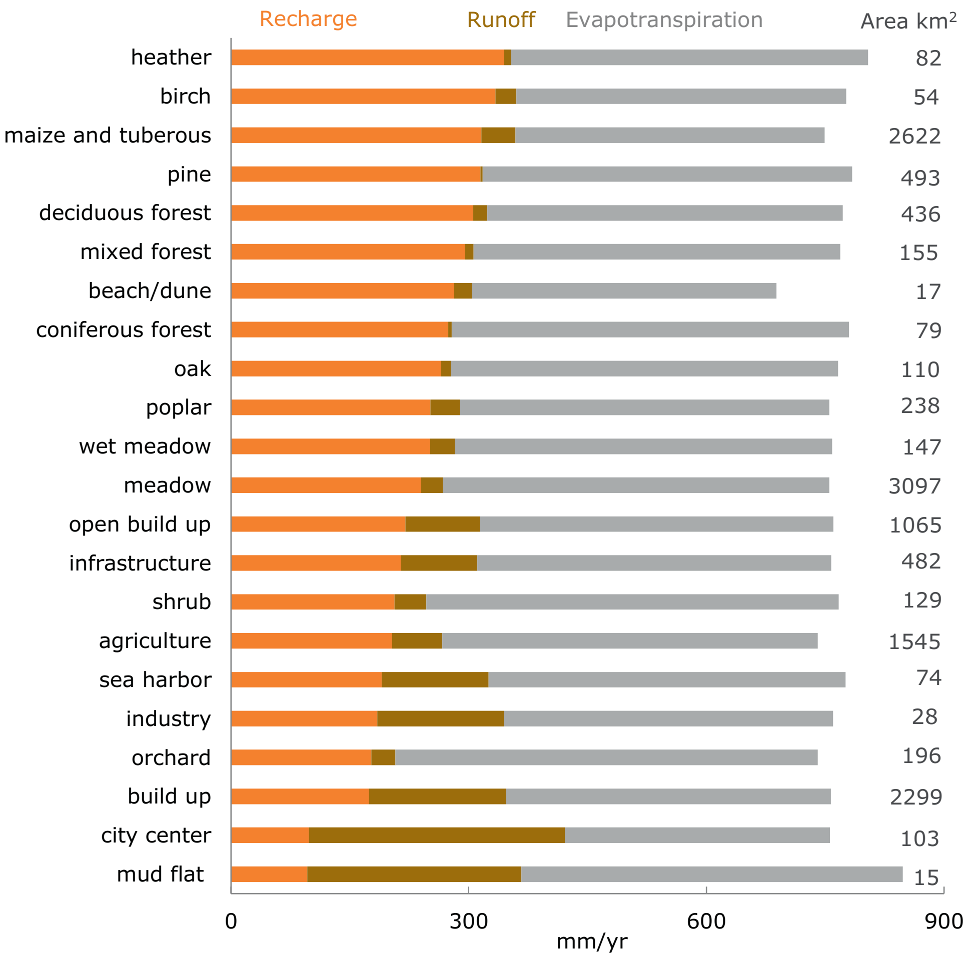

Fig. 8. Average annual groundwater recharge, runoff and evapotranspiration as a function of land-use type. The areal coverage of each land-use class is given on the right hand side.

lowest recharge rate (168 mm/year), since it is dominated by loamy soil and mainly covered by agriculture for more than 75%.

Figs. 7 and 8 present the water balance components (average annual groundwater recharge, evapotranspiration, and runoff) as a function of different soil textures and land-use types in Flanders, respectively. Groundwater recharge appears to be strongly dependent on soil texture. For the light soil types, sand, and loamy-sand, recharge shows similar values, while for the slightly heavier soils (light sandy-loam, sandy-loam, and loam), it is clear that the recharge values fall between the values of the sandy and the clay soil. For clay, the groundwater recharge decreases to about half the value of the loamy soil textures. For heavy clay, the recharge becomes less than 50 mm.

The simulated groundwater recharge is also highly dependent on land-use (Fig. 8). Built up area has a low groundwater recharge as it is characterized by a full or partial impervious surface. Built up area comprises 24% of the surface of Flanders and is scattered over the whole area. The degree of surface sealing of the ground surface depends on the type of land-use. The rural area comprises different land-use types and covers 62% of the total area of Flanders. These areas have both positive and negative impacts on groundwater recharge. For agricultural area, maize, tuberous crops, and to a lesser extent for orchard, there is a clear influence of the seasons. It is assumed that these lands are in the winter almost bare, which results in increased surface runoff, and reduced actual evapotranspiration. The summer season is characterized by a higher actual evapotranspiration, leading to lower recharge. Especially orchards show a low average groundwater recharge. Pastures and wet grasslands have still vegetated area in winter, resulting in relatively higher evapotranspiration and lower surface runoff. For open water (lake class), the WetSpass model assigns a zero recharge, as it is assumed that the recharge derived from the precipitation on the open water fraction is negligible compared to the possible recharge from the surface water body itself (Batelaan and De Smedt, 2007).

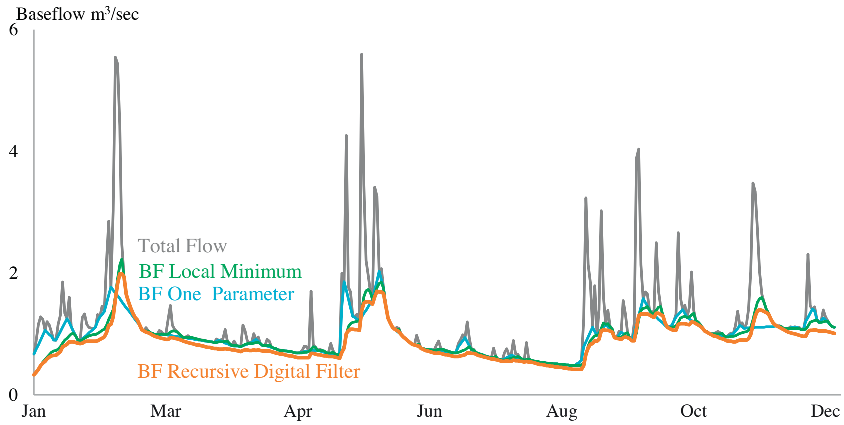

Fig. 9. Base flow separation with the local minimum, one parameter and recursive digital filter for discharge of the Rummen/Melsterbeek gauging station for 1984.

4.2. Base flow estimates

We calculated the base flow rates with the LMM, OPM, and RDF methods for the daily historical stream flow records of 67 gauging stations. Fig. 9 shows an example of the Rummen/Melsterbeek gauging station (see for location Fig. 5, No. 47). In this station, the total flow amounts to 1.09 m^3/s on average and the base flow rates are 0.92, 0.90, and 0.83 m^3/s for LMM, OPM, and RDF, respectively. Computed mean annual base flow indices for all stations range from 0.51 to 0.95. LMM results in slightly higher average estimates (0.75) than OPM (0.74) and RDF (0.70). The OPM and RDF methods roughly demonstrate similar patterns in seasonal response. However, the result of LMM shows higher base flow values during the rising limb of the hydrograph.

The base flow indices for the Dijle, Demer, and Nete neighbouring catchments located in the east of Flanders, ranged from 60% to 89%. This is in agreement with Batelaan and De Smedt (2007), who estimated average base flow indices for these catchments in the range of 69–87%. Van Camp et al. (2010) simulated the groundwater balance in northern Belgium, showing that 85% of river discharge is groundwater drainage. This is in agreement with our results, where in average 80% of the stream flow is attributed to base flow for the same extended area.

4.3. Comparison of base flow and recharge

Fig. 10 presents the scatter plots, which display the correlation between simulated recharge and the three base flow separation methods. We chose two statistical correlation tests, Pearson and Kendall tau to test the hypothesis that recharge correlates significantly with base flow. Pearson's correlation coefficient (r) is a measure of the strength of the correlation between the two variables. The comparison shows strong significant correlation between any pair of base flow separation methods but only moderate significant Pearson correlation between base flow and recharge. The Kendall test for correlation analysis measures the association between original pairs of data points while being insensitive to the effect of outliers (Combalicer et al., 2008). Under this test, the base flow methods also demonstrate positive association to each other, while they reveal moderate correlation with recharge. The correlation between all methods was statistically significant at the level of 0.01. It must be pointed out that the three base flow estimates from the WHAT system were based on a common set of stream flow data (variable length per station—on average 10 years), which explains the high correlation between these methods, while the recharge estimates from the WetSpass model were based on a long-term average dataset (1833–1995) (Batelaan et al., 2007).

For many sub-catchments, the correlation between recharge and base flow is good as shown in Fig. 10, but there is an important group of cases which are situated below the 45-degree line. The comparison between WetSpass and RDF is taken as an example to investigate these biased cases (marked with red numbers in Fig. 10). The location of these sub-catchments is shown in Fig. 5.

Silty loam soil textures dominate these sub-catchments and as Fig. 7 indicates silty loam has clearly a lower recharge than the coarser soil textures. Silty loam is characterized by low permeability and high water holding capacity. The permeability of the soil has a great effect on base flow (Hewlett, 1961). Streams that originate in terrain having low permeability generally have highly variable flow, and tend to have small recession indexes because most precipitation runs off rather than recharging groundwater, resulting in a minimal release of groundwater to the stream (Winter, 2006). So, base flow could be expected to be rather low in these sub-catchments. However, this does not explain yet why the estimated recharge is higher than the baseflow.

The land use of these sub-catchments is dominated by urban areas, agriculture, and meadow. Agricultural land use may have a positive or negative effect on recharge and base flow, depending on management practices (Price, 2011). In Flanders,

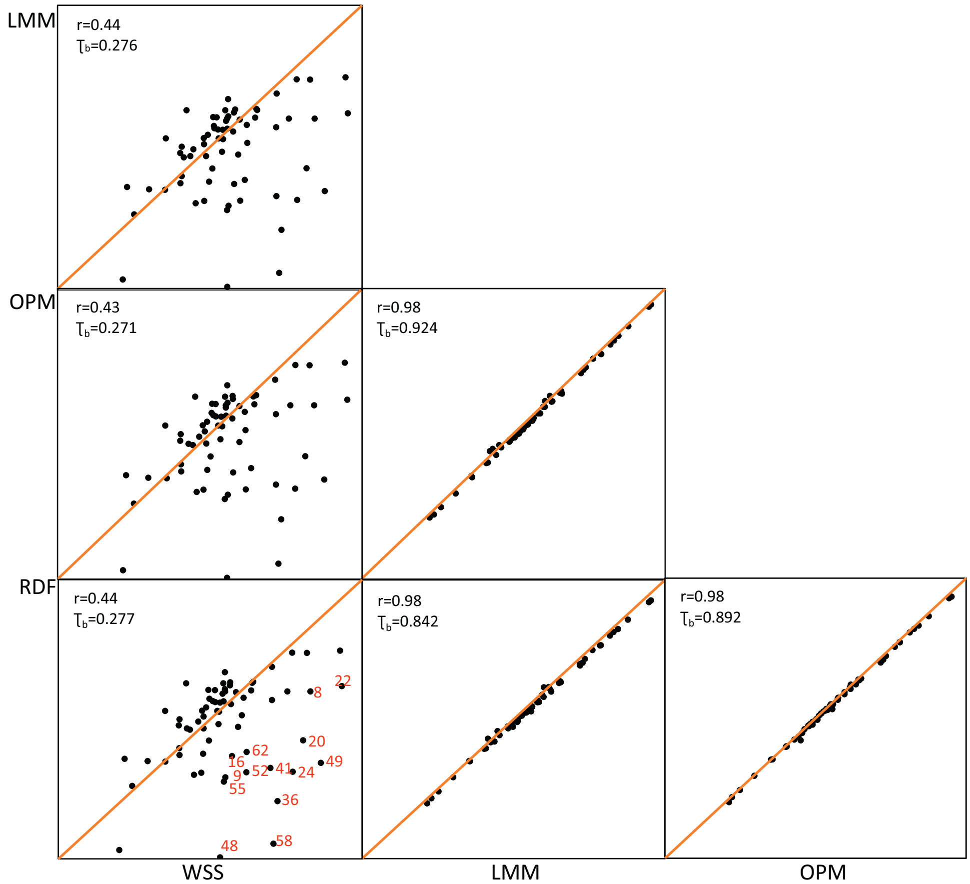

Fig. 10. Scatter plots showing the relationship between recharge estimates by WetSpass (WSS) and base flow separation methods, Local Minimum Method (LMM), One Parameter Method (OPM), and Recursive Digital filter (RDF) method for 67 watersheds distributed over the Flanders. r: person correlation coefficient and $\tau_{b:}$ Kendall's tau_b. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

40% of irrigation comes from groundwater (Varone and Aubin, 2004), so as these sub-catchments are located in agricultural areas and are often irrigated from groundwater, the base flow may be reduced. Urbanization is another human impact affecting base flow and recharge, which may be associated with a total rearrangement of surface and subsurface pathways. Hence, this complicates the pathways between subsurface recharge and channel flow (Price, 2011).

On the other hand, the most common characteristic among these sub-catchments is their upstream location in more topographic elevated regions (deeper water tables) and small catchment areas (except sub-catchments 8 and 22). This increases significantly the likelihood that the surface water divides of these small sub-catchments do not coincide with groundwater divides and that these sub-catchments are net exporters of groundwater as can be concluded from their higher recharge than base flow (Fig. 10). The assumption that base flow equals recharge implies that the groundwatershed is equivalent to the surface watershed, and no groundwater flow crosses the boundary (Erickson and Stefan, 2008). However, groundwater flow systems sometimes overlap more than one catchment, within catchments surface water and groundwater boundaries often do not coincide, and they can change dynamically with time (White, 1999; Winter et al., 2003; Ross, 2012). This makes it very difficult to know the size of a groundwater shed that contributes to a stream whether it is in a headwater area or anywhere along the length of a stream (Winter, 2006). In general, there is often a mismatch between the calculated recharge rates and base flows observed in streams due to scale effects and inadequate accounting for lateral fluxes in a purely vertical analysis (Tuteja et al., 2003; Hughes, 2012).

Previous studies have shown that watershed topography, geomorphology and climatic setting influence base flow (Winter et al., 1998; Brutsaert, 2005; Price, 2011). For example, a stream in a wet climate might receive groundwater inflow, but a stream in an identical physiographic setting in an arid climate might lose water to groundwater (Winter et al., 1998).

It should of course also be noted that in this paper we are comparing modeled recharge values with base flow estimates. The WetSpass model has different sources of uncertainty, which obviously affects the comparison. Although the model parameters were calibrated for Flemish conditions and the uncertainty was estimated by Batelaan and De Smedt (2007) and Batelaan et al. (2007), the calculated recharge values from WetSpass are of course only one possible realization.

Table 3
Pearson correlation coefficients between recharge, base flow and watershed characteristics.

Variables	Symbol	Recharge	Base flow index
Sandy soil	SA	0.72**	0.04
Loamy sandy soil	LSA	0.55**	−0.12
Sandy loam	SAL	−0.17	−0.36**
Silty loam	STL	−0.41**	0.29*
Silty soil	ST	−0.42**	−0.26*
Sandy clay soil	SAC	0.24	0.19
Clay loam soil	CLO	−0.09	−0.11
Clay soil	CL	−0.26*	0.15
Meadow	MW	0.34**	−0.35**
Wet meadow	WMW	0.13	0.26*
Orchard	ORC	−0.29*	0.28*
Heather	HT	0.38**	0.15
Lake	LK	0.26*	0.21
Catchment drainage area	CDA	0.09	0.11
Catchment slope	CS	−0.30*	0.29*
Precipitation	PPT	0.75**	0.27*
Potential evapotranspiration	PET	0.287*	−0.42**
Groundwater depth	GWD	−0.19	0.52**
Forest	FS	0.57**	0.42**
Build up area	BU	−0.13	−0.01
Agriculture	AG	−0.50**	−0.37**

* Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

We may conclude that the relation between recharge and base flow is controlled by various watershed characteristics and groundwater–surface water interaction. Hence, base flow could be considered as a proxy for recharge, with the exception of some small catchment and catchments with silty soil. Hereafter, we will investigate the controlling factors of recharge and base flow.

4.4. *Identification of factors controlling recharge and base flow*

4.4.1. *Correlation analysis*

A first step towards identifying the controlling factors of recharge and base flow is to determine the significantly correlated watershed variables (Table A1). We used the Pearson correlation test to determine the correlation among groundwater recharge, base flow index, and the seven selected watershed variables (Table 3). Urban land-use classes (built up, city center built up, open built up, industry, and infrastructure) were grouped to one variable named urban areas. Also forest classes (deciduous forest, coniferous forest, mixed forest, and pine) were grouped into one class called forest. Agriculture, maize and tuberous crops land-use types were grouped into one class named agriculture.

In general we found a high correlation between variables (Table A1) and it can be concluded that these variables are quite redundant thus share the same driving principle in defining the spatial variance of recharge and/or base flow. Groundwater recharge shows more variables with significant correlation than base flow index. Precipitation shows strong positive correlation with groundwater recharge and moderate to base flow index. This finding is considered to be a general rule which was shown in many groundwater recharge studies (Freeze and Cherry, 1979; Bredenkamp, 1988; Edmunds and Gaye, 1994; Jan et al., 2007; Stonestrom et al., 2007). Potential evapotranspiration was found to be positively correlated to recharge, as the result of a correspondence between the temperature gradient (determining PET significantly) and the soil texture distribution in the study area.

Soil properties appear to have a major contribution in spatial variation of recharge, five of the eight different soil textures were found to be significantly correlated (loam soil type was excluded <0.01 km^2). Sandier soils (sandy soil and loamy sandy soil) reveal high positive correlation with recharge while clayey soils (silty soil, silty loam soil, and clay soil) were negatively correlated to recharge. Built up area shows no correlation with recharge and base flow index, however, one should not confuse built-up areas with impervious areas. Built-up area consists of different land use classes (open build up area, urban area, city center, and infrastructure) that can have a very different degree of imperviousness. Additionally, the average recharge is calculated at the sub-catchment level. This average value is a function of a complex combination of different land-use types, soil textures and other factors.

Forest and agriculture show similar but contrasting correlation, respectively the third and the fourth significant correlated variables after precipitation and sandier soils. Deforestation tends to decrease evapotranspiration, increase storm runoff and soil erosion, and decrease infiltration to groundwater and base flow of streams (Winter et al., 1998). Groundwater depth is the most significant correlated variable for the base flow index. This finding confirms the study Lo et al. (2008) who show the strong correlation between groundwater depth and base flow based on results for a case study in Illinois, USA. Larger groundwater depth associate with higher slopes and indicate higher contribution of base flow to streams (Table A1).

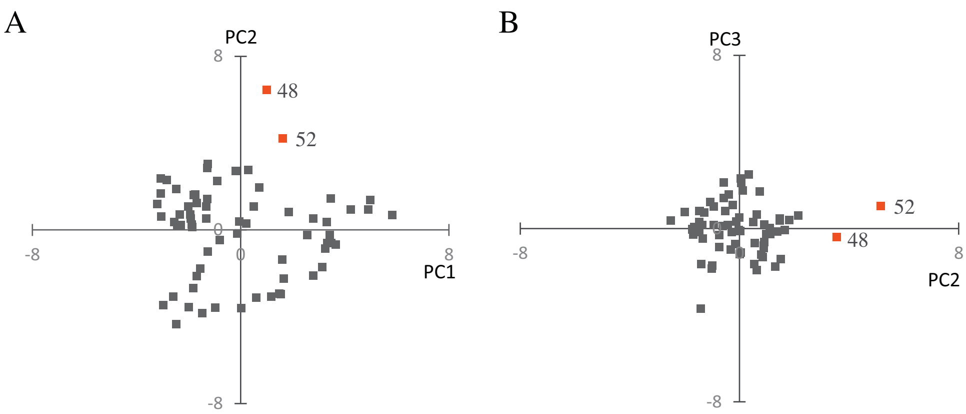

Fig. 11. Plot of the 67 observations with respect to the first (A) and the last two principal components (B) (outliers are marked in red). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 4
Principal component analysis (PCA1) of watershed characteristics that are most closely correlated with recharge and base flow.

	Recharge			Base flow index		
	PC1	PC2	PC3	PC1	PC2	PC3
Eigenvalue	3.73	1.46	1.40	2.16	1.64	1.11
Variance %	37.93	19.15	16.36	28.23	27.50	26.29
Cumulative %	37.93	57.07	73.43	28.239	55.74	82.03
Rotated factor loading[a]						
SA	**0.767**	0.406	0.136			
LSA	0.320	0.494	0.617			
SAL				**0.901**	0.141	−0.151
STL	−0.135	**0.974**	−0.050			
ST	−0.661	0.435	−0.468			
MW	−0.140	0.031	**0.825**	−0.024	−0.015	**0.927**
HT	0.575	0.214	0.247			
PPT	**0.766**	−0.117	0.217			
PET				0.476	0.071	0.586
GWD				**−0.781**	0.239	−0.380
FS	**0.821**	0.248	−0.215	0.153	**−0.887**	−0.311
AG	**−0.811**	−0.233	0.012	0.147	**0.884**	−0.333

[a] Bold type denotes variables with a high factor loading >0.75.

However, the groundwater discharge is obviously also determined by the size and permeability of the groundwater basin that contributes water to the stream (Winter, 2006).

4.4.2. Principal component analysis

The major goal of principal components analysis is to reveal hidden structure in a dataset and to reduce a larger set of variables into a smaller set of 'artificial' variables, called 'principal components', which account for most of the variance in the original variables. As shown in the previous section, the high correlation between variables is a significant sign of high redundancy in the data (Table A1). Therefore, we used PCA, to decrease redundancy in the data and to identify the controlling factors that explain most of the variance of recharge and base flow. The derivation of the principal components was based on the correlation matrix of standardized data, as these PC's are not independent of the scales in which the original variables are measured (Jolliffe, 2002).

Another statistical problem that was solved by PCA is detecting outliers. Outliers are observations that are in some way different from, or inconsistent with, the remainder of a dataset (Barnett and Lewis, 1994), resulting in a strong effect on the results of different statistical analysis. Therefore, we perform a PCA with the selected variables to detect the outliers by plotting the first and the last two principal components (PCs) of our dataset (Jolliffe, 2002). The most extreme observations with respect to the last two PCs, namely observations 48 and 52 are also among the most extreme with respect to the first two PCs (Fig. 11).

After the removal of the outliers we carried out a PCA (PCA1) for the remaining 65 river gauging stations to extract the principal components corresponding to the different sources of spatial variation of recharge and base flow. We used only the significant correlated variables with recharge and/or base flow at the 0.01 level 2-tailed, because other variables were moderately to weakly correlated to recharge and base flow (Wang et al., 2013).

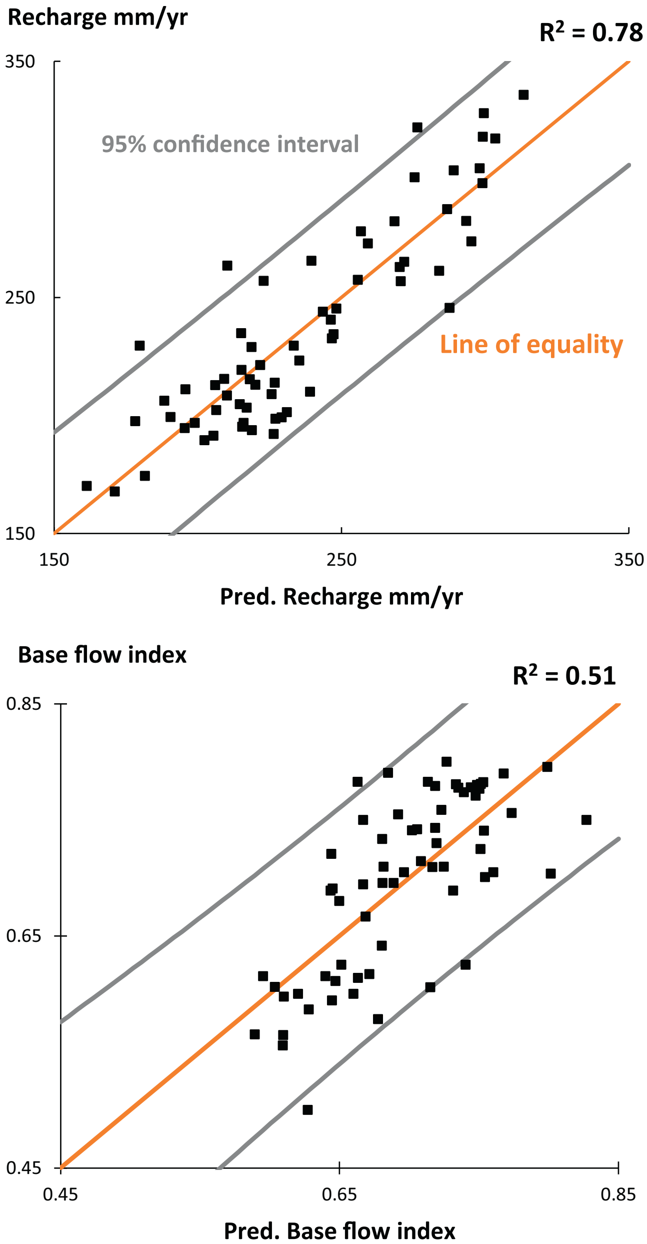

Fig. 12. The two regression models for groundwater recharge and base flow index, accounting for 78% and 51% of the variation respectively.

For groundwater recharge, three principal components with eigenvalues greater than 1 were extracted and rotated using the varimax normalization (Table 4). The PC's account for more than 73% of the spatial variance in the groundwater recharge. In PC1 the percentage of forest land-use type had the highest loading factor; followed by percentage of agriculture, sandy soils, and amount of precipitation. Percentage of silty loamy soil and percentage of meadow land-use type are the greatest contributor in PC2 and PC3 respectively.

The PCA of base flow index resulted in three rotated principal components accounting for 82% of the spatial variance in base flow (Table 4). Percentage of sandy loamy soil had the highest loading factor in PC1 followed by groundwater depth. Agriculture and forest land-use types are the best representative variables in PC2, while percentage of meadow land-use type is the only variable contributing to the variance in PC3.

According to the PCA the spatial variation of groundwater recharge is explained in order of importance by vegetation cover, soil texture and precipitation, while base flow index variation is explained by soil texture, groundwater depth, and vegetation cover.

Table 5
Principal component analysis (PCA2) of high loading variables in PCA1 and multiple linear regression models of principal components for recharge and base flow.

PCA	Recharge			Base flow index		
	PC1	PC2	PC3	PC1	PC2	PC3
Eigenvalue	2.97	1.23	1.09	1.82	1.58	1.09
Variance %	49.54	20.52	16.07	36.52	31.77	21.93
Cumulative %	49.54	70.06	86.14	36.52	68.29	90.22

MLR model RE = 237 + 21.4 × PC1 + 3.5 × PC2 + 6.3 × PC3.
BFI = 0.69 + 0.026 × PC1 + 0.029 × PC2 − 0.017 × PC3.

Table 6
Transformed regression models and relative importance analysis for recharge and base flow.

Predictor[a]	b	β	RW	CI-L	CI-U	RS-RW (%)	DW	RS-DW (%)
Recharge model (R^2 = 0.780, P < 0.0001)								
Intercept	−69.99							
SA	0.38	0.25	0.23	0.16	0.29	24.7	0.25	26.9
STL	−0.09	−0.08	0.15	0.09	0.21	17.0	0.14	15.0
AG	−1.31	−0.27	0.09	0.02	0.12	9.3	0.11	12.2
MW	0.82	0.13	0.04	-0.01	0.09	4.2	0.04	3.9
PPT	0.38	0.27	0.31	0.21	0.44	34.2	0.29	31.8
FS	0.84	0.20	0.10	0.02	0.14	10.6	0.09	10.1
Base flow index model (R^2 = 0.51, P < 0.0001)								
Intercept	0.715							
SAL	−0.001	−0.16	0.06	−0.01	0.19	13.2	0.07	12.8
AG	0.000	0.04	0.02	−0.07	0.05	5.2	0.02	4.5
MW	−0.004	−0.37	0.21	0.06	0.39	41.8	0.20	39.3
GWD	0.006	0.27	0.12	0.02	0.26	24.0	0.13	24.4
FS	0.002	0.29	0.08	0.00	0.17	15.9	0.10	19.0

b unstandardized regression weight, β standardized regression weight, RW raw relative weight (with rounding error weights will sum to R^2), CI-L lower bound of confidence interval used to test the statistical significance of raw weight, CI-U upper bound of confidence interval used to test the statistical significance of raw weight, RS-RW relative weight rescaled as a percentage of predicted variance in the dependent variable attributed to each predictor (with rounding error rescaled weights sum to 100%), DW dominance weight, RS-DW general dominance rescaled as a percentage of predicted variance in the dependent variable attributed to each predictor (with rounding error rescaled weights sum to 100%).
[a] The full names of the abbreviated variables are listed in Table 3.

4.4.3. Regression models

We carried out a new PCA analysis (PCA2) for recharge and base flow index with the high loading variables only (>0.75), followed by a multiple linear regression (MLR) analysis with the principal component scores with an eigenvalue greater than one to identify the most influential variables affecting recharge and base flow.

For groundwater recharge the new PCA analysis (PCA2) (Table 5) with the high loading variables (sandy soil, precipitation, forest, agriculture, silty loamy soil, and meadow land use type) produced three principal components with eigenvalues greater than 1. The PC's account for more than 86% of the spatial variance in the groundwater recharge. While the new PCA analysis of base flow with the high loading variables (sandy loamy soil, groundwater depth, agriculture, forest, and meadow) produced three principal components with an eigenvalue above 1 and accounting for more than 90% of the spatial variance.

Next, we performed multiple linear regression analysis with the principal component scores resulting from PCA2. The recharge and base flow index models included the three uncorrelated principal components and account for 78 and 51 percent of the total variance respectively (Fig. 12). Then we performed a back-transformation of principal components in order to express the recharge and base flow models in terms of the original watershed variables (Table 6).

4.4.4. Relative importance analysis

Following regression analysis, we were interested to assess how each variable contributes toward the spatial variance in recharge and base flow in order of importance. The importance of variables and its contribution to the total variance was first examined using standardized regression coefficient (beta weights) (Table 6). For the recharge model, according to beta weights, precipitation and agriculture were the highest contributors to the total variance in recharge across the dataset and explained 22.3 and 22.2% of the statistical variation respectively (Table 5). Other significant variables in order of decreasing importance were sandy soil (20%), forest (16.7%), meadow (10%), and silty loamy soil (7%). However, according to LeBreton et al. (2007) interpreting the MLR results for correlated variables using beta weights leads us to potentially misunderstand a variables true relative contribution. Therefore, we examined our MLR results using more sophisticated statistical analysis like relative weight analysis and dominance analysis as recommended by Johnson and LeBreton (2004).

Results of relative weight analysis and dominance weight analysis are summarized in Table 6, The RWA and DWA shows that the overall R^2 of recharge model accounts for 90 percent of the total variance. For relative weight analysis, confidence intervals (CIS) (at a significance alpha level of 0.05) were computed based on bootstrapping with 10,000 replications as recommended by Tonidandel and LeBreton (2014). The examination of the relative weights revealed that five variables explained a statistical significant amount of variance, using the approach outlined by Tonidandel et al. (2009) where none of the 95% CIS for the tests of significance contained zero, while only meadow land use type was not significant. The rescaled relative weight (RS-RW) and rescaled dominance weight (RS-DW) were obtained by dividing each raw relative (RW) and dominance weight (DW) by the model R^2 (Table 5). These rescaled weights provide estimates of relative importance using the metric of percentage of predicted variance attributed to each variable (Tonidandel and LeBreton, 2014). For example, for RWA, in the recharge model: precipitation explains 34.2% of total variance in recharge (0.31 (RW)/0.90 (R^2) = 0.342 × 100 = 34.2%).

Precipitation was the most important variable contributing to the total variance of the recharge in the recharge model (RS-RW = 34.2%), followed by sandy soil (RS-RW = 24.7%), silty loam soil (RS-RW = 17 %), forest (RS-RW = 10%), agriculture (RS-RW = 9.3%), and meadow (RS-RW = 4.2%). The order of importance of relative weight results are in agreement with general dominance weights but differ from beta weights, where dominance weight analysis demonstrated the same order as relative weight analysis except for forest and agriculture. RWA and DWA demonstrated dominance of precipitation over other variables with 34% and 32%, respectively. Sandy loamy soil and silty loamy soil are the second (RS-RW = 24.7%) and the third (RS-RW = 17%) major contributors to the total variance of spatial estimation of groundwater recharge among other variables, followed by forest (RS-RW = 10.6%) and agriculture (RS-RW = 9.3%). While meadow had the lowest percentage of variance amounting to 4.2% (RS-RW) (Table 6). The RW and DW analysis was in good agreement with beta weights for base flow index model except for forest land use type (Table 5), because the predictor variables were uncorrelated. According to RS-RW, the base flow index variation was explained in order of importance by meadow (41.8%), groundwater depth (24%), and forest (15.9%), sandy loamy soil (13.2%), and agriculture (5.2%).

As stated above, the amount of precipitation is the highest controlling factor for the spatial estimation of groundwater recharge. This finding is a confirmation of results of Kim and Jackson (2012), who performed a MLR global analysis for recharge and found that precipitation had the strongest effect and explained 29% of the global variance in recharge. Nolan et al. (2007) studied the factors influencing groundwater recharge in the eastern United States using nonlinear regression analysis, and precipitation was the most influencing factor for recharge in the region.

Soil texture appear to be the second most important factor in controlling the variance of recharge, i.e., recharge increased with coarse-textured soil and decreased with fine-textured soil. These results are in accordance with the results of Athavale et al. (1980), Kennett-Smith et al. (1994), and Kim and Jackson (2012).

Our results also exposed the important role of vegetation cover (forest and agriculture) in controlling the variance of recharge, explaining 20% of the total variance (Table 6). Globally, vegetation explains about 1.3 and 3 times as much variation in recharge as potential evapotranspiration and soil saturated hydraulic conductivity (Kim and Jackson, 2012). Percentage of forest land-use type is shown to have a positive higher effect on groundwater recharge, as indicated in Fig. 8, the seven different types of forest revealed high annual rates of recharge in Flanders. This finding was confirmed by Dams et al. (2008) on basis of results from a case study in the Kleine Nete basin, Belgium. They showed that the future land-use scenarios modelled with the CLUE-S model indicated an increase in the annual rates of recharge with +12% as a result of complete afforestation of the basin with deciduous forest.

Meadow land use type was found to be an important controlling factor for base flow. Some meadows have shown to be groundwater-dependent ecosystems (Allen-Diaz 1991; Chambers and Miller, 2004), while they can either serve as groundwater recharge (Weller, 1981; Mitsch and Gosselink, 1993) or discharge areas (Batelaan et al., 2003; Hoffman et al., 2013) depending on the hydrogeological conditions. The geomorphic and hydrologic characteristics of meadows vary considerably and affect the connectedness of groundwater systems with stream channels (Lord et al., 2011), which will affect the contribution of groundwater to base flow of a stream. Groundwater depth is the second highest contributor of the variance of base flow, as maximum groundwater discharges to streams occur when the minimum groundwater depth and slope at the channel is achieved (Hursh and Brater, 1941).

5. Conclusions

The spatial distribution of recharge is traditionally not taken properly into account in groundwater simulations. The GIS-based WetSpass methodology is a tool which can simulate the spatial distribution of long-term average recharge. Results of this study show that recharge has a very strong regional variation at the scale of Flanders, while in smaller basins the variation is less pronounced. Groundwater recharge is strongly influenced by soil texture and land-use; the spatial correlation, however, is relatively low. The analysis of groundwater recharge with different combinations of soil texture and land-use shows positive and negative correlations.

It is very hard to assess the accuracy of any recharge estimation method. For this reason, we have used a base flow analysis of 67 stream gauging stations as a multiple confirmation strategy, and tests under which conditions long-term averaged base flow fluxes can be used as a proxy for average recharge values. Based on the results of three separation base flow methods (WHAT system) on average 73% of the stream flow can be attributed to base flow. The high correlation between the three methods demonstrates that the base flow methods are comparable to each other, while it shows only moderate correlation to recharge estimates from the WetSpass model. The correlation was mainly affected by the size of the sub-catchment, soil and land use conditions. Hence recharge-base flow matching is mainly controlled by watershed characteristics and groundwater–surface water interaction.

Considering a wide range of different watershed characteristics, Pearson correlation analysis, PCA, MLR and relative importance analysis (RWA and DWA) identified the closely correlated factors influencing the variance of the spatial estimation of groundwater recharge and base flow over Flanders. Groundwater recharge variance is strongly controlled by precipitation, soil texture (sandy soil and silty loam soil), and vegetation cover (forest and agriculture land-use type), while base flow index variance is controlled by vegetation cover (meadow and forest) and groundwater depth. Mean annual precipitation explains around 34% of the variation in recharge, followed by soil type (sandy soil 25% and silty loam soil 17%). Vegetation cover/land use is a third important factor, with forest explaining 10.6%, agriculture 9.3%, and meadow 4.2% of the total variance of recharge. Moreover, vegetation is found to be the first dominating factor for spatial variation of base flow with around 42% followed by groundwater depth with around 24%.

Although the conclusions are made for the whole of Flanders, one should be aware that the results are based on analysis of 67 sub-catchments and that some regions with specific conditions (e.g., coastal zone and polders) are not well represented.

In general, it is concluded that spatial characteristics play an important role in estimation of base flow and recharge, while base flow is a moderate proxy of groundwater recharge. Our results also highlight the potential importance of land-use changes on the groundwater system, and hence a necessity to include land-use change in proper management practices of water resources.

Conflict of interest

None.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ejrh.2015.07.005.

References

Abebe, A., Foerch, G., 2006. Catchment characteristics as predictors of base flow index (BFI) in Wabi-shebele river basin, East Africa. In: Conference on International Agricultural Research for Development, Tropentag 2006. University of Bonn, pp. 1–5.

Allen-Diaz, B.H., 1991. Water table and plant species relationships in Sierra Nevada meadows. Am. Midl. Nat. 126 (1), 30–43, http://dx.doi.org/10.2307/2426147.

Anderson, M.P., Woessner, W.W., 1992. Applied Groundwater Modeling: Simulation of Flow and Advective Transport. Academic Press, San Diego, pp. 381.

Arnold, J.G., Allen, P.M., 1999. Validation of automated methods for estimating base flow and groundwater recharge from stream flow records. J. Am. Water Resour. Assoc. 35 (2), 411–424.

Arnold, J.G., Muttiah, R.S., Srinivasan, R., Allen, P.M., 2000. Regional estimation of base flow and groundwater recharge in the Upper Mississippi river basin. J. Hydrol. 227, 21–40.

Athavale, R.N., Mur, C.S., Chand, R., 1980. Estimation of recharge to the phreatic aquifers of the Lower Maner Basin, India, by using the titrium injection method. J. Hydrol. 45, 185–202, http://dx.doi.org/10.1016/0022-1694(80)90019-0.

Azen, R., Budescu, D.V., 2003. The dominance analysis approach for comparing predictors in multiple regression. Psychol. Methods 8, 129–148.

Barnett, V., Lewis, T., 1994. Outliers in Statistical Data, 3rd ed. Wiley, Chichester.

Batelaan, O., De Smedt, F., 2007. GIS-based recharge estimation by coupling surface-subsurface water balances. J. Hydrol. 337, 337–355, http://dx.doi.org/10.1016/j.jhydrol.2007.02.001.

Batelaan, O., De Smedt, F., Triest, L., 2003. Regional groundwater discharge: phreatophyte mapping, groundwater modelling and impact analysis of land-use change. J. Hydrol. 275, 86–108, http://dx.doi.org/10.1016/S0022-1694(03)18-0.

Batelaan, O., Meyus, Y., De Smedt, F., 2007. De grondwatervoeding van Vlaanderen. Tijdschrift Water 28, 64–71.

Best, L.C., Lowry, C.S., 2014. Quantifying the potential effects of high-volume water extractions on water resources during natural gas development: Marcellus Shale, NY. J. Hydrol. Reg. Stud. 1, 1–16, http://dx.doi.org/10.1016/j.ejrh.2014.05.001.

Bloomfield, P., Allen, J., Griffiths, J., 2009. Examining geological controls on baseflow index (BFI) using regression analysis: an illustration from the Thames Basin, UK. J. Hydrol. 373, 164–176, http://dx.doi.org/10.1016/j.jhydrol.2009.04.025.

Bredenkamp, D.B., 1988. Quantitative estimation on of ground-water recharge in dolomite. In: Simmers, I. (Ed.), Proc. NATO Adv. Res. Worksh. on Estimation of Natural Recharge of Groundwater (with special reference to arid and semi-arid regions. Antalya (Side), Turkey, 8–15 March 1987. D. Reidel Publ., Co., Dordrecht, the Netherlands, pp. 449–460.

Brejda, J.J., Moorman, T.B., Karlen, D.L., Dao, T.H., 2000. Identification of regional soil quality factors and indicators, I. central and southern high plains. Soil Sci. Soc. Am. J. 64, 2115–2124.

Brutsaert, W., 2005. Hydrology: An Introduction. Cambridge University Press, Cambridge, pp. 605.

Bücker, A., Crespo, P., Frede, H.G., Vaché, K., Cisneros, F., Breuer, L., 2010. Identifying controls on water chemistry of tropical cloud forest catchments: combining descriptive approaches and multivariate analysis. Aquat. Geochem. 16 (1), 127–149, http://dx.doi.org/10.1007/s10498-009-9073-4.

Budescu, D.V., 1993. Dominance analysis: a new approach to the problem of relative importance of predictors in multiple regression. Psychol. Bull. 114, 542–551.

Cey, E.E., Rudolph, D.L., Parkin, G.W., Aravena, R., 1998. Quantifying groundwater discharge to a small perennial stream in southern Ontario, Canada. J. Hydrol. 210 (1), 21–37.

Chambers, J.C., Miller, J.R. (Eds.), 2004. Great Basin Riparian Ecosystems – Ecology, Management and Restoration. Island Press, Covelo, CA, p. 303.

Combalicer, E.A., Lee, S.H., Ahn, S., Kim, D.Y., Im, S., 2008. Comparing groundwater recharge and base flow in the Bukmoongol small-forested watershed, Korea. J. Earth Syst. Sci. 117 (5), 553–566.

Cooper, D.J., Wolf, E.C., Ronayne, M.J., Roche, J.W., 2015. Effects of groundwater pumping on the sustainability of a mountain wetland complex, Yosemite National Park, California. J. Hydrol. Reg. Stud. 3, 87–105, http://dx.doi.org/10.1016/j.ejrh.2014.10.002.

Courville, T., Thompson, B., 2001. Use of structure coefficients in published multiple regression articles: b is not enough. Edu. Psychol. Meas. 61, 229–248.

Dams, J., Woldeamlak, S.T., Batelaan, O., 2008. Predicting land-use change and its impact on the groundwater system of the Kleine Nete catchment, Belgium. Hydrol. Earth Syst. Sci. 12 (6), 1369–1385.

Dassargues, A., Walraevens, K., 2014. Watervoerende Lagen in Grondwater in België/Aquifers and Groundwater in Belgium. Academia Press, Gent.

Delin, G.N., Healy, R.W., Lorenz, D.L., Nimmo, J.R., 2007. Comparison of local-to regional-scale estimates of ground-water recharge in Minnesota, USA. J. Hydrol. 334 (1–2), 231–249.

Eckhardt, K., 2005. How to construct recursive digital filters for base flow separation. J. Hydrol. Process. 19 (2), 507–515.

Eckhardt, K., 2008. A comparison of base flow indices, which were calculated with seven different baseflow separation methods. J. Hydrol. 352, 168–173.

Edmunds, W.M., Gaye, C.B., 1994. Estimating the spatial variability of groundwater recharge in the Sahel using chloride. J. Hydrol. 156, 47–59, http://dx.doi.org/10.1016/0022-1694(94)90070-1.

Eilers, V.H.M., Carter, R.C., Rushton, K.R., 2007. A single layer soil water balance model for estimating deep drainage (potential recharge): an application to cropped land in semi-arid North-east Nigeria. Geoderma 140, 119–131.

Erickson, T., Stefan, H., 2008. Baseflow Analysis of the Upper Vermillion River. Minnesota, Dakota.

Feinstein, D.T., Eaton, T.T., Hart, D.J., Krohelski, J.T., Bradbury, K.R., 2005. A regional aquifer simulation model for southeastern Wisconsin. Southeastern Wisconsin Regional Planning Commission Technical Report Number 41, 63.

Flynn, R.H., Tasker, G.D., 2004. U.S. Geological Survey Scientific Investigations Report27.

Freeze, A.R., Cherry, J.A., 1979. Groundwater. Prentice Hall, Upper Saddle River, NJ.

Fröhlich, K., Fröhlich, W., Wittenberg, H., 1994. Determination of groundwater recharge by base flow separation, regional analysis in northeast China. In: Seuna, P., Gustard, A., Arnell, N.W., Cole, G.A. (Eds.), FRIEND: Flow Regimes from International Experimental and Network Data, Proceedings of the Braunschweig Conference. October 1993. IAHS Publ. No. 221, pp. 69–76.

Gebert, W.A., Mandy, J.R., Ellen, J.C., Kennedy, J.L., 2007. Use of stream flow data to estimate base flow/ground-water recharge for Wisconsin. J. Am. Water Resour. Assoc. 43, 220–236.

Gonzales, L., Nonner, J., Heijkers, J., Uhlenbrook, S., 2009. Comparison of different Base flow separation methods in a lowland catchment. Hydrol. Earth Syst. Sci. 13, 2055–2068.

Harbaugh, A.W., 2005. MODFLOW-2005. The U.S. Geological Survey modular ground-water model—the Ground-Water Flow Process: U.S. Geological Survey Techniques and Methods. 6-A16.

Healy, R.W., Cook, P.G., 2002. Using groundwater levels to estimate recharge. J. Hydrol. 10, 91–109.

Healy, R.W., 2010. Estimating Groundwater Recharge. Cambridge University Press, Cambridge, pp. 264.

Helsel, D.R., Hirsch, R.M., 2002. Statistical Methods in Water Resources. Chapter A3, Book 4, Hydrologic Analysis and Interpretation, Techniques of Water-Resources Investigations of the United States. USGS, Reston, VA, pp. 510.

Hemmings, B., Whitaker, F., Gottsmann, J., Hughes, A., 2015. Hydrogeology of Montserrat review and new insights. J. Hydrol. Reg. Stud. 3, 1–30, http://dx.doi.org/10.1016/j.ejrh.2014.08.008.

Hewlett, J., 1961. Soil Moisture as a Source of Base Flow from Steep Mountain Watersheds. Southeast. For. Exp. Stn. Asheoilie, North Carolina U.S. Dep. Agric. Seroice.

Hoffman, J., Roby, K., Bohm, B., 2013. Effects of Meadow Restoration on Stream Flow in the Feather River Watershed: A Review Based on Monitoring Data and Pertinent Research. Report to Feather River Coordinated Resource Management Council Executive Committee33.

Holtschlag, D.J., 1997. A generalized estimate of ground-water-recharge rates in the lower peninsula of Michigan. Water Supply Pap. U. S. Geol Surv. 2437, 37.

Hughes, A., Mansour, M., Robins, N., 2008. Evaluation of distributed recharge in an upland semi-arid karst system: the West Bank Mountain Aquifer, Middle East. Hydrogeol. J. 16, 845–854, http://dx.doi.org/10.1007/s10040-008-0273-6.

Hughes, D.A., 2012. Implementing uncertainty analysis in water resources assessment and planning. Deliverable No. 3: First general report on uncertainty reduction. Pretoria, South Africa, Water Research Commission. WRC Project No:K5/2056.

Hursh, R., Brater, F., 1941. sprating storm hydrographs from small drainage areas into surface and subsurface flow. Am. Geophys. Union 22, 863–871.

Jan, C.D., Chen, T.H., Lo, W.C., 2007. Effect of rainfall intensity and distribution on groundwater level fluctuations. J. Hydrol. 332, 348–360, http://dx.doi.org/10.1016/j.jhydrol.2006.07.010.

Johnson, J.W., 2000. A heuristic method for estimating the relative weight of predictor variables in multiple regression. Multivar. Behav. Res. 35 (1), 1–19, http://dx.doi.org/10.1207/S15327906MBR3501_1.

Johnson, J.W., LeBreton, J.M., 2004. History and use of relative importance indices in organizational research. Organ. Res. Methods 7, 238–257, http://dx.doi.org/10.1177/1094428104266510.

Jolliffe, I.T., 2002. Principal Component Analysis. In: Springer Series in Statistics, 2nd ed. Springer-Verlag, New York.

Jyrkama, M.I., Sykes, J.F., Normani, S.D., 2002. Recharge estimation for transient ground water modeling. Ground Water 40 (6), 638–649.

Jyrkama, M.I., Sykes, J.F., Normani, S.D., 2007. The impact of climate change on spatially varying groundwater recharge in the Grand River watershed (Ontario). J. Hydrol. 338, 237–250, http://dx.doi.org/10.1016/j.jhydrol.2007.02.036.

Kennett-Smith, A., Cook, P.G., Walker, G.R., 1994. Factors affecting groundwater recharge following clearing in the south western Murray Basin. J. Hydrol. 154, 85–105, http://dx.doi.org/10.1016/0022-1694(94)90213-5.

Kim, J.H., Jackson, R.B., 2012. A global analysis of groundwater recharge for vegetation, climate, and soils. Vadose Zone J. 11 (1), 0, http://dx.doi.org/10.2136/vzj211.21RA.

Kraha, A., Turner, H., Nimon, K., Zientek, L.R., Henson, R.K., 2012. Interpreting multiple regression in the face of multicollinearity. Front. Psychol. 3, 1–10.

Leavesley, G.H., Lichty, R.W., Troutman, B.M., Saindon, L.G., 1983. Precipitation-Runoff Modeling System: User's Manual. U.S. Geological Survey Water Resources Investigation report, 83-4238.

LeBreton, J.M., 2006. EXCEL File for estimating general dominance weights for up to 6 predictors from user-Provided R-sq values. <http://www1psych.purdue.edu/~jlebreto/dominance%20analysis%204.4.xls>.

LeBreton, J.M., Hargis, M.B., Griepentrog, B., Oswald, F.L., Ployhart, R.E., 2007. A multidimensional approach for evaluating variables in organizational research and practice. Pers. Psychol. 60, 475–498, http://dx.doi.org/10.1111/j.1744-6570.2007.00080.x.

Lee, J., Ko, K.S. Kim, J.M. Chang, H.W., 2008. Multivariate statistical analysis of underground gas storage caverns on groundwater chemistry in Korea. Hydrol. Process. 22, 3410–3417, http://dx.doi.org/10.1002/hyp.6921.

Lerner, D.N., Issar, A.S., Simmers, I., 1990. Groundwater Recharge: A Guide to Understanding and Estimating Natural Recharge. IAH, 8. Hannover, Heise.

Lim, K.J., Engel, B.A., Tang, Z., Choi, J., Kim, K., Muthukrishnan, S., Tripathy, D., 2005. Automated web GIS-based hydrograph analysis tool, WHAT. J. Am. Water Recour. Assoc. 41 (6), 1407–1416.

Lim, K.J., Engel, B.A., Tang, Z., Choi. J., Kim, K.S., Muthukrishnan, S., Tripathy, D., 2004. WHAT: Web-based Hydrograph Analysis Tool; <http://cobweb.ecnpurdue.edu/~what/>.

Liu, C.W., Lin, K.H., Kuo, Y.M., 2003. Application of factor analysis in the assessment of groundwater quality in a blackfoot disease area in Taiwan. Sci. Total Environ. 313, 77–89, http://dx.doi.org/10.1016/S0048-9697(02) 683-6.

Longobardi, A., Villani, P., 2008. Base flow index regionalization analysis in a Mediterranean area and data scarcity context, Role of the catchment permeability index. J. Hydrol. 355, 63–75.

Lo, M.-H., Yeh, P., Famiglietti, S., 2008. Constraining water table depth simulations in a land surface model using estimated baseflow. Adv. Water Resour. 31, 1552–1564, http://dx.doi.org/10.1016/j.advwatres.2008.06.007.
Lord, M.L., Jewett, D.G., Miller, J.R., Germanoski, D., Chambers, J.C., 2011. Chapter 4: Hydrologic Processes Influencing Meadow Ecosystems. General technical report, USDA Forest Service.
Lyne, V.D., Hollick, M., 1979. Stochastic Time-Variable Rainfall- Runoff Modeling. Hydro. Water Resour. Symp. Institution of Engineers Australia, Perth, Australia, pp. 89–92.
Markstrom, S.L., Niswonger R.G., Regan, R.S., Prudic D.E., Barlow P.M., 2008. GSFLOW—Coupled ground-water and surface water flow model based on the integration of the Precipitation-Runoff Modeling System (PRMS) and the Modular Ground-Water Flow model (MODFLOW-2005). U.S. Geological Survey techniques and methods 6-D1. Reston, Virginia: USGS, 240.
Mazvimavi, D., Meijerink, A.M.J., Savenije, H.H.G., Stein, A., 2005. Prediction of flow characteristics using multiple regression and neural networks: a case study in Zimbabwe. Phys. Chem. Earth 30, 639–647.
McAdams, H.T., Crawford, R.W., Hadder, G.R., 2000. AVector Approach to Regression Analysis and Its Application to Heavy-duty Diesel Emissions. Society of Auto-Motive Engineers, Inc. Contract with the Energy Division of Oak Ridge National Laboratory (ORNL), Contract No. DE-AC05-00OR22725.
Meyus, Y., Adyns, D., Woldeamlak, S.T., Batelaan, O., De Smedt, F., 2004. Opbouw van een Vlaams Grondwatervoedingsmodel. Deelrapport 2 Totaal VGM-karteeergebied en Vlaanderen. Ministerie van de Vlaamse Gemeenschap, Administratie Milieu-, Natuur-, Land-en Waterbeheer, Afdeling Water. 70.
Minor, T.B., Russel, C.E., Mizell, S.A., 2007. Development of a GIS-based model for extrapolating mesoscale groundwater recharge estimates using integrated geospatial datasets. J. Hydrol. 15, 183–195.
Mitsch, W.J., Gosselink, J.G., 1993. Wetlands, 2nd ed. John Wiley, New York.
Moya, C.E., Raiber, M., Cox, M.E., 2014. Three-dimensional geological modelling of the Galilee and central Eromanga basins, Australia: new insights into aquifer/aquitard geometry and potential influence of faults on inter-connectivity. J. Hydrol. Reg. Stud. 2, 119–139, http://dx.doi.org/10.1016/j.ejrh.2014.08.007.
Nathan, R.J., McMahon, T.A., 1990. Evaluation of automated techniques for base flow and recession analysis. Wat. Resour. Res. 26 (7), 1465–1473.
Nathans, L.L., Oswald, F.L., Nimon, K., 2012. Interpreting multiple linear regression: a guidebook of variable importance. PARE 9, 1–19.
Nimmo, J.R., Stonestrom, D.A., Healy, R.W., 2003. Aquifers Recharge. In: Stewart, B.A., Howell, T.A. (Eds.), Encyclopedia of Water Science. Agropedia, New York, Marcel Dekker, pp. 22–25.
Nolan, B.T., Healy, R.W., Taber, P.E., Perkins, K., Hitt, K.J., Wolock, D.M., 2007. Factors influencing ground-water recharge in the eastern United States. J. Hydrol. 332 (1–2), 187–205, http://dx.doi.org/10.1016/j.jhydrol.2006.06.029.
GIS-Vlaanderen, O.C., 2001. Digital Version of DEM and River Network of Flanders. Agentschap voor Geografische Informatie Vlaanderen, Ghent, Belgium.
Piggott, A.R., Moin, S., Southam, C., 2005. A revised approach to the UKIH method for the calculation of base flow. Hydrolog. Sci. J. 50, 911–920.
Poelmans, L., Engelen, G., Van Daele, T., 2014. Land-Use Map NARA-T 2014. VITO, by order of INBO.
Price, K., 2011. Effects of watershed topography, soils, land use, and climate on baseflow hydrology in humid regions: a review. Prog. Phys. Geogr. 35, 465–492, http://dx.doi.org/10.1177/0309133311402714.
Rajab, J.M., Mat Jafri, M.Z., Lim, H.S., Abdullah, K., 2012. Regression analysis in modelling of air surface temperature and factors affecting its value in Peninsular Malaysia. Opt. Eng. 51 (10), 101702.
Rajab, J.M., MatJafri, M.Z., Lim, H.S., 2013. Combining multiple regression and principal component analysis for accurate predictions for column ozone in Peninsular Malaysia. Atmos. Environ. 71, 36–43, http://dx.doi.org/10.1016/j.atmosenv.2013.01.019.
Risser, D.W., Conger, R.W., Ulrich, J.E., Asmussen, M.P., 2005. USGS Open-file report30.
Risser, D.W., Gburek, W.J., Folmar, G.J., 2009. Comparison of recharge estimates at a small watershed in east-central Pennsylvania, USA. J. Hydrol. 17, 287–298, http://dx.doi.org/10.1007/s10040-008-0406-y.
Risser, D.W., Thompson, R.E., Stuckey, M.H., 2008. Regression method for estimating long-term mean annual ground-water recharge rates from base flow in Pennsylvania, U.S. Geological Survey Scientific Investigations Report, 2008–5185, 23.
Ross, A., 2012. Easy to say, hard to do: integrated surface water and groundwater management in the Murray-Darling Basin. Water Policy 14, 709, http://dx.doi.org/10.2166/wp.2012.129.
Rutledge, A.T., 2005. Appropriate use of the Rorabaugh model to estimate ground water recharge. Ground Water 43 (3), 292–293.
Scanlon, B.R., Healy, R.W., Cook, P.G., 2002. Choosing appropriate techniques for quantifying groundwater recharge. J. Hydrol. 10, 18–39.
Seiler, K.P., Gat, J.R., 2007. Groundwater Recharge form Runoff, Infiltration and Percolation. Springer, Dordrecht (Netherlands), pp. 241.
Shiklomanov, I.A., 2000. Appraisal and assessment of world water resources. Water Int. 25, 11–32.
Simmers, I., 1988. Estimation of Natural Groundwater Recharge. D. Reidel, Dordrecht, Holland.
Sloto, R.A., Crouse, M.Y., 1996. HYSEP: A Computer Program for Stream Flow Hydrograph Separation and Analysis, USGS Water Resources Investigations Report, 96-4040. USGS, Washington, D.C.
Sophocleous, M., 2004. Groundwater recharge. In: Luis Silveira, Usunoff, E.J. (Eds.), Groundwater, in Encyclopedia of Life Support Systems (EOLSS), vol. I. Developed under the auspices of the UNESCO, EOLSS, Publishers, Oxford, UK, p. 41 (http://www.eolss.net/).
Stewart, M., Cimino, J., Ross, M., 2007. Calibration of base flow separation methods with stream flow conductivity. Ground Water 45 (1), 17–27.
Stonestrom, D.A., Constantz, J., Ferré, T.P.A., Leake, S.A. (Eds.), 2007. Prof. Pap. 1703. USGS, Denver, Co.
Suk, H., Lee, K.K., 1999. Characterization of a groundwater hydrochemical system through multivariate statistical analysis: clustering into groundwater zones. Ground Water 37, 358–366.
Thyne, G., Gler, C., Poeter, E., 2004. Sequential analysis of hydrochemical data for watershed characterization. Ground Water 42, 711–723.
Tonidandel, S., LeBreton, J.M., Johnson, J.W., 2009. Determining the statistical significance of relative weights. Psychol. Methods 14, 387–399, http://dx.doi.org/10.1037/a0017735.
Tonidandel, S., LeBreton, J.M., 2010. Determining the relative importance of predictors in logistic regression: an extension of relative weight analysis. Organ. Res. Methods 13 (4), 767–781, http://dx.doi.org/10.1177/1094428109341993.
Tonidandel, S., LeBreton, J.M., 2011. Relative importance analysis: A useful supplement to regression analysis. J. Bus. Psychol. 26, 1–9, http://dx.doi.org/10.1007/s10869-010-9204-3.
Tonidandel, S., LeBreton, J.M., 2014. RWA-Web-A free, comprehensive, web-based, and user-friendly tool for relative weight analysis. J. Bus. Psychol., http://dx.doi.org/10.1007/s10869-014-9351-z.
Tuteja, N.K., Beale, G., Dawes, W., Vaze, J., Murphy, B., Barnett, P., Rancic, A., Evans, R., Geeves, G., Rassam, D.W., Miller, M., 2003. Predicting the effects of landuse change on water and salt balance—a case study of a catchment affected by dryland salinity in NSW, Australia. J. Hydrol. 283, 67–90, http://dx.doi.org/10.1016/S0022-1694(03)236-1.
Van Camp, M., Coetsiers, M., Martens, K., Walraevens, K., 2010. Effects of multi-annual climate variability on the hydrodynamic evolution (1833 to present) in a shallow aquifer system in northern Belgium. Hydrol. Sci. J. 55, 763–779, http://dx.doi.org/10.1080/02626667.2010.488075.
Varone, F., Aubin, D., 2004. The Evolution of the National Water Regime in Belgium. Université Catholique de Louvain (UCL).
VMM, 2010. Vlaamse Milieu Maatschappij, <www.hydronet.be>.
Wang, Y., Shao, M., Liu, Z., Horton, R., 2013. Regional-scale variation and distribution patterns of soil saturated hydraulic conductivities in surface and subsurface layers in the loessial soils of China. J. Hydrol. 487, 13–23, http://dx.doi.org/10.1016/j.jhydrol.2013.02.006.
Weller, M.W., 1981. Freshwater Marshes, Ecology and wildlife Management. University of Minnesota Press, Minneapolis, Minn.
Westenbroek, S.M., Kelson, V.A., Dripps, W.R., Hunt, R.J., Bradbury, K.R., 2010. SWB – A modified Thornthwaite-Mather Soil–Water-Balance code for estimating groundwater recharge, U.S. Geological Survey Techniques and Methods, 6-A31, 60p.

White, W.B., 1999. Groundwater flow in krastic aquifers. In: Delleur, J.W. (Ed.), The Handbook of Groundwater Engineering. CRC, Boca Raton (Fla), pp. 21.2–21.41.
Winter, T.C., 2006. The role of ground water in generating streamflow in headwater areas and in maintaining base flow. JAWRA J. Am. Water Resour. Assoc. 43, 15–25, http://dx.doi.org/10.1111/j1752-1688.2007.00003.x.
Winter, T.C., Harvey, J.W., Franke, O.L., Alley, W.M., 1998. Ground Water and Surface Water, A Single Resource. U.S. Geological Survey Circular, 1139, pp. 79.
Winter, T.C., Rosenberry, D.O., LaBaugh, J.W., 2003. Where does the ground water in small watersheds come from? Ground Water 41, 989–1000, http://dx.doi.org/10.1111/j.1745-6584.2003.tb02440.x.
Zhang, Y., Ahiablame, L., Engel, B., Liu, J., 2013. Regression modeling of baseflow and baseflow Index for Michigan USA. Water 5, 1797–1815.