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Land classification based on hydrological landscape units

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Hydrological land classification

S. Gharari et al.

[Title Page](#)

[Abstract](#)

[Introduction](#)

[Conclusions](#)

[References](#)

[Tables](#)

[Figures](#)

[I◀](#)

[▶I](#)

[◀](#)

[▶](#)

[Back](#)

[Close](#)

[Full Screen / Esc](#)

[Printer-friendly Version](#)

[Interactive Discussion](#)



Abstract

This paper presents a new type of hydrological landscape classification based on dominant runoff mechanisms. Three landscape classes are distinguished: wetland, hillslope and plateau, corresponding to three dominant hydrological regimes: saturation excess overland flow, storage excess sub-surface flow, and deep percolation. Topography, geology and land use hold the key to identifying these landscapes. The height above the nearest drain (HAND) and the surface slope, which can be readily obtained from a digital elevation model, appear to be the dominant topographical parameters for hydrological classification. In this paper several indicators for classification are tested as well as their sensitivity to scale and sample size. It appears that the best results are obtained by the simple use of HAND and slope. The results obtained compare well with field observations and the topographical wetness index. The new approach appears to be an efficient method to “read the landscape” on the basis of which conceptual models can be developed.

1 Introduction

Large scale hydrological behavior is still poorly understood, mainly as a result of the lack of realistically observable variables on the one hand and the complexity of catchment processes on the other. Catchment topography, readily available as digital elevation models (DEM), has the potential to provide important additional information on catchment processes, particularly due to its inherent co-evolution and diverse feedback processes with hydrology and ecology (Savenije, 2010). A number of previous studies investigated relationships between topography and hydrological behavior in an attempt to identify hydrologically different functional landscape units and to better characterize model structure, parameter sets as well as metrics of catchment similarity. For example, Winter (2001) classified the catchment into hydrological landscape units (upland, valley side and lowland) exploiting the combination of topographic, geological

HESSD

8, 4381–4425, 2011

Hydrological land classification

S. Gharari et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



and climatic conditions. Based on this concept Wolock et al. (2004) classified hydrological units for the entire United States of America using GIS data. Topography, land use and geology have also been used to directly infer dominant runoff process within a catchment (Naef et al., 2002; Müller et al., 2009; Hellebrand and van den Bos, 2008).

Another widely used indicator is the topographical wetness index (Beven and Kirkby, 1979) which is the basis of TOPMODEL. The topographical wetness index is based on the similarity of hydrological behavior between different places. The topographical wetness index was further developed by Hjerdt et al. (2004), considering how far a water particle needs to move to lose a certain amount of potential energy. Topography was also used to investigate the relationship of catchment transit times with numerous catchment characteristics such as flow path length, gradient and connectivity (McGuire et al., 2005; Jencso et al., 2009, 2010) or drainage density (Hrachowitz et al., 2009, 2010) using tracer techniques. Other tracer studies directly linked topography and hydrological behaviour (Uhlenbrook et al., 2004; Tetzlaff et al., 2007). A wide range of further topographical indices, describing, amongst others, the shape or the age and stability of a catchment have been suggested like hypsometric integral (Ritter et al., 2002) and their relation to various catchments and fluvial processes (Singh et al., 2008).

In spite of the rich information content of topography, its general usefulness for hydrology is controversial. It has been argued that climate and geology exert stronger influence than topography on the rainfall runoff behavior of a catchment (Devito et al., 2005). Furthermore, it was shown that flow patterns may be dominated by bedrock rather than surface topography (McDonnell et al., 1996; Tromp-van Meerveld and McDonnell, 2006). According to McDonnell (2003) the “catchment hydrologist will need to develop hypotheses from non-linear theory that are testable on the basis of observations in nature. This will not come about via model intercomparison studies or DEM analysis”. These comments highlight the perception that DEM analysis alone may be of limited value for gaining deeper understanding of catchment processes and that this needs to be brought into a wider context, accounting for the subtle interplay of topography, geology, climate, ecology and hydrology.

Hydrological land classification

S. Gharari et al.

Title Page

Abstract Introduction

Conclusions References

Tables Figures

◀ ▶

◀ ▶

Back Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper

Hydrological land classificationS. Gharari et al.

[Title Page](#)[Abstract](#)[Introduction](#)[Conclusions](#)[References](#)[Tables](#)[Figures](#)[◀](#)[▶](#)[◀](#)[▶](#)[Back](#)[Close](#)[Full Screen / Esc](#)[Printer-friendly Version](#)[Interactive Discussion](#)

In spite of the complexity of catchment processes and due to the frequent lack of data for bottom-up modeling approaches, using relatively simple, lumped conceptual models can, due to the self-organizing nature of catchments, be efficient in identifying dominant flow generation processes and modeling stream flow (cf., Sivapalan et al., 2003; Savenije, 2009). However, even for these top-down models additional data, other than precipitation and stream flow, are desirable for meaningful development and evaluation.

An elegant way of incorporating readily available information in conceptual models was recently suggested by Savenije (2010): different topographical features are perceived to exhibit distinct hydrological functioning. This can be used to construct a catchment model based on hydrological units, each representing specific dominant flow generation processes.

A more adequate metric to identify these hydrologically different landscape units than the frequently used elevation above mean sea level, is the recently formalized Height Above the Nearest Drain, (HAND; Rennó et al., 2008). HAND landscape classification is based on the elevation of each point in the catchment above the nearest stream it drains to, following the flow direction. HAND thus extracts from the relatively uninformative topographic elevation the far more informative “hydrologic” elevation, thereby increasing the hydrologic information content of elevation data. This has for example allowed identifying and classifying different ecological zones, using HAND and local slope as thresholds between the different zones (Nobre et al., 2011).

Landscape classification based on HAND is sensitive to different aspects, such as the definition of the threshold for channel initiation when deriving streams from a DEM, the seasonal fluctuations of the channel starting points, and the resolution of the DEM. Furthermore, it is unknown to what extent local landscape features can introduce bias and how robust HAND is to the sample size and the locations of the observed calibration points. Hence, the application of HAND is still subject to considerable uncertainties. In addition, it is not well-understood how HAND relates to other landscape descriptors, such as the topographical wetness index.

The objectives of this paper are thus to (1) assess different hydrologically meaningful landscape classification tools based on the HAND metric and further parameters such as slope and the distance to the nearest drain, (2) test the sensitivity of HAND-based landscape classification to different effective smoothing window sizes and resolutions of the DEM, (3) evaluate the effect of the sample size of the calibration data set on the robustness of HAND-based landscape classification and to (4) analyze the relation of HAND to topographical wetness index in a mesoscale catchment in a temperate climate.

2 Study site

The study area is the Wark Catchment in the Grand Duchy of Luxembourg (Fig. 1); the catchment has an area of 82 km² (49.81°–49.91°N, 5.91°–6.10°E) with the catchment outlet located downstream of the town of Ettelbrück at the confluence with the Alzette River. With average annual precipitation of 850 mm y⁻¹ and average annual potential evaporation of 650 mm y⁻¹ the annual runoff is approximately 250 mm y⁻¹. The geology in the northern part is dominated by schist while the southern part of the catchment is mostly underlain by sandstone and conglomerate. The dominant land uses are forest on hillslopes, agricultural land on plateaus and pastures in the valley bottoms. The elevation varies between 195 to 532 m with an average of 380 meters above sea level. The slope of the catchment varies between 0–200% (–), with an average value of 17%.

3 Methods

3.1 Terms

The HAND-based hydrologic landscape classification in this paper distinguishes three hydrologically, ecologically and morphologically different landscape units, which, in the

Hydrological land classification

S. Gharari et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



following, will be referred to as wetland, hillslope and plateau. The use of these terms might seem inconsistent as they originate from different disciplines – ecology (wetland), hydrology (hillslope) and morphology (plateau) – where they do have clear definitions. These terms were nevertheless deliberately chosen as they highlight distinct hydrological landscapes with different rainfall-runoff behavior (cf., Savenije, 2009). Note that in other catchments more or different units may be necessary to adequately describe the landscape. The terminology used in this paper is defined as follows:

Wetlands (W), are areas in which the water level is expected to be high relative to the other two landscapes entities. In classical ecological terms they refer to the land where saturation with water is a dominant factor influencing the animal and plant species of that area (Cowardin et al., 1979). From a hydrological point of view, wetlands comprise a broader type of landscape units than the commonly used terms: riparian zone or valley bottom area. They can be seen as areas which, due to the shallow depth of the water table, have limited residual storage capacity and therefore demonstrate a fast response to precipitation, independent from their location in the catchment. The term shallow in this regard means that in a normal wet season the groundwater table reaches the surface during heavy rainfall events. The predominant locations of wetlands, however, allow a subdivision of this class into (a) flat wetlands (W_f), which are characterized by modest slopes, such as stream source areas and valley bottoms (b) sloped wetlands (W_s) in hollows close to streams where hillslopes end in valley bottoms or steep headwater regions, but which can nevertheless be characterized by considerably sloped terrain along the flow direction of the stream. Thus, while both wetland types exhibit relatively low HAND, they are distinguished by different slope angles. The dominant flow generation process for wetlands is saturation overland flow.

Hillslopes (H) are areas which connect concave and convex landscapes (Chorley et al., 1984). The widespread perception that floods are mainly generated on hillslopes (cf. Beven, 2010) makes them a crucial element in landscape analysis. The co-evolution of ecology and hydrology, and thus the presence of preferential flow paths (Weiler and McDonnell, 2004), makes rapid subsurface flow the most effective and

Hydrological land classification

S. Gharari et al.

[Title Page](#)[Abstract](#)[Introduction](#)[Conclusions](#)[References](#)[Tables](#)[Figures](#)[◀](#)[▶](#)[◀](#)[▶](#)[Back](#)[Close](#)[Full Screen / Esc](#)[Printer-friendly Version](#)[Interactive Discussion](#)

dominant runoff process as it fulfills the two essential hillslope functions, drainage and moisture retention.

Plateaus (P) are flat or undulating landscape units relatively high above streams. Due to the low gradients and comparably deep ground water levels, plateaus mainly fulfill storage and evaporation functions, with mainly vertical flow processes, in particular deep percolation (Savenije, 2010).

3.2 Data

Landscape classification in the Wark catchment is based on a 5 m × 5 m DEM with a vertical resolution of 0.01 m. The flow direction network has been derived from the DEM using a D8 algorithm (Jenson and Domingue, 1988; O'Callaghan and Mark, 1984). Although HAND is critically sensitive to the stream initiation threshold, the threshold upslope contributing area has been fixed at a value of 10 ha. This value has been selected to maintain a close correspondence between the derived stream network and the mapped stream network. The value is also in the range of stream initiation thresholds reported by others (e.g., Montgomery and Dietrich, 1988). The relative height, i.e. HAND, was then calculated from the elevation of each raster cell above nearest grid cell flagged as stream cell following the flow direction. Similarly, the distance to nearest drain was also computed along the flow path to the nearest stream cell. The slope of each grid cell was calculated using the average maximum technique (Burrough and McDonnell, 1998).

During a field campaign (16–20 November 2010), 5611 points in the catchment, hereafter referred to as sampling points, were mapped using GPS waypoints along various paths throughout the catchment and in-situ visually classified into the three landscape units – wetland, hillslope and plateau - in order to establish a “ground truth” according to expert knowledge or hydrological dominant behavior (Fig. 2). The resolution of observed points is 5 m along the walking path.

Hydrological land classification

S. Gharari et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



3.3 HAND-based landscape classification

The landscape units have been classified according to HAND (H), slope (S) and distance to the nearest drain (D). A cell with a steep slope was classified as hillslope or sloped wetland and a cell with a low slope was classified either as flat wetland or plateau, depending on HAND or distance to the nearest drain (Table 1). To divide the HAND, slope and distance to nearest drain into high or low category, a threshold has to be decided. The threshold should be adjusted in a way that the modeled landscape classes correspond sufficiently well with the landscape classes of the observed sampling points.

In reality the boundary between the different landscape units may not be sharply defined. The transition from one landscape to another may have to be determined by fuzzy threshold. These reflect, similar to fuzzy set theory, the modeler's and observer's "degree of belief" (cf. Bárdossy et al., 1990) that a point belongs to a certain landscape unit, as shown in the illustrative example in Fig. 3. In the present case this results in three different percentages for one cell indicating to what extent a cell belongs to a landscape unit. Here, the fuzzy nature of the parameters is considered by using a two parameter cumulative Gaussian distribution function (CGDF):

$$\text{CGDF}(x|\mu, \sigma) = \frac{1}{2} \left[1 + \text{efr}\left(\frac{x - \mu}{\sqrt{2 \times \sigma^2}}\right) \right] \quad (1)$$

Where μ is the mean and σ is standard deviation. Both parameters μ and σ are introduced as free calibration parameters in the landscape classification model. Note, that for very small standard deviations the model can be considered as "crisp" or deterministic.

Three landscape classification models have been tested using HAND, slope, distance to nearest drain and a combination of them. The first classification model, based on HAND and slope (Model ID: M_{SH}) uses the four fuzzy threshold parameters μ_H , σ_H , μ_S and σ_S . The classification rules for the models are as below:

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



Hydrological land classification

 S. Gharari et al.

[Title Page](#)
[Abstract](#)
[Introduction](#)
[Conclusions](#)
[References](#)
[Tables](#)
[Figures](#)
[◀](#)
[▶](#)
[◀](#)
[▶](#)
[Back](#)
[Close](#)
[Full Screen / Esc](#)
[Printer-friendly Version](#)
[Interactive Discussion](#)


The probability of having high values of slope:

$$X = \text{CGDF}(S|\mu_S, \sigma_S) \quad (2)$$

The probability of having high values of HAND:

$$Y = \text{CGDF}(H|\mu_H, \sigma_H) \quad (3)$$

5 Thus, the probability of being hillslope is the same as the probability of high slope values and high HAND values:

$$P_H = XY \quad (4)$$

Likewise, the probability of being a plateau is defined as the probability of high HAND values and low values for slope:

$$10 P_P = (1 - X)Y \quad (5)$$

Similarly the probability of being wetland is defined as the probability of low HAND values and high (sloped wetland) or low (flat wetland) slope values.

$$P_W = X(1 - Y) + (1 - X)(1 - Y) = (1 - Y) \quad (6)$$

15 Where the first term reflect the probability of being sloped wetland P_{W_s} and the second represent the probability of flat wetland P_{W_f} .

The second model defines X and Y based on slope (μ_S, σ_S) and distance (μ_D, σ_D) to the nearest drain (Model ID: M_{SD}) to classify the landscape:

The probability of having high values of slope:

$$X = \text{CGDF}(S|\mu_S, \sigma_S) \quad (7)$$

20 The probability of having high distance to nearest drain:

$$Y = \text{CGDF}(D|\mu_D, \sigma_D) \quad (8)$$

Hydrological land classification

S. Gharari et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



For the third landscape classification model a combination of HAND and distance to the nearest drain is used. HAND is normalized to range from 0 to 1 by dividing the HAND value of each grid cell by the maximum HAND value. The same is done for distance to the nearest drain. The multiplication of these two rasters results in a third raster, the H^*D^* raster (Model ID: M_{SHD}). The values for this new raster are low and the distribution is highly skewed with more than 86 % of the raster cells showing a value below 0.1. In order to homogenize this raster it has been power transformed with an exponent between 0 and 1 (HD^*). The procedure is as below briefly:

$$H^* = \frac{H}{H_{\max}} \quad (9)$$

$$D^* = \frac{D}{D_{\max}} \quad (10)$$

$$(H^*D^*)^{0 < n < 1} = HD^* \quad (11)$$

The power of the raster has been chosen by manual calibration and kept constant at $n=0.1$.

The probability of having high values of slope:

$$X = \text{CGDF}(S | \mu_S, \sigma_S) \quad (12)$$

The probability of having high distance to nearest drain:

$$Y = \text{CGDF}(HD^* | \mu_{HD^*}, \sigma_{HD^*}) \quad (13)$$

3.4 Model calibration

The model calibration procedure has been designed to minimize a set of objective functions, set-up as an objective matrix. The objective matrix is divided into two parts. The first part consists of the coordinates and landscape classes of the observed sample points and the second part the modeled landscape classes for the respective points.

The objective function has been designed to evaluate the goodness of fit based on the probability that a modeled point belongs to the same class as the observation point and is defined as:

$$O = \left[1 - \frac{\sum_{i=1}^{N_H} P_{H,i}}{N_H} \right] + \left[1 - \frac{\sum_{i=1}^{N_P} P_{P,i}}{N_P} \right] + \left[1 - \frac{\sum_{i=1}^{N_W} P_{W,i}}{N_W} \right] \quad (14)$$

Where $P_{H,i}$, $P_{P,i}$ and $P_{W,i}$ are the probabilities of observed hillslope, plateau and wetland grid cells i , to be classified by the model as hillslope, plateau or wetland respectively. N_H , N_P and N_W are the numbers of observed grid cells for the hillslope, plateau and wetland classes.

For crisp models the probability of a certain point is 1 for one class and 0 for the two other classes. For fuzzy models the probability of a modeled point is divided into three classes summing up to unity, while leaving the observed sample points crisp, i.e. the observed points are clearly defined as wetland, hillslope or plateau. The idea behind this approach is to let the model decide about the functionality of a cell which may not be unique given the large number of crisp observed points. The objective matrix is designed in a way that the number of sample points in each class does not affect the calibration process. Thus, statistical bias is avoided if the proportion of one landscape class is large compared to others, that is if it is the most dominant feature in the catchment, or if the in-situ observed points are not a statistically representative sample. Note, that the maximum value of the objective function can be 3 but in practice it will not exceed 2 because with an extremely unrealistic set of parameters the entire basin will be classified as one unit. As a result, objective function for that unit will be zero and for the remaining classes will each sum up to unity.

Calibration of the models in this paper has been done using Monte-Carlo sampling, i.e. the parameters were sampled, in absence of further prior information, from uniform distributions, within predefined threshold ranges ($S(-) \in [0,0.2]$, $H(m) \in [0,20]$, $D(m) \in [0,100]$, $HD^*(-) \in [0,1]$) in 20 000 Monte-Carlo realizations. Similar to the idea behind the Generalized Likelihood Uncertainty Estimation (GLUE; Beven and Binley,

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



1992), it has been assumed that there is, due to equifinality, no single best model parameter set. A range of acceptable (i.e. behavioral) sample rates (ASR; Li et al., 2010) is tested in sensitivity analysis. The parameters are reported based on the best performance and their likelihood weighted 95 % uncertainty interval (UI) for an ASR of 5 %, whereby the value of the objective function is used as likelihood value. For sensitivity analysis ASR of 1–10 % has been used.

3.5 Optimal effective DEM window size and resolution

The 5 m × 5 m resolution of the DEM allowed a relatively accurate representation of landscape units. However, High resolution DEMs can introduce a bias in the results as hydrologically negligible local landscape features, such as steep, small scale rock outcrops, can cause certain grid cells to be inappropriately classified. To reduce this problem the DEM has been smoothed using a Gaussian filter with mean μ_{SM} and standard deviation σ_{SM} (hereafter referred to as characteristic smoothing scale). Applied as a moving window with $\mu_{SM} = 0$ and different values of $\sigma_{SM} = 0.5, 1, 1.5, 2, 5, 10$ grid cells (equivalent to 2.5, 5, 7.5, 10, 25, 50 m) this allowed the removal of "noise" in the landscape while keeping the high DEM resolution by assigning each grid cell the Gaussian weighed elevation of the neighboring cells (truncated at a distance of $3\sigma_{SM}$) (cf. Hrachowitz and Weiler, 2011). The optimal effective window size, i.e. $2 \times 3\sigma_{SM}$, was the one minimizing the objective function.

Furthermore the effect of lower DEM resolutions (10, 20, 50 or 100 m) on the model parameters and performances has been investigated, to test which DEM resolution is necessary to provide acceptable model results. For model runs with lower resolution no filter was used as it was assumed that local landscape features would automatically average out in the process of resampling the DEM at lower resolutions.

Hydrological land classification

S. Gharari et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



3.6 Effect of calibration point sample size on model results

The effect of different calibration point sample sizes on the robustness and predictive power of models has been assessed by cross-validation. More specifically, repeated random sub-sampling validation (Vapnik, 1998) was used to investigate how best fit parameter sets change for calibration point sample sizes of 2806 (s_1), 1122 (s_2), 561 (s_3), 281 (s_4), 112 (s_5), 56 (s_6) and 28 (s_7) points (i.e. 50, 20, 10, 5, 2, 1 and 0.5% of the complete of 5611 calibration points which consisted of 1501 (26.8%), 1385 (24.6%), 2725 (48.6%) points for wetland, hillslopes and plateau respectively). 100 random sub-samples for each of the sample sizes s_1 – s_7 were drawn from the complete set of 5611 calibration points. The best parameter set for each of the 100 sub-samples was then estimated by 500 Monte-Carlo realizations. Thus, a central parameter estimate together with a spread around that central value was obtained from the 100 sub-samples for each of the samples sizes s_1 – s_7 . The objective function for the remaining 5611- s_1 – s_7 points not used for calibration (validation points) was then predicted using the 100 individual parameter sets. The mean and spread of the deviation of the validation point objective function from the calibration point objective function was used as an indicator for the predictive power of models with different calibration point sample sizes, i.e. the closer the validation objective function is to the calibration objective function the higher is the predictive power of the models at a given calibration sample size. Likewise, the robustness of the models was further assessed by relating the 100 central parameter estimates and their spreads to the respective sample sizes, i.e. the higher the spread in the parameter estimates the less robust or the more sensitive the model is to the chosen calibration points, indicating a too small calibration point sample size.

3.7 Effect of calibration point location on model results

As the topography of the Wark catchment sharply changes from undulating hills in the Western part to plateaus above steep, incised valleys in the Eastern part, this allows assessing the robustness of the landscape classification models to changing

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



landscape structures. That is, the ability of the model to correctly predict landscape classes when it was calibrated in a structurally different landscape. Here this was done by splitting the Wark Catchment into four zones; north, east, west and south, by using mean latitude and longitude (the mean of maximum and minimum of latitude within the catchment and the same procedure for longitude). While the Eastern parts of the catchment has very pronounced landscape features with sharp hillslopes and narrow valleys, the Western part is characterized by a comparably subdued profile with wider valleys. The models were subsequently calibrated using observed points from one zone, while the observed points in the remaining zones were predicted. The changes in objective functions and parameter sets were then used as indicators of the model sensitivity to changing landscapes.

4 Results and discussion

4.1 Comparing the performance of different models for original DEM

In order to identify the most adequate landscape classification model, the three models (M_{SH} , M_{SD} , M_{SHD}) have been run with the original 5 m \times 5 m DEM. Model M_{SH} , which is equivalent to the original HAND-based model (Rennó et al., 2008), is found to be the most adequate model with an objective function (Eq. 20) value of $O = 0.527$, while the objective function values for the M_{SD} and M_{SHD} models are moderately higher with values of 0.702 and 0.584, respectively. For the model M_{SH} the best fit threshold values for slope (S) and HAND (H) are found to be $S = 0.129$ (95 % UI: 0.096–0.166) with $\sigma_S = 0.002$ (95 % UI: 0.001–0.039) and $H = 5.9$ m (95 % UI: 3.2–8.9 m) with $\sigma_H = 0.23$ m (95 % UI: 0.05–2.9 m). Correspondingly, for model M_{SD} the threshold values for slope (S) and distance to the nearest drain (D) are $S = 0.127$ (95 % UI: 0.102–0.150) with $\sigma_S = 0.001$ (95 % UI: 0–0.026) and $D = 62.6$ m (95 % UI: 42.6–84.5 m) with $\sigma_D = 2.80$ (95 % UI: 0.3–22.5 m) for M_{SD} . While for M_{SHD} , the slope and the normalized metric of combined H and D (HD^*) are $S = 0.135$ (95 % UI: 0.092–0.183) with $\sigma_S = 0.004$ (95 %

Hydrological land classification

S. Gharari et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



5 UI: 0–0.044) and $HD^* = 0.512$ (95 % UI: 0.454–0.585) with $\sigma_{HD^*} = 0$ (95 % UI: 0.001–0.075). Since in M_{SH} the σ values for the Gaussian distribution are very low, these results suggest that all grid cells with $S < 0.129$ and $H < 5.9$ m are to be classed as flat wetlands, while grid cells with $S > 0.129$ and $H < 5.9$ m are classified as sloped wetlands. Grid cells with $S > 0.129$ and $H > 5.9$ m are defined as hillslopes while those with $S < 0.129$ and $H > 5.9$ m represent plateaus.

10 The classified landscapes are illustrated in Fig. 4. The worst performance was obtained with model M_{SD} . This model cannot model flat wetland especially headwater, narrow valley bottom and wide valley simultaneously. For head water and wide valleys the model needs to use a high distance from the stream to correctly model the observed point, however for narrow valley bottoms the distance should be as little as possible not to overlap with neighboring hillslopes. This causes a poor performance of M_{SD} . The model which used HAND performs the best; it can predict the headwater and wide and narrow valley bottoms better than M_{SD} .

15 One problem which is obvious in Fig. 4 is the noise within a specific landscape. Some raster cells with very high resolution have completely different characteristic from their neighboring cells. For example a cell (which may be a road or other human interference) may have a zero slope and be classified as plateau while the rest of its neighboring cell have a high slope are classified as hillslope.

20 The relatively low spread for both parameters, HAND and slope, in the M_{SH} highlights that the landscape units can be classified with a surprisingly low fuzziness, i.e. there is only limited uncertainty if a landscape element belongs to one class or to another and it shows that a crisp model with $\sigma_{slope} = \sigma_{HAND} = 0$ (Model ID: $M_{SHcrisp}$) would produce results very close, in terms of model performance and parameter estimates, to those from the fuzzy approach.

25 The results of M_{HD} furthermore suggest that HAND is a better indicator for landscape classification than distance to the nearest drain or than a combination of distance and HAND, as used in M_{SD} and M_{SHD} models. It shows that additional or similar parameters do not necessarily lead to equally good representations of landscape units as

Hydrological land classification

S. Gharari et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



shown in Fig. 4, were several areas of obvious landscape misclassification can be seen, especially for M_{SD} . This underlines the potential of HAND to meaningfully characterize landscapes as it originates, other than elevation, directly from the feedback processes between water and geology and as it is, other than distance to the nearest drain, directly linked to the dominant driver of storage-discharge relationships, which has co-evolved with the landscape: the hydraulic head.

4.2 Effect of smoothing on models performance and parameters

Relatively prominent, though small scale, landscape features, such as rock outcrops or hollows, can be present in landscapes of any type. However, up to a certain size they do not significantly change the appearance of the overall landscape or the associated dominant runoff process. Thus they should be smoothed out in order to reduce noise in the resulting landscape classification. Here it is found that, with increasing characteristic smoothing scale between $\mu_{SM} = 0$ (original 5 m \times 5 m DEM) and $\sigma_{SM} = 10\text{--}25$ m, equivalent to an actual window size of 60–150 m (truncating the normal distribution at cumulative probabilities of 0.005 and 0.995 or 3σ) the model performance of all three models M_{SH} , M_{SD} and M_{SHD} significantly increased and sharply declined thereafter (Fig. 5). With an objective function value of $O = 0.491$, the crisp (i.e. $\sigma_{slope} = \sigma_{HAND} = 0$) $M_{HScrisp}$ with $\sigma_{SM} = 10$ m, $H = 4.7$ m (95 % UI: 3.5–7.1 m) and $S = 0.113$ (95 % UI: 0.103–0.140) clearly outperformed all other models. The parameters H and S developed contrarily with increasing size of the smoothing window. While H did not show any consistent relationship and a rapid increase for window size of 300 m, S increased generally with increasing characteristic smoothing scale (Fig. 6a, b). The improved model performance with smoothed landscapes, however, comes at the price of a considerable trade-off with parameter identifiability. As the smoothing implies an assimilation of landscape features, clear distinctions between them are lost and a wider range of parameter combinations can lead to the same model results. This is shown using the parameter rang for different ASR. As the smoothing window size increases the parameter identifiability for H increases and for the largest window size of

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



300 m the ranges decrease for lower value of ASR (Fig. 6c). As the smoothing window size increases, S shows a general decrease up to window size of 150 m and for the largest window size of 300 m it shows an increasing trend (Fig. 6d).

Using the best model, M_{SH} , and comparing the resulting landscape class derived from a smoothed DEM ($\sigma_{SM} = 10$ m, Fig. 7c), to the map obtained from the raw, high resolution DEM ($\sigma_{SM} = 0$ m, Fig. 7b) it can be seen that much of the scattered small scale noise and obvious misclassifications disappeared in favor of a more consistent and smooth representation of hydrologically dominant landscape classes. Hillslope and plateau are the two landscapes which are classified more uniformly with less scatter noises for larger smoothing window. On the other hand by increasing the size of smoothing window, the small valley bottom is smoothed out and is classified as plateau.

From these results it can be inferred that the characteristic scale of landscape features that determine landscape classes is in the order of approximately 50 m in this study area and landscape features larger than that do significantly change the appearance of the landscape and its associated dominant runoff processes based on visual observation. However, note that this characteristic landscape feature size should be treated as site specific as it can potentially vary in other regions, where different or additional landscape classes are present.

4.3 Effect of DEM resolution on model performance and parameters

Frequently, only DEMs with resolutions coarser than $5\text{ m} \times 5\text{ m}$ are available. Therefore the robustness and sensitivity of the landscape classification models M_{SH} , M_{SD} and M_{SHD} have been assessed with several re-sampled, coarser DEMs, similar to what was done earlier by Zhang and Montgomery (1994), who tested the effect of DEM resolution on topographic wetness index and slope. Again, the crisp model $M_{SHcrisp}$ (i.e. $\sigma_{slope} = \sigma_{HAND} = 0$) is generally the best performing one (Fig. 8) with objective function values between $0.515 < O < 0.993$, depending on the DEM resolution. It is found that the objective function first slightly decreases up to a resolution of 10 m starting to sharply increase thereafter, implying that DEMs with resolutions of higher than 20 m

Hydrological land classification

S. Gharari et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



Hydrological land classification

S. Gharari et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



show sufficient detail to effectively produce results close to those obtained from a 5 m × 5 m DEM. DEMs with resolutions lower than 20 m, on the other hand, gradually lose important detail, causing a relatively sharp increase in the objective function. Such low resolutions do not contain sufficient fine detail of the landscape and in particular fail to correctly represent narrow but incised, deep valleys or small head water convergences, thus introducing considerable bias in the HAND as well as in the slope threshold values. For coarse resolution DEMs an additional source of error has been identified. The models were calibrated to observed, clustered sample points, which were, within the clusters, generally located at distances <10 m from each other. It was thus possible that observed points next to each other represent different landscape classes. For coarse DEM resolutions, several classes could thus be contained within a one DEM cell (e.g. 100 m × 100 m). For this reason it was possible that one cell could represent all three observed classes at the same time. This phenomenon clearly increased the objective function and hence reduced the performance of the models for landscape separation. The parameters H and S developed differently with decreasing DEM resolution. While H shows a slight convex relation to resolution with minimum values for resolution of 10 m, slope shows a strong convex behavior, decreasing to resolution of 50 m and increasing for resolution of 100 m (Fig. 9a, b). The parameter identifiability, however, decreased with decreasing DEM resolution for H , which was not true for parameter S (Fig. 9c, d).

From the analysis in the previous three sections it is found that the most adequate landscape classification in this study could be obtained by the use of the highest resolution DEM (5 m × 5 m), smoothed with a Gaussian filter with a characteristic smoothing scale $\sigma_{SM} = 10$ m, which is equivalent to an effective window size of 60 m, and a crisp (i.e. $\sigma_S = 0$ $\sigma_{HAND} = 0$) model set-up $M_{SHcrisp}$, with landscape classification threshold parameters $H = 4.7$ m (95 % UI: 3.5–7.1 m) and $S = 0.113$ (95 % UI: 0.102–0.140), which resulted in an objective function value of $O = 0.491$. This model set-up has been used for comparative analysis in the remainder of this study and is hereafter referred to as M_{SHopt} . The statistical analysis of the different landscape classes and

their topographical indicators for model M_{SHopt} : slope, HAND and distance to nearest drain, is presented in Table 2. The classified map of the Wark catchment resulting from M_{SHopt} is illustrated in Fig. 10.

4.4 Effect of calibration sample size on model performance and parameters

The landscape classification obtained from the above suggested model depends strongly on what the model was calibrated to and how robust the parameter estimates are. Inadequate calibration strategies could thus cause considerable bias and inaccuracies in the results. The sensitivity of M_{SHopt} model results and threshold parameters to the sample size of calibration points has been estimated by comparing the results obtained from different sub-sample sizes (s_1 – s_7).

The results are summarized in Fig. 11. While clearly the objective function for the calibration points only can take on occasional very low values for small calibration point sets, its mean value also decreases with smaller sample size (Fig. 11c). This is, however, largely an artifact of the reduced constraints to the model, as can be seen in the pattern of the objective function for the validation points (Fig. 11d). As the calibration sample set is reduced, the performance of the models in validation deteriorates. This is also illustrated by Fig. 11e, where the deviations from line of perfect agreement of the relationship between calibration and validation objective functions are shown, i.e. the higher the deviation the more the objective functions in calibration and validation modes differs. For very robust models only small deviations would be expected. It can also be seen that as the sample size of calibration points decreases, the range of the two landscape classification threshold parameters H and S increase exponentially (Fig. 11a, b). In other words, for the given study catchment the best fit parameters for the model results of the corresponding calibration point sub-sets show, little surprisingly, an increased scatter with smaller sample sizes. The smaller the calibration sample set the less representative it is for the landscape, resulting in considerably different parameters for each realization of each different sub-sample of size n , depending on which points are chosen in the calibration sample set, and consequently the less

Hydrological land classification

S. Gharari et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



robust is the predictive capability of the model. This also implied better parameter identifiability for larger calibration sample sets, i.e. fewer parameter combinations were able to produce equally good model results. In general it can be said that the model stabilizes and remains relatively robust, thus showing reasonable predictive capability, with calibration sample sets of at least $n = 560$ points (in this study approximately 10% of the available sample size), or more specifically with an average calibration sample density of 7 points per km^2 . However this does not necessarily imply that using uniformly distributed sample points in a catchment area with density of 7 points per km^2 will give a good performance of the model and well defined landscapes. Actually the random samples are representing the observation densities across the respective walking paths taken during the field campaign. The sample observation density during field visit was five meters along walking distance. Fairly good performance of the 10% sub-sample shows that the observed points on the walking path can give a reasonable result with a one point in 50 m density along the walking path.

4.5 Effect of location of calibration points on the performance of the models

Subsequently we tested how well the calibration sample set represents the landscape features of the overall catchment in order to produce good and robust model performance. This is considered helpful, as it can potentially give future modelers the possibility to a priori assess if there are landscape features with a higher, landscape classification relevant information content than others. Information like that can subsequently help to identify and constrain areas where it is most useful to collect calibration sample points.

The results of the four analyzed sub-sets of calibration points taken from four parts of the catchment have been compared for M_{SHopt} . These four parts of the catchment are summarized in Table 3 and it can be seen that using calibration points only from the Northern and Eastern parts results in the best model performances in the calibration mode ($O = 0.407$ and 0.402). These two parts are characterized by a very pronounced landscape profile, dominated by steep, incised valleys and narrow valley bottoms. In

Hydrological land classification

S. Gharari et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures



Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



Hydrological land classification

S. Gharari et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



the remaining two parts, South and West, which are dominated by a more subdued landscape with undulating hills and wide valley bottoms the model performance in calibration mode is less good ($O = 0.520$ and 0.565). Clearly, the distinction between landscape units is more ambiguous in areas with subdued profile, as the transition between different landscape classes, such as wetland and hillslope, is much more subtle, due to the limited variability in slope angles. This consequently leads to uncertainties, misclassifications and thus a reduced model performance. However, the results are different in the validation mode. Calibration point sub-sets from the northern and eastern parts, characterized by a very pronounced profile, do not serve very well for predicting landscape classes in areas with gentle slopes and wide valley bottoms like southern and eastern parts respectively ($O = 0.902$ and 0.669). This is caused by the models inability to recognize subtle landscape transitions as these were not available for model conditioning. On the other hand, models calibrated to low profile landscapes like the southern and western parts, in spite of a less good calibration performance, show a significantly better performance in predicting landscape classes in areas with different topographical characteristics northern and eastern part respectively ($O = 0.607$ and 0.506). This is not entirely surprising as it may be assumed that a model conditioned to recognize subtle landscape differences will also recognize much clearer differences in the profile. Based on these findings an efficient strategy to choose calibration points would include a few points characterizing pronounced landscape features, such as incised valleys. The majority of sampling points, however, should cover parts of the catchment with subdued topography and rather subtle landscape features, were classification can be most ambiguous.

4.6 Comparison between topographical wetness index and different classes

As mentioned above the land classification aims at categorizing the catchment into hydrologically similar zones. For this study the land classification has been based on visual observation. In reality it is expected that the position of the ground water table can provide a more objective selection criterion as the ground water for wetlands can

be assumed to be shallower than the ground water for plateaus and hillslopes. To see how well the model predicts the likely position of the ground water table, hereafter referred to as indicator of “wetness” of each landscape, the models and their result have been compared to the Topographical Wetness Index (I_{TW}), which is the base for TOPMODEL (Beven and Kirkby, 1979). The I_{TW} is defined as follows:

$$I_{TW} = \ln(A/\tan\beta) \quad (15)$$

Where A is the upstream contributing area and β is local slope. The principle behind TOPMODEL is that locations with similar wetness indices are considered to have similar hydrological behavior. I_{TW} was further developed by Hjerdt et al. (2004), considering the distance for a defined drop in elevation following the flow direction instead of the local slope:

$$\beta = d/L \quad (16)$$

Where L is the horizontal distance a water particle has to move in order to reach a defined drop in elevation d . It was shown that the resulting wetness index can predict the “wet” area more accurately than the original wetness index. Nobre et al. (2011) reported a relatively weak, inverse relation between HAND and I_{TW} in the Amazon region, meaning that with increasing HAND the wetness index decreases.

To investigate how the wetness index differs for different landscapes, the I_{TW} has been calculated for the entire catchment using the smoothed DEM with $\sigma_{SM} = 10$ m in order to allow comparison with the best performing model M_{SHopt} . The scatter in the relationship (cf., Nobre et al., 2011) has been reduced by classifying I_{TW} values of all cells in the study catchment into different bins, in order to facilitate clearer interpretation. Different bins or class sizes (5, 10 and 20 classes) show similar behavior regarding the proportions and changes of each landscape for each class. As the wetness index for each class increases the proportion of plateau and wetland increases and the proportion of hillslope decreases; for the class with highest wetness index the proportion of plateau also decreases and proportion of wetland shows a rapid increase. From Fig. 12

Hydrological land classification

S. Gharari et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



(10 classes) it is clear that by increasing the wetness index the proportion of wetland in each class gradually increases and the proportion of hillslope is gradually less. It can be inferred from Fig. 12 that the locations which were defined as hillslope and wetland are the driest and wettest areas respectively in the Wark catchment according to I_{TW} .

The mean value for each class shows that wetland areas have the highest wetness index values (Table 4). Within the wetland class, flat wetlands have a higher wetness index than sloped wetlands.

Hillslopes are the driest classified landscape based on the I_{TW} . Although the aim of the land classification is not to predict the exact depth and behavior of the water table, since many factors play a role in the position of the groundwater table such as the recharge, boundary conditions (Haitjema and Mitchell-Bruker, 2005) and bedrock topography, the classified landscape can potentially give a good estimate of groundwater depth.

One aspect regarding the I_{TW} is that in a GIS a stream in general has a width of one cell size. Adjacent cells with steep slopes and small contributing areas may be much drier than stream cells while in reality it is expected that most of the cells close to a stream change gradually and uniformly (Burrough and McDonnell, 1998). For example, a raster cell with steepest slope in the catchment area, which is located near a cell flagged as stream and drains to it with a contributing area of one cell (the lowest contributing area possible) will exhibit the lowest I_{TW} compared to the rest of the cells. For the HAND based method this cell, however, will, arguably more realistically, be classified as sloped wetland because of low HAND index and steep slope. A visual comparison between the I_{TW} and classified map with aerial picture is presented in Fig. 13.

5 Conclusions

In this study we tested and assessed the applicability and sensitivity of a HAND based landscape classification framework in a meso-scale headwater catchment in

Hydrological land classification

S. Gharari et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



Hydrological land classification

S. Gharari et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



Luxembourg, characterized by a temperate, humid climate. With this approach it was possible to classify landscape units into flat wetland, sloped wetland, hillslopes and plateaus, which are perceived to exhibit distinct dominant runoff generation processes. Three different model types, using different parameter combinations, such as HAND, slope, distance to nearest drain and a combined HAND-distance parameter, were investigated. Best landscape classification results were obtained from the model based merely on HAND and slope. This implies that HAND is a stronger indicator for different dominant runoff processes than for example the distance to the nearest drain or absolute elevation, as this links more directly to the hydraulic gradient, arguably the most dominant factor for any type of runoff generation. Based on experiments on sample size and observation density, it was furthermore shown that landscape classes and thus dominant runoff processes are determined by a characteristic landscape feature scale of approximately 50–100 m. Local landscape features smaller than that generally do not influence the overall landscape class and thereby the dominant runoff processes. Landscape classification based on DEMs with resolutions of 20 m × 20 m and above can give sufficiently accurate results, whereas lower resolution DEMs lack the fine detail necessary to identify critical features, such as narrow valleys. As the landscape classification model needs to be calibrated to observed points, the sensitivity of the calibration point set was analyzed and it was found that sample density of 50 m along walking path can be assumed to be representative in this study, giving robust model results with high predictive power. It was also shown that calibration sample points from subdued landscapes, with subtle and frequently ambiguous transitions between landscape classes contain more information for model calibration than calibration points in clearly defined landscape classes. The classification model was compared with topographical wetness index and a clear relation between classified landscape and ground water table based on binned topographical wetness index values was found.

The landscape classification results could in future work be refined by using additional information such as distributed soil moisture or ground water data, which could help establishing a yet stronger link between landscape classes and runoff processes.

Hydrological land classification

S. Gharari et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



The resulting maps show a relatively realistic, high accuracy landscape classification associated closely to the dominant runoff generation processes in the individual parts of the study catchment. Such results can in the future serve as basis for the development of conceptual hydrological models by assigning different model structures to the individual landscape classes, thereby potentially improving model realism without the need for further parameters.

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Hydrological land classification

S. Gharari et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



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Hydrological land classification

S. Gharari et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



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Hydrological land classification

S. Gharari et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



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Hydrological land classification

S. Gharari et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



Table 1. Criteria for land classification using HAND and slope.

	Low HAND	High HAND
Low Slope	Wetland (flat)	Plateau
High Slope	Wetland (sloped)	hillslope

Hydrological land classification

S. Gharari et al.

Table 2. Mean and standard deviation values for HAND, slope and distance to the nearest drain for each landscape class of the best model performance M_{SHopt} (threshold values $H = 4.7$ m, $S = 0.113$).

	HAND (m)		slope(–)		distance to nearest drain(m)	
	μ	σ	μ	σ	μ	σ
wetland	2.44	1.83	0.091	0.087	74.99	78.31
wetland (flat)	2.05	1.76	0.047	0.030	88.53	86.13
wetland (sloped)	3.45	1.60	0.206	0.083	39.35	31.54
hillslope	40.96	28.07	0.262	0.144	233.49	152.31
plateau	39.81	26.69	0.066	0.028	410.51	185.00

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



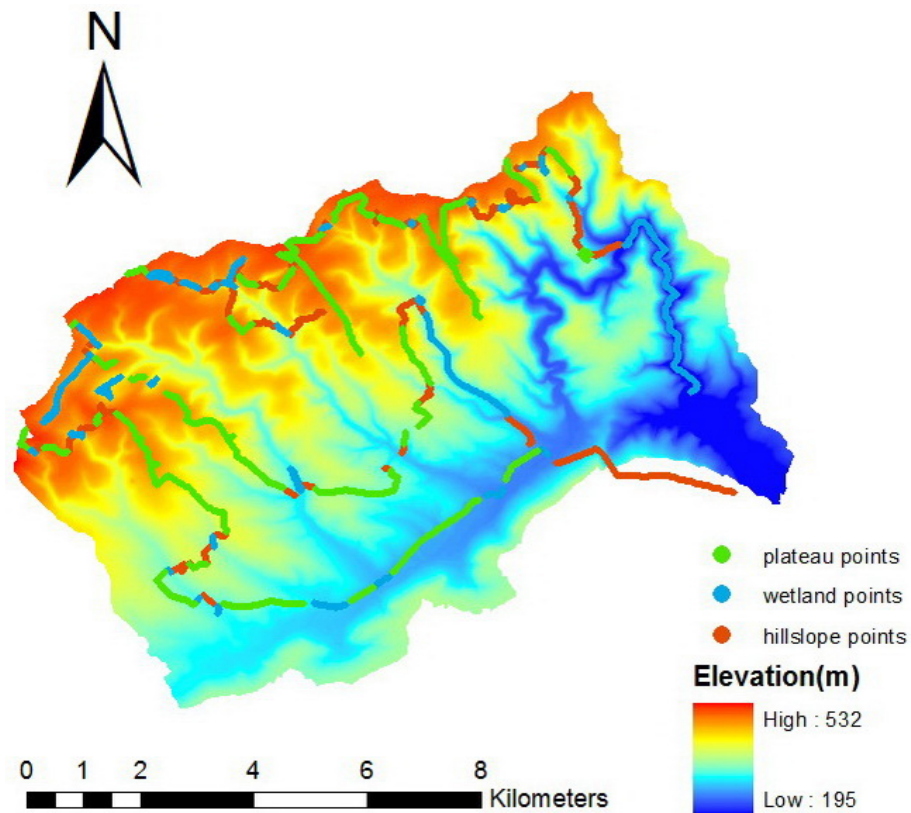


Fig. 2. Observation points in the Wark Catchment and their corresponding classification.

Hydrological land classification

S. Gharari et al.

Title Page

Abstract Introduction

Conclusions References

Tables Figures

◀ ▶

◀ ▶

Back Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



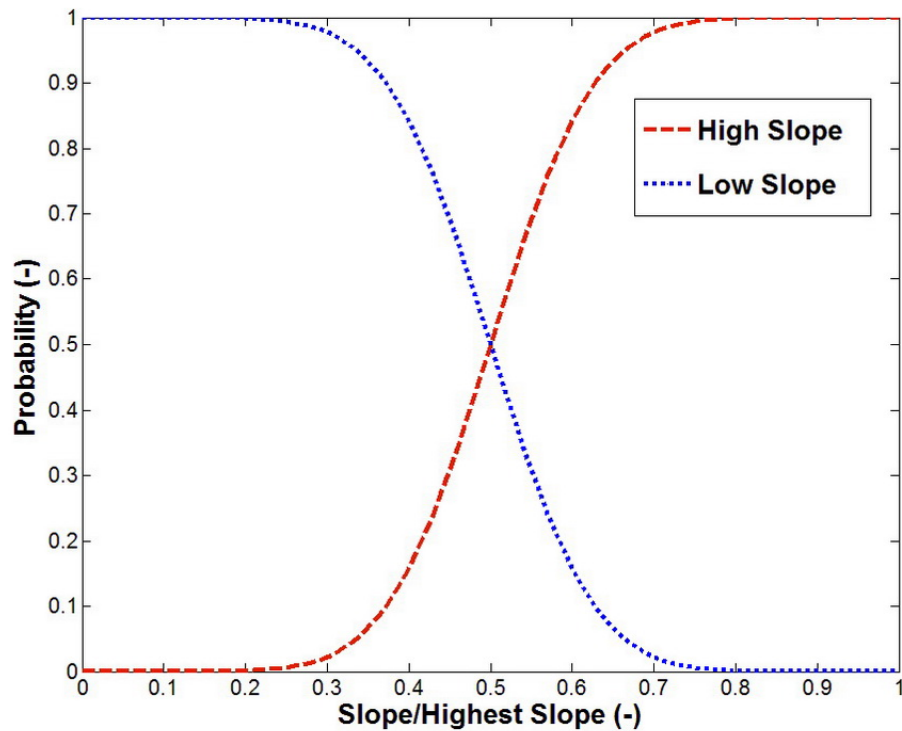


Fig. 3. An example of fuzzy classification for high and low slope. In the central part of the graph the classification is uncertain while at the extremes the uncertainty is low.

Hydrological land classification

S. Gharari et al.

Title Page

Abstract Introduction

Conclusions References

Tables Figures

◀ ▶

◀ ▶

Back Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



Hydrological land classification

S. Gharari et al.

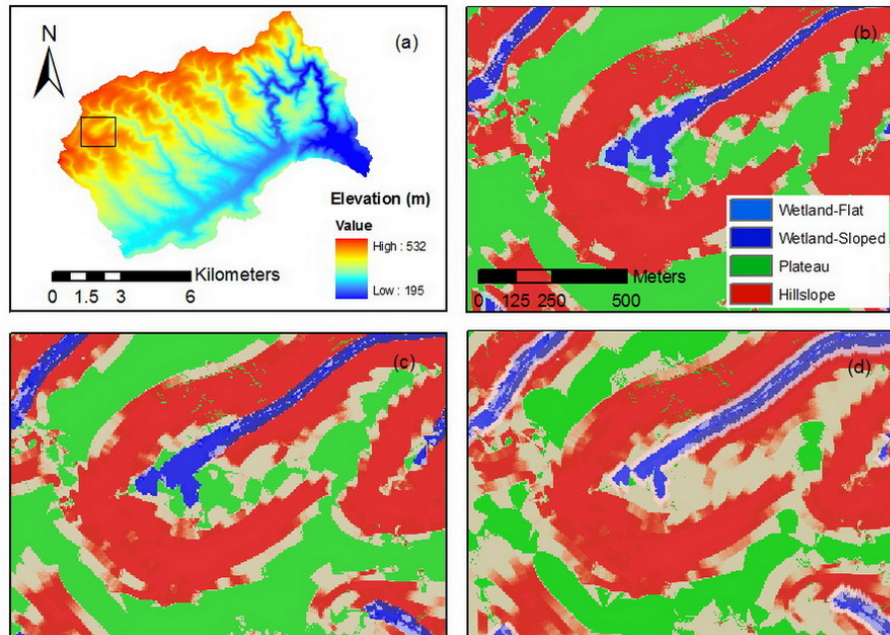


Fig. 4. Comparison between different models for land classification in a headwater of one of the tributaries of the Wark. **(a)** The location of the headwater in the Wark Catchment; **(b)** model using HAND and slope (M_{SH}); **(c)** model using distance to nearest drain and slope (M_{SD}); **(d)** model using HAND, distance to nearest drain and slope (M_{SHD}).

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



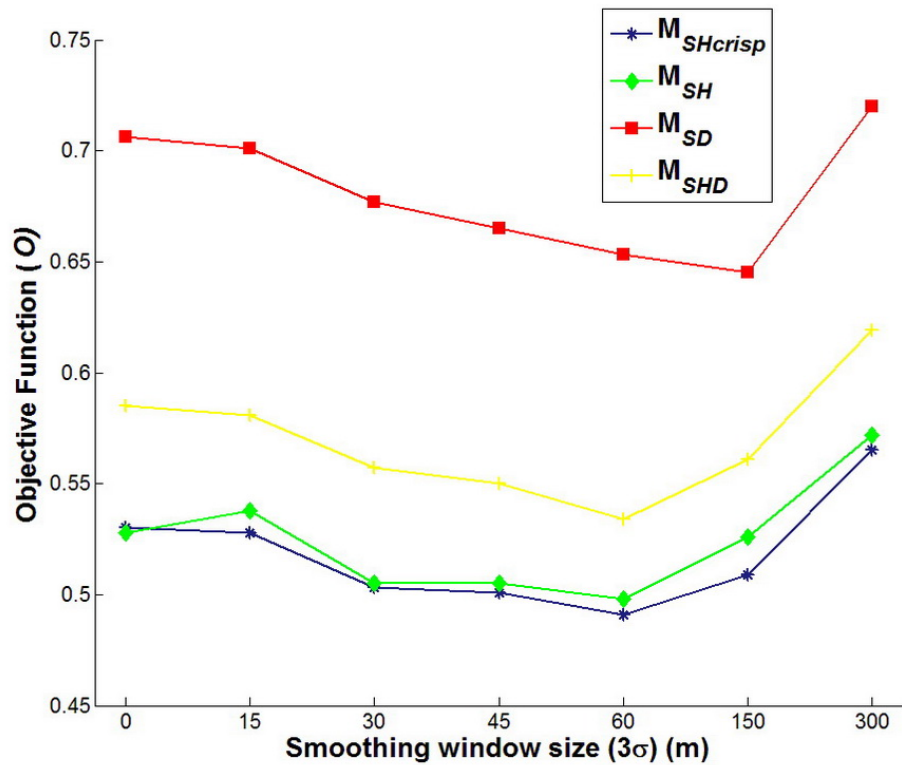


Fig. 5. Performance of different classification models for different Gaussian smoothing windows based on the original DEM of 5 m × 5 m.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



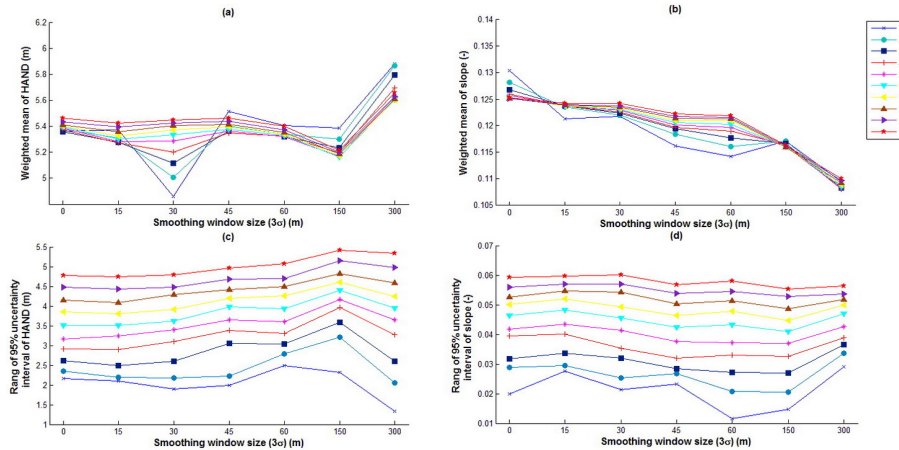


Fig. 6. (a) Weighted mean value of HAND vs. different Gaussian smoothing windows for acceptable sample rate (ASR) of 1–10 %; (b) weighted mean value of slope vs. different Gaussian smoothing windows for acceptable sample rate (ASR) of 1–10 %; (c) parameter range for 95 % uncertainty interval of HAND (d) parameter range for 95 % uncertainty interval for slope. Note that for comparative reasons and due to the inherent subjectivity in the choice of a threshold for defining behavioral parameter sets, the sensitivity of the parameter uncertainty ranges to varying thresholds here is illustrated by showing the parameter ranges for best 1–10 % of the acceptable sample rate (ASR).

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



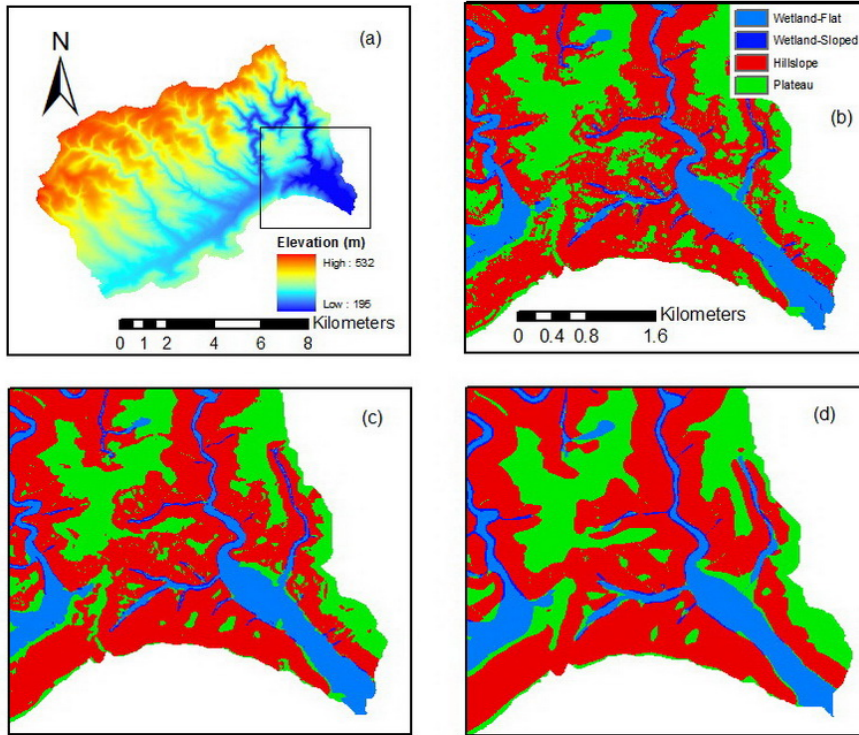


Fig. 7. Comparing the smoothing window effect on the land classification. **(a)** Location of selected area in the Wark catchment; **(b)** classified landscapes for original DEM with resolution of 5 m × 5 m without using a smoothing window; **(c)** classified landscapes using a smoothing window of 60 m ($\sigma = 10$ m); **(d)** classified landscapes using smoothing window of 300 m ($\sigma = 50$ m).

Hydrological land classification

S. Gharari et al.

Title Page

Abstract Introduction

Conclusions References

Tables Figures

◀ ▶

◀ ▶

Back Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



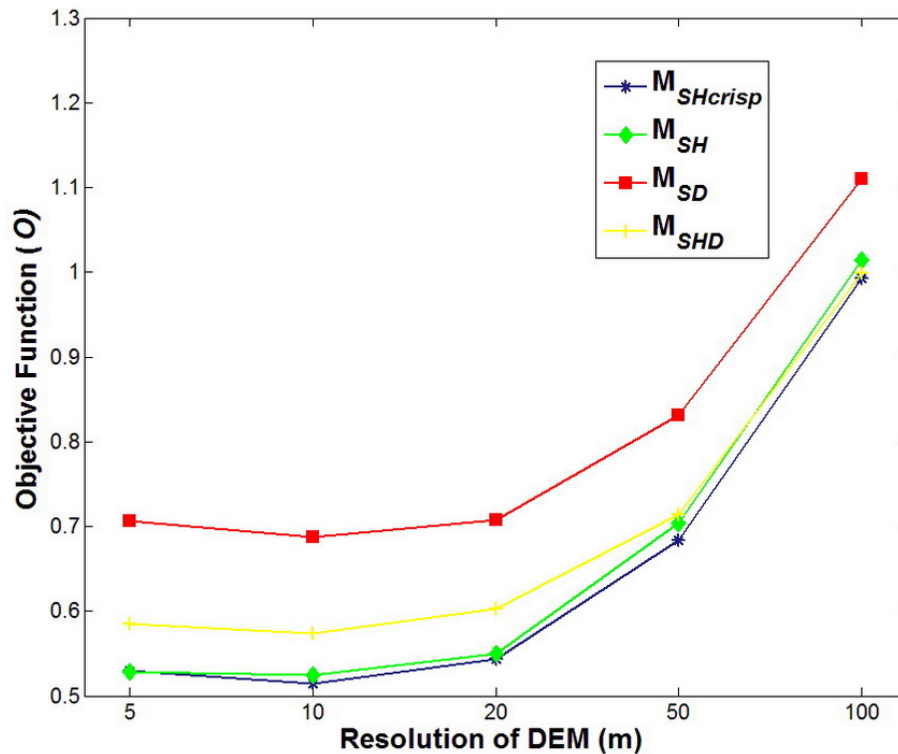


Fig. 8. Performance of different classification models for different DEM resolution.

Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper

Title Page

Abstract Introduction

Conclusions References

Tables Figures

◀ ▶

◀ ▶

Back Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



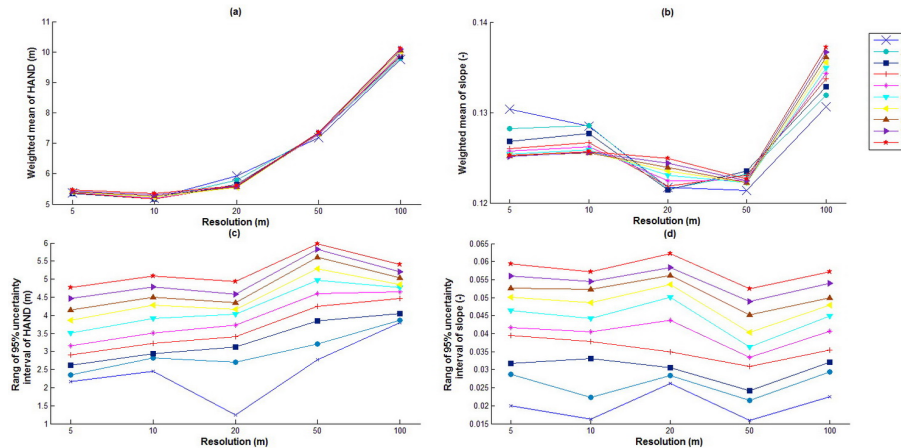


Fig. 9. (a) Weighted mean value of HAND vs. different DEM resolution for an acceptable sample rate (ASR) of 1–10 %; (b) weighted mean value of slope vs. different DEM resolution for an acceptable sample rate (ASR) of 1–10 %; (c) parameter range for 95 % uncertainty interval of HAND for different resolutions (d) parameter range for 95 % uncertainty interval for slope for different resolutions. Note that for comparative reasons and due to the inherent subjectivity in the choice of a threshold for defining behavioral parameter sets, the sensitivity of the parameter uncertainty ranges to varying thresholds is illustrated by showing the parameter ranges for best 1–10 % of the acceptable sample rate (ASR).

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



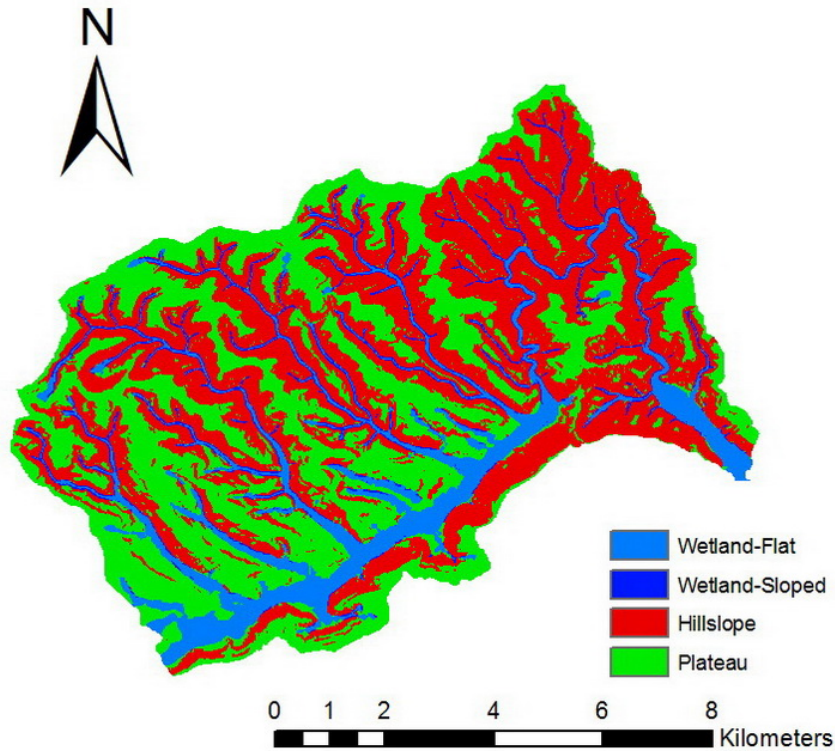


Fig. 10. Classified map of the Wark catchment resulting from the best model performance M_{SHopt} .

Hydrological land classification

S. Gharari et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion



Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

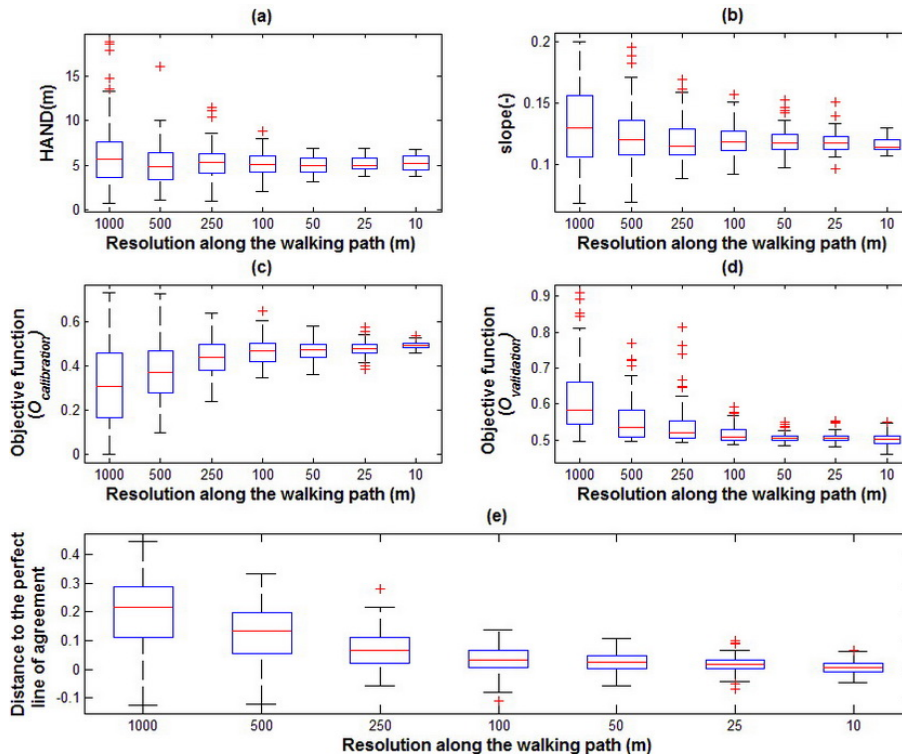


Fig. 11. Behavior of parameter and objective function depending on different calibrating sample sizes; different sample sizes are shown based on resolution along walking path **(a)** the behavior of slope for different sample sizes **(b)** behavior of HAND for different sample sizes **(c)** behavior of calibration objecting function (O) and **(d)** behavior of validation objective function (O) **(e)** behavior of distance of calibration-validation points to the line of perfect agreement. The distance is positive for points above the line and negative for the points below the line. Red crosses show the outliers or values outside of the whiskers range (the most top and bottom lines).

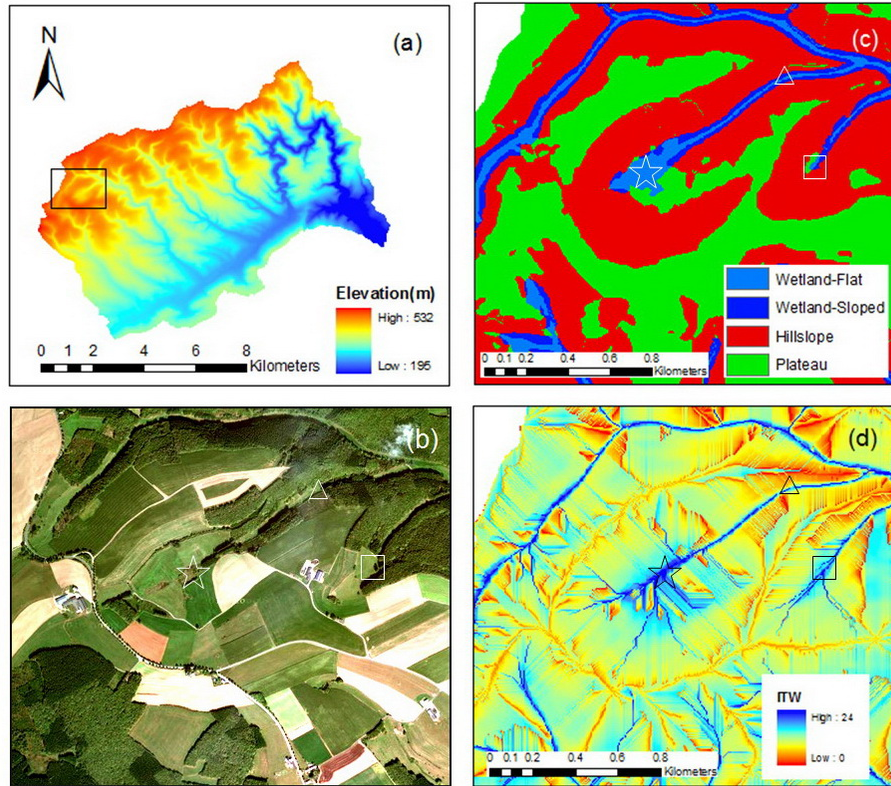


Fig. 13. (a) Location of a selected headwater of a Wark tributaries, (b) aerial photo of the headwater (a) categorized landscapes by the best parameters of M_{SHopt} (d) topographical wetness index (I_{TW}). The location of identical points are indicated by a star, triangle and square.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

