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An approach to computing topographic wetness index based on maximum downslope gradient

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Abstract As an important topographic attribute widely-used in precision agriculture, topographic wetness index (TWI) is designed to quantify the effect of local topography on hydrological processes and for modeling the spatial distribution of soil moisture and surface saturation. This index is formulated as TWI = $\ln(a/\tan\beta)$, where a is the upslope contributing area per unit contour length (or Specific Catchment Area, SCA) and $\tan\beta$ is the local slope gradient for estimating a hydraulic gradient. The computation of both a and $\tan\beta$ need to reflect impacts of local terrain on local drainage. Many of the existing flow direction algorithms for computing a use global parameters, which lead to unrealistic partitioning of flow. β is often approximated by slope gradient around the pixel. In fact, the downslope gradient of the pixel is a better approximation of β. This paper examines how TWI is impacted by a multiple flow routing algorithm adaptive to local terrain and the employment of maximum downslope gradient as β. The adaptive multiple flow routing algorithm partitions flow by altering the flow partition parameter based on local maximum downslope gradient. The proposed approach for computing TWI is quantitatively evaluated using four types of artificial terrains constructed as DEMs with a series of resolutions (1, 5, 10, 20, and 30 m), respectively. The result shows that the error of TWI computed using the proposed approach is generally lower than that of TWI by the widely used approach. The new approach was applied to a low-relief agricultural catchment (about 60 km^2) in the Nenjiang watershed, Northeastern China. The results of this application show that the distribution of TWI by the proposed approach reflects local terrain conditions better.

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Introduction

The concept of topographic wetness index (TWI) was first introduced by Beven and Kirkby (1979). TWI can quantify the effect of topography on runoff generation and serves as a physically-based index approximating the location of zones of surface saturation and the spatial distribution of soil water (Beven and Kirkby 1979; O'Loughlin 1986; Barling et al. 1994). In a catchment, areas having similar TWI value are assumed to have a similar hydrological response to rainfall when other environmental conditions (such as land cover, soil) are the same or can be treated as being the same. Compared with other compound topographic attributes (e.g. Stream Power Index), TWI is more widely used in many applications related directly to precision agriculture. Examples include:

- The use of TWI map as an indicator to the pattern of potential soil moisture on a field (especially over undulating farmlands) (Schmidt and Persson 2003).
- The inclusion of TWI together with primary topographic attributes (such as slope gradient, curvatures) as inputs for digital soil mapping to predict spatial distribution of both soil type and soil attribute at finer scale (e.g., Moore et al. 1993; Zhu et al. 2009).
- The use of TWI together with slope gradient, profile curvature and specific catchment area calculated from DEM with 1-m resolution for analyzing the spatial variability of corn yield (Marques da Silva and Alexandre 2005).
- TWI along with elevation, slope, apparent soil electrical conductivity, and digital soil maps used to develop autologistic model for delineating nitrogen management zones based on corn yield response to nitrogen fertilization (Kyveryga et al. 2008).
- TWI combined with stream power index, steepest slope angle and 9 other soil properties to make a principal component analysis and a fuzzy *k*-means classification for delineating potential management classes for precision agriculture (Vitharana et al. 2008).

The calculation of TWI is usually based on a gridded DEM and the value of TWI at a point is computed as follow:

$$\mathrm{TWI} = \ln(a/\tan\beta) \tag{1}$$

where a is the upslope contributing area per unit contour length (or Specific Catchment Area, SCA) and β is the local slope gradient for reflecting the local drainage potential. The value of TWI is influenced by the algorithms to calculate a and estimate $\tan\beta$ (Güntner et al. 2004). Computation of a is dependent on the flow direction algorithm used. Among the different flow direction algorithms, the Multiple Flow Direction (MFD) algorithms are getting more acceptances in computing a (Wolock and McCabe 1995; Pan et al. 2004). MFD assumes that flow from the current position could drain into more than one down-slope neighboring pixel (Quinn et al. 1991). Many of the existing MFD algorithms are based on the model proposed by Quinn et al. (1991):

$$d_i = \frac{(\tan\beta_i)^p \times L_i}{\sum_{j=1}^{8} (\tan\beta_j)^p \times L_j} \tag{2}$$

where d_i is the fraction of flow into the ith neighboring cell; β_i is the slope gradient of the ith neighboring cell; the exponent p is the flow partition exponent ($p > 0$); L_i is the "effective contour length" of pixel i. The value of L_i is 0.5 for downslope pixels in cardinal directions, 0.354 for downslope pixels in diagonal directions, and 0 for non-downslope neighboring pixels (Quinn et al. 1991). The global partition exponent p leads to unrealistic partitioning of flow (Qin et al. 2007). As a result, upslope contributing area and corresponding TWI would give unrealistic values. β in Eq. 1 is often approximated by the average slope gradient surrounding the central cell but that approximation is also improper because the drainage condition is influenced by the slope gradient around the area down from the central cell (Hjerdt et al. 2004; Güntner et al. 2004).

A new approach to calculating topographic wetness index

In this paper, we propose a new approach to calculating TWI. With this approach, a is calculated using a MFD algorithm (Qin et al., 2007) which is adaptive to local terrain conditions and β is approximated by the maximum downslope gradient, instead of the widely-used average local slope gradient.

An adaptive multiple-flow-direction algorithm (MFD-md)

Qin et al. (2007) proposed a flow partition function, which allows the partition of flow to be adaptive to the local terrain conditions. The new MFD method is

$$d_i = \frac{(\tan \beta_i)^{f(e)} \times L_i}{\sum_{j=1}^{8} (\tan \beta_j)^{f(e)} \times L_j} \tag{3}$$

where $f(e)$ is a function determining the flow partition exponent (p in Eq. 2) based on local topographic attribute e. Qin et al. (2007) selected maximum downslope gradient as e among many local topographic attributes because maximum downslope gradient can better reflect the local terrain conditions which are relevant to water movement on a terrain surface with less sensitivity to subtle variations in DEM. $f(e)$ is then defined as a function of maximum downslope gradient:

$$f(e) = 8.9 \times \min(e, 1) + 1.1 \tag{4}$$

where e is the maximum downslope gradient, $\min(e, 1)$ is the minimum between e and 1. The coefficient 8.9 and the constant 1.1 in Eq. 4 are set in such a way that $f(e)$ will be 1.1 for modeling the flow when the local terrain condition is flat as proposed by Freeman (1991) and will be 10 for modeling the flow when the local terrain is very steep as recommended by Quinn et al. (1995). Quantitative evaluation using artificial surfaces has shown that flow accumulation computed using MFD-md is more realistic than those computed by the widely used flow direction algorithms (Qin et al. 2007).

Maximum downslope gradient as β

β in the calculation of TWI is to model the local drainage potential. Hjerdt et al. (2004) argued that the downslope topography is an important factor for estimating hydraulic gradient. Among the topographic attributes related to soil water content of a catchment, many researches (Quinn et al. 1991; Güntner et al. 2004) have shown that some kind of local downslope gradient computed around the center cell and its downslope neighboring

Fig. 1 The mathematical models, the contour maps of artificial surfaces, the theoretical SCA and the ▶ theoretical TWI distributions of four typical mathematical surfaces: **a** ellipsoid; **b** inverse ellipsoid; **c** saddle; and **d** plane. The unit represented is meters

cell can quantify drainage of water better than the average local slope gradient at the cell. Therefore, we use maximum downslope gradient to approximate β.

Quantitative assessment

The most commonly used method for assessing error is to apply the algorithm to a real DEM. However, this assessment is dependent on the landscape condition of the application area and is hard to quantify (Zhou and Liu 2002). If the theoretical values of both slope gradient and SCA of artificial surfaces can be pre-determined by mathematical inference, TWI algorithms can be assessed based on the theoretical TWI values computed by the definition of TWI (as shown in Eq. 1). Efforts have been made to define the theoretical value of SCA of artificial surfaces in the context of quantitative assessment of grid-based flow routing algorithms (Qin et al. 2006). There are two methods with which artificial DEMs are used to assess the error of grid-based flow routing algorithms. One was developed by Zhou and Liu (2002) and the other by Pan et al. (2004). Both of them create artificial DEMs to simulate typical terrain conditions, such as planar, convergent and divergent. The theoretical SCA of each artificial DEM is also inferred. Zhou and Liu (2002)'s method included one more terrain type: the saddle surface representing the ridge area. The ellipsoid surface in Zhou and Liu (2002) is more similar to the practical convex slope than the cone surface in Pan et al. (2004). In this paper, we apply Zhou and Liu (2002)'s method to assess the proposed approach.

Methods and material

For assessing the proposed method, four types of artificial surfaces were constructed using mathematical models based on Zhou and Liu (2002), representing convex slopes (ellipsoid), concave slopes (inverse ellipsoid), ridges (saddle) and straight slopes (plane), respectively. Figure 1 shows an example of the mathematical models, the contour maps of the artificial surfaces, the theoretical SCA and the theoretical TWI inferred from the mathematical models. The details of computing SCA and slope gradient at any given point on a given mathematical surface are not discussed here and can be found in Zhou and Liu (2002).

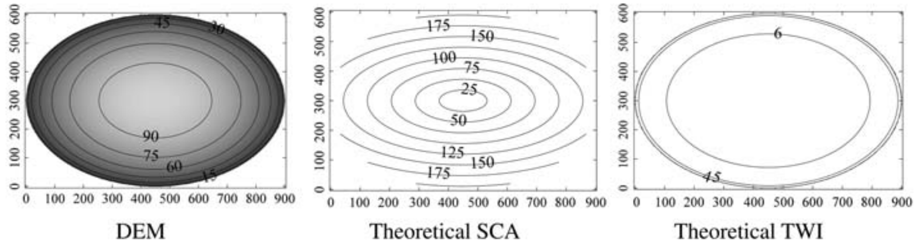
The error at each cell caused by a TWI algorithm can be computed:

$$E_i = \ln\left(\frac{SCA_i^t}{\tan \beta_i^t}\right) - \ln\left(\frac{SCA_i}{\tan \beta_i}\right) \tag{5}$$

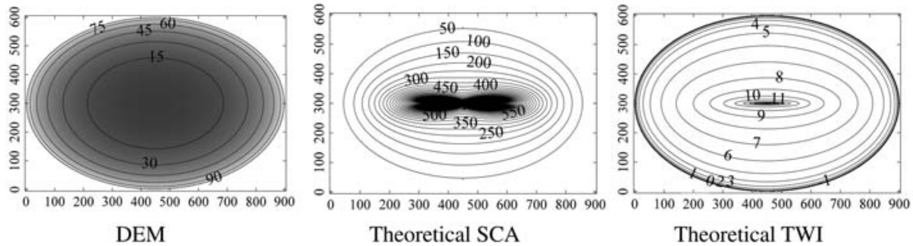
where E_i is the error of TWI value at ith cell; SCA_i^t and SCA_i are the theoretical and computed SCA values for the cell, respectively; β_i^t and β_i are the theoretical and computed slope gradient values for the cell, respectively. Thus the Root Mean Square Error (RMSE) can be computed for each TWI algorithm and can be used to assess the performance of different TWI algorithms.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (E_i)^2}{n}} \tag{6}$$

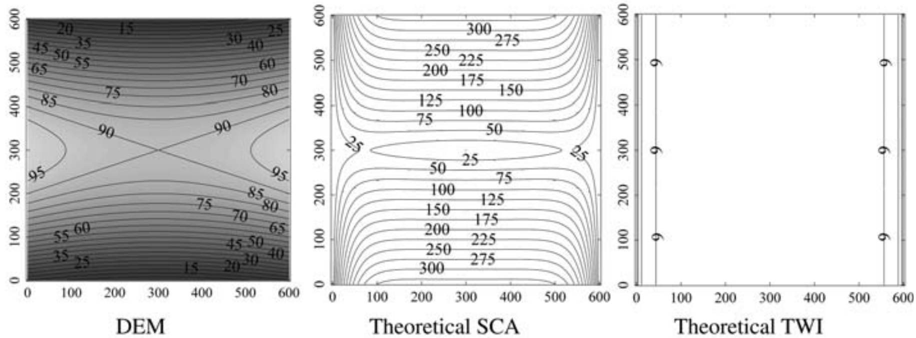
where n is the number of cells used for assessment.



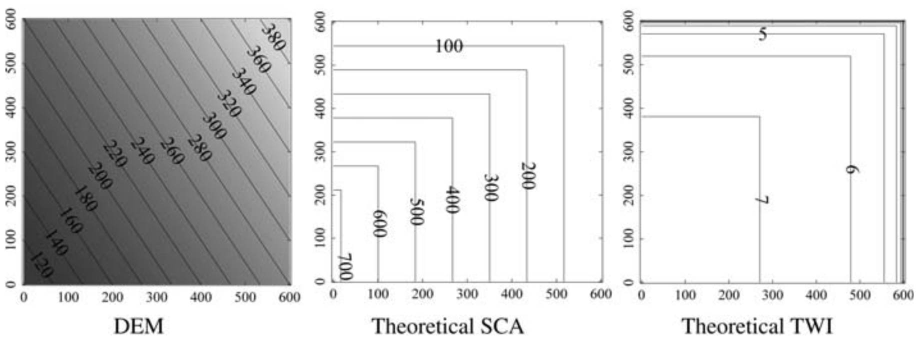
(a) ellipsoid: $\frac{(x-450)^2}{450^2}+\frac{(y-300)^2}{300^2}+\frac{z^2}{100^2}=1 \quad (z>0);\ 0<x<900; 0<y<600$



(b) inverse ellipsoid: $\frac{(x-450)^2}{450^2}+\frac{(y-300)^2}{300^2}+\frac{(z-100)^2}{100^2}=1 \quad (z<100); 0<x<900; 0<y<600$



(c) saddle: $\frac{(x-300)^2}{3^2}-\frac{(y-300)^2}{1^2}=\frac{z}{0.001};\ 0<x, y<600$



(d) plane: $z=0.3x-0.2y-100;\ 0<x, y<600$; slope=19.8º

We used the artificial DEMs with a series of resolutions (i.e., 1, 5, 10, 20, and 30 m) generated from the mathematical surfaces in Fig. 1 and the assessment method described above to quantitatively assess the proposed TWI approach and the effect of DEM resolution on the proposed TWI approach. For comparing the proposed algorithm with other approaches, we computed TWIs of artificial DEMs using the D8-based approach, the FD8-based approach, and the proposed approach, respectively. The D8-based approach computes TWI with a computed by O'Callaghan and Mark (1984)'s D8 (a representative Single Flow Direction algorithm with which all water from a pixel flows into one and only one neighboring pixel which has the lowest elevation) and slope gradient calculated from ArcInfo which uses a third order finite difference method (Burrough and McDonnell 1998). The FD8-based approach computes TWI with a computed by Quinn et al. (1991)'s FD8 (a representative MFD) and slope gradient calculated from ArcInfo. The series of resolutions selected in this study is finer than 30 m because we think the DEM resolution coarser than 30 m is not useful for precision agriculture applications.

Results of quantitative assessment

Table 1 lists the RMSE of TWI values. TWI values computed by the D8-based approach, the FD8-based approach and the proposed approach are named as TWI(D8), TWI(FD8) and TWI(MD), respectively. For almost all tested terrain conditions with a series of resolutions, TWI(MD) produces the lowest RMSE among the three approaches. Only under the inverse ellipsoid surface with resolution of 30 m, the RMSE from TWI(MD) is higher than that from TWI(D8) but still lower than that from TWI(FD8). The surface which the artificial inverse ellipsoid represents is similar to a depression in a real DEM. A depression in DEM could be real terrain component in the real world but it is often thought to be an error or interpolation artifact created during the DEM-generating process. In real applications, the depressions will commonly be removed by the DEM pre-processing algorithm (Gallant and Wilson 2000). In this sense, we can say that the new approach can produce the TWI with lower RMSE than current widely-used approaches under most real world situations.

For convex terrain conditions modeled by an ellipsoid surface, the RMSE from TWI(MD) increases constantly when the resolution of the artificial DEM is progressively coarsened from 1 to 30 m. This trend is similar to that from TWI(FD8) but the level of increase is much lower for TWI(MD) than for TWI(FD8). Contrarily, the RMSE from TWI(D8) decreases when the resolution of the artificial DEM is progressively coarsened from 1 to 30 m. This is related to the high sensitivity of the D8 algorithm used in TWI(D8) to subtle variation in the DEM. With the coarsening of DEM resolution, the subtle variation reduces and the computed TWI becomes stable.

For concave terrain conditions modeled by an inverse ellipsoid surface, the RMSE from TWI(MD) or TWI(FD8) is higher than under any of the other three terrain conditions modeled. The performances of TWI(MD), TWI(FD8) and TWI(D8) when the resolution gets coarser for inverse ellipsoid surface are similar to those under an ellipsoid surface. The levels of increase in RMSE for TWI(MD) and TWI(FD8) are very similar and both higher than those under any of the other three terrain conditions modeled. Meanwhile, the level of decrease in RMSE for TWI(D8) is lower than under the other three types of terrain conditions.

For terrain conditions modeled by saddle and plane surfaces, the RMSEs from TWI(MD) are stable when the resolution gets coarser. However, the RMSEs from

Table 1 The RMSE of TWI values for four mathematical surfaces with different DEM resolutions in Fig. 1 using the D8-based approach, the FD8-based approach and the new approach

	Ellipsoid					Inverse ellipsoid					Saddle					Plane				
	1 m	5 m	10 m	20 m	30 m	1 m	5 m	10 m	20 m	30 m	1 m	5 m	10 m	20 m	30 m	1 m	5 m	10 m	20 m	30 m
TWI(D8)	0.920	0.712	0.602	0.441	0.349	0.657	0.690	0.682	0.653	0.586	0.489	0.316	0.228	0.177	0.202	0.406	0.424	0.441	0.464	0.480
TWI(FD8)	0.091	0.112	0.141	0.198	0.250	0.212	0.444	0.569	0.671	0.863	0.088	0.114	0.128	0.148	0.154	0.169	0.201	0.214	0.232	0.243
TWI(MD)	0.088	0.110	0.122	0.149	0.141	0.170	0.370	0.479	0.578	0.786	0.045	0.055	0.056	0.051	0.045	0.086	0.078	0.076	0.079	0.085

TWI(FD8) increase constantly when the resolution of the artificial DEMs is progressively coarsened from 1 to 30 m.

Application

Study area and data

The proposed approach for computing TWI was applied to a small agricultural catchment (about 60 km^2) with low relief in the Nenjiang watershed in Northeastern China (Fig. 2). The relief is about 100 m and the average slope angle is about 2°. The grid size of DEM is 10 m. Current land use in this area is mainly corn and wheat farming.

Artificial pits and flat areas are problematic for TWI computation. It is necessary to pre-process the original DEM for pit removal and flat area alteration before TWI calculation. The DEM in this study area was pre-processed using an algorithm proposed by Planchon and Darboux (2001). Their algorithm can remove depressions and also modify flat areas with a user-specific, very gentle slope gradient, which is more suitable for TWI calculation than other DEM pre-processing algorithms (Qin et al. 2006). The specifics of this method are not included in this paper and interested readers are referred to Planchon and Darboux (2001) for details.

Discussion of the application result

The pre-processed DEM was then used to compute the Specific Catchment Area (a) using MFD-md and the maximum downslope gradient. The results are shown in Figs. 3 and 4. The computed a as shown in Fig. 3 shows a much smoother spatial distribution which corresponds well to the state of flow in the low relief areas. Qin et al. (2007) showed that a by MFD-md is more reasonable than that by Quinn et al. (1991).

TWI was thus calculated by maximum downslope gradient and a by MFD-md (Fig. 5a). Figure 5a shows that the value of TWI by the new approach changes smoothly from lower to higher when slope position transits from the top of slope to the bottom of slope.

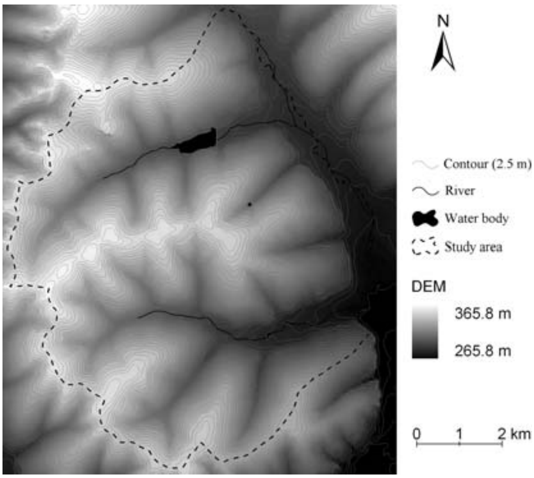


Fig. 2 Map of study area (contours with a 2.5 m interval of DEM)

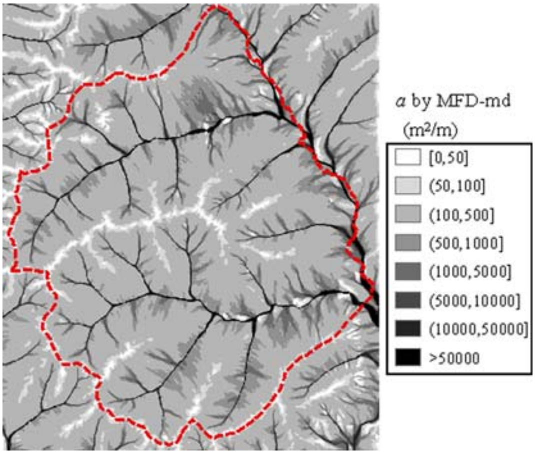


Fig. 3 Specific catchment area, *a*, by MFD-md

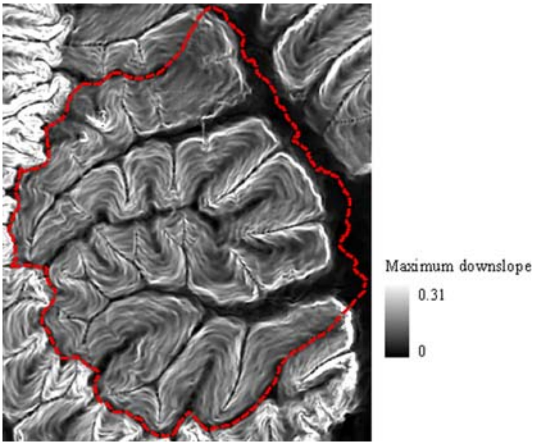


Fig. 4 Maximum downslope, $\tan\beta$

To compare the new approach with the FD8-based approach, the difference between TWI values by the new approach and TWI values by the FD8-based approach was computed (Fig. 5b). The negative value in Fig. 5b means that the TWI value by the new approach is smaller than that by the FD8-based approach. In general, the difference is related to the slope positions. Over the ridge and shoulder areas, TWI by the new approach has lower values than TWI by the FD8-based approach. This is understandable in that water over these areas is more likely to be drained. So the TWI by the new approach reflects this situation better. Over the backslope areas, the difference seems to be related to the curvature of land surface. The TWI values by the new approach are lower than the TWI values by the FD8-based approach over the convex part of the backslope. This again matches the reality that water over the divergent shape of these areas drains more quickly and the soil moisture in these areas should be lower. The TWI values by the new approach are almost the same as that by the FD8-based approach in the planar part of the backslope. In the concave part of the backslope, TWI by the new approach has higher values than TWI by the FD8-based approach because the convergent shape in this area is more likely to retain water thus should have better moisture conditions.

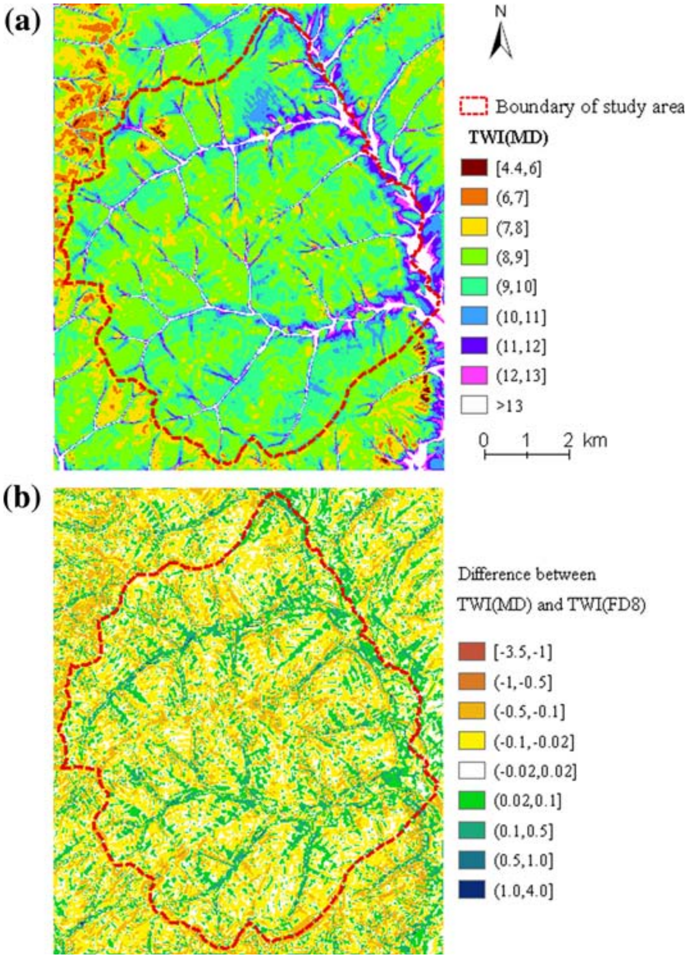


Fig. 5 **a** TWI by the new approach, and **b** the difference between TWIs by the new approach and the FD8-based approach. Negative value means that TWI value by the new approach was smaller than that by the FD8-based approach

Over the footslope area and the headwater area, TWI by the new approach has higher values than those by the FD8-based approach. This phenomenon is due to the concave and convergent conditions where the soil moisture is expected to be higher.

Over the wide and flat valleys, the TWI values are high and similar between the two methods. It should be noticed that TWI by the proposed approach shows a "braiding" pattern in flat and wide valley bottoms where the soil moisture in these areas should be equally wet and spatially smooth (Fig. 5a). This braiding pattern, which is also shown in TWI by the widely-used TWI approach, is an artifact related to the errors in the DEM over areas of low relief (Lindsay 2003; Burrough et al. 2000).

The comparison of the new TWI approach and widely-used TWI approaches when applied to a real DEM shows that the proposed approach is adaptive to terrain conditions and is advantageous in indicating the spatial distribution of soil moisture.

Conclusion

TWI is an important topographic index which can quantify the control of local topography over hydrological processes and indicates the spatial distribution of soil moisture and surface saturation. It is used in some aspects of precision agriculture. The value of TWI is influenced by both the algorithm to calculate upslope contributing area, a, and the approximation of slope gradient, β. This paper proposed a new TWI approach which combines an adaptive MFD algorithm (MFD-md) to calculate a with the maximum downslope gradient to approximate β. MFD-md algorithm is adaptive to local terrain conditions by altering the flow partition exponent based on a function of local maximum downslope gradient. So the flow accumulation from upslope can be modeled better than currently widely-used flow direction algorithms. And the maximum downslope gradient can reflect the local drainage potential better than does the local slope gradient which is widely used in current TWI approaches.

The proposed approach to calculating TWI was evaluated using four types of artificial DEMs with resolutions ranging from 1 to 30 m. The results of quantitative assessment show that TWI by the new approach generally has the lowest error in comparison with TWIs by the D8-based approach and the FD8-based approach. The proposed approach to calculating TWI was also applied in a small, low-relief agricultural catchment in North-eastern China. The results showed that the spatial distribution of TWI computed by the proposed approach is more adaptive to terrain conditions than that by the widely-used approaches.

The adaptability of the proposed TWI to local terrain conditions is a clear advantage to the existing approaches. However, it still needs additional work to show the level of difference between the proposed TWI and that by other methods in the context of precision agriculture applications. One of the ways to illustrate whether the difference is significant would be to conduct comparative studies between the proposed approach and the existing approaches in precision agriculture applications, such as prediction of detailed soil property maps, mapping of the pattern of potential soil moisture on a field and other TWI applications in precision agriculture as mentioned at the beginning of this paper.

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