Implementation of a multiple flow algorithm into the dynamic ecosystem model LPJ-GUESS

Jing Tang, Petter Pilesjö
Dept. of Physical Geography and Ecosystem Sciences
Lund University
Lund, Sweden
Jing.Tang@nateko.lu.se

Abdulghani Hasan
Department of Water Resources Engineering,
Duhok University
Duhok, Iraq

Abstract— **The dynamic ecosystem model LPJ-GUESS includes explicit representation of vegetation dynamics as well as soil biogeochemistry, and has been widely and successfully implemented in predicting vegetation biomass and carbon cycling at different scales. However, the water cycling for each grid cell in the model is only considering the movement between atmosphere, vegetation and soil, ignoring the lateral water movement between grid cells. A previous study has proposed a distributed scheme in LPJ-GUESS incorporating topographic indices to redistribute lateral water movement, and has demonstrated the impacts on ecological functioning and carbon cycling at the Stordalen catchment, northern Sweden. The topographic indices, extracted based on a Digital Elevation Model (DEM), were based on a single flow (SF) algorithm at 50 m resolution, restricting the flow movement to the downslope cell with maximum gradient. In this study we have incorporated the Triangular Form-based Multiple Flow algorithm (TFM) to redistribute lateral water in LPJ-GUESS and analyzed the influences and differences between the two flow algorithms on runoff prediction as well as carbon cycling estimations. The results indicate that the runoff estimated by the TFM algorithm is more realistic than the SF algorithm. Besides, the comparison with observed runoff data demonstrates the monthly runoff estimated using the SF algorithm tends to overestimate the runoff in May and June as well as in the lower flatter peatland region. For the TFM algorithm, the underestimated runoff during the growing season can be compensated by the decreased soil depth in the elevated area. Moreover, the implementation of the TFM algorithm results in a significant increase of the catchment mean value of vegetation uptake of carbon as well as net ecosystem exchange carbon. We conclude that the advanced multiple flow algorithm (TFM) with more accurate estimation of flow accumulation can improve the hydrological predictions in LPJ-GUESS. Meanwhile, the results have proved that the flow routing algorithms do influence the vegetation pattern estimations for the study area.**

INTRODUCTION

LPJ-GUESS is a dynamic ecosystem model, simulating vegetation dynamics as well as soil biogeochemistry [*Sitch et al.*, 2003; *Smith et al.*, 2001]. The model has been successfully implemented in predicting vegetation biomass, carbon balance, and carbon cycling at local and global scales [*Ahlström et al.*, 2012; *Hickler et al.*, 2004]. However, as an ecosystem model, the water cycling [*Gerten et al.*, 2004] is only limited to the interactions between atmosphere, plants and soil [*Wolf*, 2011]. There is no consideration of lateral water movement. A previous study proposed a distributed scheme by implementing topographic indices to add lateral water movement in LPJ-GUESS to conquer this limitation, and was renamed as LPJ-Distributed Hydrology (LPJ-DH) [*Tang et al.*, In Review]. The topographic indices, including drainage area (*DA*), flow direction (*Fdir*) and slope (*S*) are extracted from a Digital Elevation Model (DEM). Through applying *Fdir* to direct the generated runoff to downslope cells and using DA to organize the processing sequence, the new proposed LPJ-DH allows water flow between grid-cells, which is directly influencing the amount of vegetation available water as well as the runoff. The single flow algorithm (SF) [*O'Callaghan and Mark*, 1984] based on a gridded DEM was chosen for this application, assuming that surface flow only occurs in the steepest downslope direction.

The SF algorithm used in the previous study, in comparison to multiple flow algorithm (MF), restricts the divergence in estimating lateral flow paths [*Hasan et al.*, 2012; *Zhou et al.*, 2011] and therefore could influence the soil moisture and vegetation pattern estimations [*Guentner et al.*, 2004]. Many studies have suggested different methods of handling the multiple flows, and the majority work is based on gridded DEMs. However, due to the regularly spaced samplings on the continuous surface the gridded DEM could produce inconsistent flow paths [*Zhou et al.*, 2011], especially for coarser scales. To overcome the limitations of the gridded structure of the DEM, the newly-developed Triangular Form-based Multiple flow algorithm

(TFM) has been developed, based on the partition of grid cells in the DEM into triangular facets and redistribution of water proportionally to down-hill adjacent cells [*Pilesjö and Hasan*, 2013]. In this way, the algorithm can better take into consideration the continuity using Triangulated Irregular Network (TIN). Besides, the improvements of flow routing over flat cells from the TFM algorithm was also evaluated [*Hasan et al.*, 2012]. The TFM algorithm then showed the capability of producing the closest and consistent outcomes in relation to theoretical values of specific catchment area (SCA) compared to other methods.

In this paper the TFM algorithm is implemented to estimate topographic indices and adapt the distributed scheme in LPJ-DH to fulfill the divergence flow routing paths. Through comparing the hydrological and ecological estimations after coupling SF and TFM algorithm in LPJ-GUESS (named LPJ-DH-SF and LPJ-DH-TFM, respectively), we aim to answer the question how important the flow routing algorithms is in terms of modeled runoff and hydro-ecological variables at the catchment scale.

METHODS

The implementations of the SF and TFM algorithms are based on the same DEM, with the resolution of 50 m (to be consistent with the resolution of climate data). The main change in the LPJ-DH using the TFM algorithms is that the generated runoff can be directed to multiple downslope cells, instead of just one cell in the SF algorithm. So, the proportions of flow to downslope cells are added to each grid-cell as input attributes. Apart from that, in comparison with the single flow algorithm, the processing sequence of grid-cells for TFM cannot be uniquely determined by the values of DA alone, since some cells flowing to a downslope cell may have higher DA value. To overcome this problem, we found that implementing elevation (from higher to lower) together with DA values (from lower to higher) could uniquely decide the cell sequence for flow accumulation. A Matlab program was developed to test and make sure that the flow accumulation has been accomplished for the "upslope cells" before draining to "downslope cells".

The sub-surface water routing is also included, and its lateral water redistribution follows the same principles as the surface water part. For the subsurface part, only vertical water movement is considered for unsaturated soil, and the saturated subsurface runoff ($R_{sub}(r,c)$) is estimated by quasi three-dimensional flow developed by Wigmosta et al. [1994]:

$$R_{sub}(r,c) = \frac{K_S}{f}\left[\exp(-fz_{wt}(i,j)) - \exp(-fD(i,j))\right] * S(i,j) * w$$

K_S is the saturated hydraulic conductivity varying with different soil types. $z_{wt}(i,j)$ is the distance from the ground surface to the water table (positive downward) and $D(i,j)$ is the total soil depth. f is the decay coefficient of saturated conductivity with depth and w is the width of the flow. $S(i,j)$ is the slope of the cell. The parameter values of K_S and f are based on the literature.

The modeled runoff is compared with observed runoff measurements and evaluated by the relative root mean square error (RRMSE). The closer value of RRMSE to zero, the better is the model performance [*Stehr et al.*, 2008]. To reveal the different flow algorithms influences on carbon fluxes, the Mann-Whitney U test was used.

$$RRMSE = \sqrt{\frac{\sum_{i=1}^{n}(S_i - O_i)^2}{n}} * \frac{1}{\overline{O}}$$

STUDY AREA

Stordalen catchment

The Stodalen catchment is located in northern Sweden, about 9.5 km from the Abisko Research Station (ANS). The whole catchment covers 16 km^2 and consists of a mountainous area in the southern part, entering into the lower flat peatland area in the north (see Fig.1). The catchment hydrology has been reported by *Persson et al.* [2012] and *Ryden et al.* [1980] and water-related carbon fluxes measurements have been presented by *Olefeldt at al.* [2012] and *Lundin et al.* [2013]. For this study, measured daily runoff during the year 2007-2009 was provided by *Olefeldt et al.* [2012] in order to evaluate the model runoff estimations.

RESULTS

Drainage area

Presented in Fig.1, two different drainage patterns are estimated using the TFM (left) and the SF (right) algorithms. Through visual comparison, the TFM extracted drainage pattern shows smoother and more realistically looking spatial patterns than the SF estimated one. Additionally, the values of Ln(DA) from the SF algorithm are not smoothly increasing downhill, and the main drainage is more distinct.

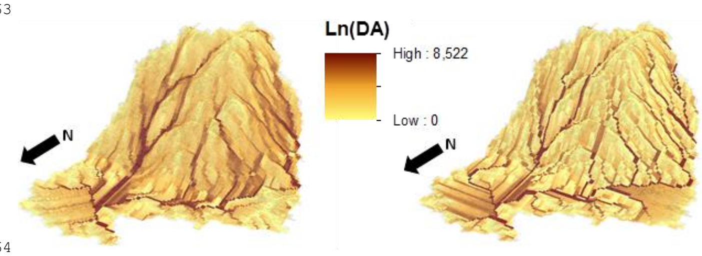

Figure 1. Map of Ln(DA) using the triangular form-based (left) and the single algorithm (right). For each grid-cell, the value 1 is added before calculating the natural logarithm. The map is draped on a digital elevation model (enhanced five times).

TABLE I. STATISTICS OF DRAINAGE AREA FROM TFM AND SF ALGORITHMS

Algorithms	*Variables*	*Mean*	*Standard variation*	*Skew*
SF	Drainage area(DA)	51.840	303.562	11.274
TFM	Drainage area(DA)	40.770	235.093	12.690

The results in Table 1 show that the TFM algorithm produces lower mean and variance values of DA and the higher and positive skew values indicate more cells with lower DA values when using the TFM algorithm. The allowances of flow divergence and consideration of consistency from the TFM algorithm reduce the DA average as well as the variances among cells.

Monthly runoff comparison

The daily runoff is summed up to get the monthly runoff, and the comparisons between observed and modeled runoff from LPJ-DH-SF and LPJ-DH-MF are presented in Fig. 2. The RRMSE values vary from point to point, but generally, the runoff peak from LPJ-DH-SF is higher than the LPJ-DH-MF, especially for the peatland cell A2. For the point A1, located at the catchment outlet, the LPJ-DH-SF produces lower RRMSE values, which capture the high runoff better in June during the observed years. For the point A2, the overestimation of runoff by LPJ-DH-SF is converse with the underestimation by LPJ-DH-MF during the summer period. For the point B2, with steeper terrain, both models are underestimating the runoff, but the LPJ-DH-SF shows values closer to the observed (RRMSE=4.14). For the relatively dry years (2008 and 2009), the runoff predictions at B2 have larger underestimation bias. For the outlet points A5 and A6, located in the comparatively flat region, both models show almost the same accuracy.

Going through the six measured points, for the LPJ-DH-MF the main discrepancy in runoff compared with observed data are the low runoff estimations in June. When the plants start to grow, there is more water supplying plants' photosynthesis and growth as well as soil evaporation, thus less water can route downslope. The distributed flow used in the TFM makes the available water to the main drainage network even less.

Carbon fluxes comparison

Due to lack of field data of spatially distributed biomass and carbon fluxes, the comparisons are based on the statistical comparison of models estimations over the whole catchment. The Mann Whitney U-tests indicate that the differences are significant for vegetation uptake carbon (VegCflux) and net ecosystem exchange (NEE) for the two models. The LPJ-DH-MF model has around 1.34% and 7.41% increase (more carbon uptake) in VegCflux and in NEE, compared with the LPJ-DH-SF outputs. There is no indication of significant difference of soil respired carbon (SoilCflux) between the two models. However, a distinctively higher soil released carbon can be found for the main drainage network cells from LPJ-DH-SF (see the whisker extend for SoilCflux in Fig. 3), which is not appearing in LPJ-DH-MF.

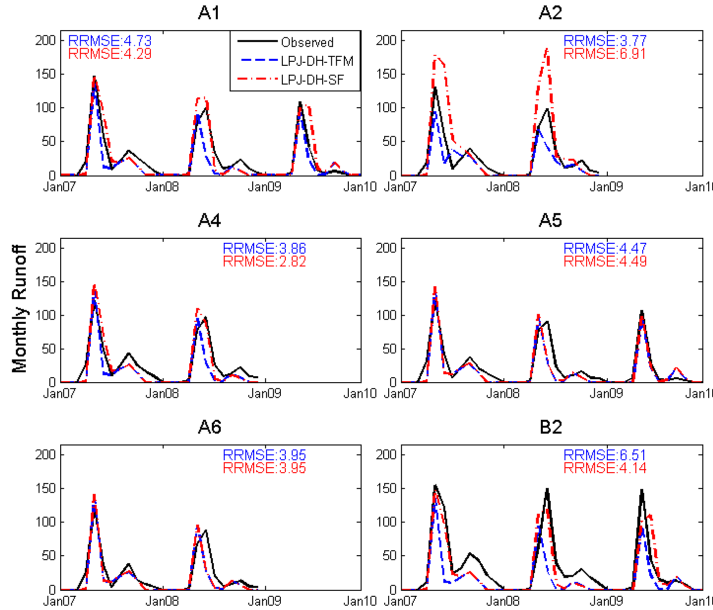

Figure 2. Point runoff comparisons between the modeled and the observed monthly runoff. There are no data for A2, A4 and A6 during the year 2009.

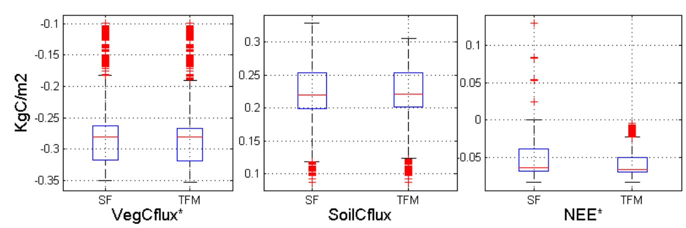

Figure 3. Catchment carbon fluxes diversity during the year 1981-2000. The asterisk (*) represents the statistical significance at the level of 0.05.

DISCUSSION AND CONCLUSION

In this study, the soil depth is set to 1.5 m, as the standard LPJ-GUESS depth, but in reality the soil is quite shallow with bare rocks in the southern mountainous area. The soil depth needs to be adjusted in forthcoming studies for the elevated area of the catchment. With reducing the soil depth, the runoff is expected to increase compared with the models outputs presented in this paper, but to what magnitude is unknown. The current results illustrate that the SF algorithm generally produces higher runoff values than the observed in May and June, with the exception of point B2. When reducing the soil depth in the southern elevated area, the runoff during the high-runoff season will become higher using the SF algorithm since the water is concentrated to the main flow paths. However, that could have less influence for the LPJ-DH-TFM due to the dispersion of water over the catchment and maybe compensate the underestimated runoff for LPJ-DH-TFM.

The allowance of flow divergence in the TFM makes the upslope area per unit contour length decreasing [*Wolock and McCabe Jr*, 1995], which means there is less water accumulating for each downslope neighboring cell. In other words, there are more cells that could receive water from upslope cells which results in significant changes in vegetation uptake carbon (total NPP) for LPJ-DH-MF. With larger catchment and water-limited area, the differences of flow routing on vegetation growth will be more pronounced.

It is novel to evaluate two different routing algorithms by implementing them into a process-based ecosystem model. In this way, both the climate conditions and vegetation dynamics are taken into the consideration. Comparing with other studies of utilizing statistical correlations between topographic wetness index (TWI) and vegetation pattern to evaluate different routing algorithms [*Kopecký and Čížková*, 2010; *Sorensen et al.*, 2006], our method is more accurate and could reveal more detailed flow algorithm differences/influences on hydrological estimations through the seasons. Besides, our method can avoid using TWI as a proxy for soil moisture conditions and can capture the effective contributing area over time. Nevertheless, with increased complexity of model structure, our method needs to be better calibrated before finally concluding which routing algorithm that is the best for different environments.

To summarize, the more advanced multiple flow algorithm (TFM), producing more accurate estimations of flow accumulation can improve the hydrological predictions in LPJ-GUESS. The comparisons of carbon fluxes outputs between LPJ-DH-SF and LPJ-DH-TFM have demonstrated that the flow routing algorithms do matter not only for hydrological variables, but also for ecological estimations, within the study area.

REFERENCES

[1] Ahlström, A., P. A. Miller, and B. Smith (2012), Too early to infer a global NPP decline since 2000, Geophys. Res. Lett., 39(15), L15403.

[2] Gerten, D., S. Schaphoff, U. Haberlandt, W. Lucht, and S. Sitch (2004), Terrestrial vegetation and water balance--hydrological evaluation of a dynamic global vegetation model, Journal of Hydrology, 286(1-4), 249-270.

[3] Guentner, A., J. Seibert, and S. Uhlenbrook (2004), Modeling spatial patterns of saturated areas; an evaluation of different terrain indices, Water Resources Research, 40(5).

[4] Hasan, A., P. Pilesjö, and A. Persson (2012), Drainage Area Estimation in Practice - how to tackle artifacts in real world data, paper presented at GIS Ostrava 2012-Surface models for geosciences, Ostrava, Czech Republic.

[5] Hickler, T., B. Smith, M. T. Sykes, M. B. Davis, S. Sugita, and K. Walker (2004), USING A GENERALIZED VEGETATION MODEL TO SIMULATE VEGETATION DYNAMICS IN NORTHEASTERN USA, Ecology, 85(2), 519-530.

[6] Kopecký, M., and Š. Čížková (2010), Using topographic wetness index in vegetation ecology: does the algorithm matter?, Applied Vegetation Science, 13(4), 450-459.

[7] Lundin, E. J., R. Giesler, A. Persson, M. S. Thompson, and J. Karlsson (2013), Integrating carbon emissions from lakes and streams in a subarctic catchment, Journal of Geophysical Research: Biogeosciences, n/a-n/a.

[8] O'Callaghan, J. F., and D. M. Mark (1984), The extraction of drainage networks from digital elevation data, Computer Vision, Graphics, & Image Processing, 28(3), 323-344.

[9] Olefeldt, D., N. Roulet, R. Giesler, and A. Persson (2012), Total waterborne carbon export and DOC composition from ten nested subarctic peatland catchments—importance of peatland cover, groundwater influence, and inter-annual variability of precipitation patterns, Hydrological Processes, n/a-n/a.

[10] Persson, A., A. Hasan, J. Tang, and P. Pilesjö (2012), Modelling Flow Routing in Permafrost Landscapes with TWI: An Evaluation against Site-Specific Wetness Measurements, Transactions in GIS, 16(5), 701-713.

[11] Pilesjö, P., and A. Hasan (2013), A Triangular Form-based Multiple Flow Algorithm to Estimate Overland flow Distribution and Accumulation on a Digital Elevation Model, Transactions in GIS.

[12] Rydén, B. E., L. Fors, and L. Kostov (1980), Physical Properties of the Tundra Soil-Water System at Stordalen, Abisko, Ecological Bulletins(30), 27-54.

[13] Sitch, S., et al. (2003), Evaluation of ecosystem dynamics, plant geography and terrestrial carbon cycling in the LPJ dynamic global vegetation model, Global Change Biology, 9(2), 161-185.

[14] Smith, B., I. C. Prentice, and M. T. Sykes (2001), Representation of vegetation dynamics in the modelling of terrestrial ecosystems: comparing two contrasting approaches within European climate space, Global Ecology and Biogeography, 10(6), 621-637.

[15] Sorensen, R., U. Zinko, and J. Seibert (2006), On the calculation of the topographic wetness index; evaluation of different methods based on field observations, Hydrology and Earth System Sciences (HESS), 10(1), 101-112.

[16] Stehr, A., P. Debels, F. Romero, and H. Alcayaga (2008), Hydrological modelling with SWAT under conditions of limited data availability: evaluation of results from a Chilean case study, Hydrological Sciences Journal, 53(3), 588-601.

[17] Tang, J., P. Pilesjö, P. Miller, A. Persson, Z. Yang, E. Hanna, and T. V. Challaghan (In Review), Incorporating topographic indices into dynamic ecosystem modeling using LPJ-GUESS, Ecohydrology.

[18] Wigmosta, M. S., L. W. Vail, and D. P. Lettenmaier (1994), A distributed hydrology-vegetation model for complex terrain, Water Resources Research, 30(6), 1665-1679.

[19] Wolf, A. (2011), Estimating the potential impact of vegetation on the water cycle requires accurate soil water parameter estimation, Ecological Modelling, 222(15), 2595-2605.

[20] Wolock, D. M., and G. J. McCabe Jr (1995), Comparison of single and multiple flow direction algorithms for computing topographic parameters in TOPMODEL, Water Resources Research, 31(5), 1315-1324.

[21] Zhou, Q., P. Pilesjö, and Y. Chen (2011), Estimating surface flow paths on a digital elevation model using a triangular facet network, Water Resour. Res., 47(7), W07522.