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Key Points:

- Subgrid variability in coarse-grid models, especially the presence of converging topography, affects all hydrological processes
- The subgrid redistribution of soil moisture by topographic downscaling can partially compensate for a coarser resolution
- Ignoring subgrid variability in soil moisture in coarse-grid hydrological models leads to strong overestimation of slope stability

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Numerical Analysis of the Effect of Subgrid Variability in a Physically Based Hydrological Model on Runoff, Soil Moisture, and Slope Stability

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Abstract In coarse resolution hydrological modeling, we face the problem of subgrid variability, the effects of which are difficult to express and are often hidden in the parameterization and calibration. We present a numerical experiment with the physically based hydrological model ParFlow-CLM with which we quantify the effect of subgrid heterogeneities in headwater catchments within the cell size typically used for regional hydrological applications. We simulate homogeneous domains and domains with subgrid heterogeneities in topography or soil thickness for two climates and soil types. The presence of side slope is the main error source, leading to large underestimation of runoff, and marginally also of evapotranspiration. The spatial distribution of soil saturation in the presence of subgrid variability in topography also leads to underestimation of landslide risk. Soil thickness is the second influential subgrid property, affecting soil moisture distribution and surface runoff formation. Results are consistent for the climates and the soil types considered. The topographic wetness index approach is tested as a way to downscale soil moisture simulations within the domain. Although this method is successful in reproducing some spatial variability and patterns, it fails when the coarse grid mean soil saturation is inaccurate or subgrid topography does not represent subsurface flow paths accurately. We conclude that ignoring subgrid variability in topography and soil thickness in coarse-scale hydrological models may lead locally to underestimation of runoff and slope instability. Users of such models should be aware of these biases and consider ways to include subgrid effects in coarse-scale hydrological predictions.

1. Introduction

The problem of spatial resolution of hydrological models has become more relevant as the number of regional or continental applications continues to increase (e.g., Melsen et al., 2016). Thanks also to recent improvements in computing capabilities, in particular parallel computing (e.g., Bierkens et al., 2015; Kollet et al., 2010; Kuffour et al., 2019; Kurtz et al., 2016), hydrological models have been employed over large areas to assess spatial and temporal patterns and trends in hydrological variables (e.g., Mastrotheodoros et al., 2019; Maxwell & Condon, 2016), simulate potential climate change scenarios and impacts (e.g., Booi, 2005), and forecast natural hazards for advanced warning systems (e.g., Krøgli et al., 2018).

The spatial resolution of these models is typically of 1 km or more, with some exceptions. There are two main reasons that one chooses to simulate at a coarser resolution: computational speed (e.g., for operational purposes or ensemble simulation) and lack of high-resolution inputs (e.g., soil classification). At the same time, reducing spatial resolution can lead to a loss of information (e.g., topographic smoothing) and to a lower accuracy in the representation of flow and other hydrological variables (e.g., Camporese et al., 2019; Sulis et al., 2011). Finally, certain modeling approaches might not be applicable at all spatial scales, for example, some hydrological processes described in physically based models at high resolutions may no longer be representative when integrated to coarser resolutions.

One way the issue of spatial resolution has been addressed in the literature is by comparing results of catchment simulations obtained with different resolutions (e.g., Bruneau et al., 1995; Etchevers et al., 2001; Shrestha et al., 2006; Sulis et al., 2011; Shrestha et al., 2018). These exercises provide a very useful estimate of the total errors associated with choosing a coarser resolution in the selected catchment. Nevertheless,

they do not allow quantifying the contribution associated with each input variable and/or parameter separately. In fact, as all spatially distributed inputs change with resolution, the quantitative contribution of each (e.g., topography, land cover, soil properties) and their interactions cannot be disentangled from the overall integrated response. This limitation can be overcome by carrying out sensitivity analysis, in which each input parameter is tested separately (e.g., Foster & M. Maxwell, 2019). An additional limitation of studies using real catchments is that the results are not easily generalized. The complex catchment response contains many feedback loops between local topography, soil, land surface, etc. that are catchment specific and resolution dependent. This is particularly true and relevant considering that the focus of most studies is mainly on the effect of spatial model resolution on streamflow, while other spatially variable components of the water cycle like soil moisture and evapotranspiration (ET), are usually not considered (Moglen & Hartman, 2001; Yang et al., 2001). Furthermore, most studies considered only the effects of horizontal resolution, for instance, by considering different Digital Elevation Models (Wolock & Price, 1994; Bruneau et al., 1995; Yang et al., 2001; Sulis et al., 2011) and land use maps (e.g., Zhao et al., 2009), without accounting for vertical resolution in multilayered soils.

Finally, the impact of resolution is often evaluated by large-scale simulations that typically employ models with some level of topographical simplifications (e.g., Bruneau et al., 1995; Wolock & Price, 1994; Yang et al., 2001) or conceptual models (e.g., HBV model, Booi, 2005), which may oversimplify physical process representation and underestimate the impacts of spatial resolution. This implies also that while streamflow, for which these models are usually calibrated and validated, might be reproduced accurately, the land surface exchanges and the subsurface flow dynamics could be misrepresented. This is a classic case of hydrologic models being right for the wrong reasons (Kirchner, 2006; Loague et al., 2006). Our conclusion from these past modeling studies is that detailed studies of hillslope hydrology are still needed to reveal complex process thresholds associated with soil layering, heterogeneity, subsurface flow convergence, and unsaturated storage dynamics, which are critical for correctly simulating runoff generation (e.g., Camporese et al., 2019; Mirus & Loague, 2013). If such nuances are neglected in coarse scale models, this is likely to have an impact especially in steeper terrain where rapid lateral redistribution of soil moisture affects water flow and slope stability. The aim of this paper is to provide a quantification of this effect on simple hypothetical topographies and to highlight its relevance for hillslope hydrology and slope stability.

We provide a systematic numerical analysis of the effect of subgrid heterogeneities in steep terrain using an integrated hydrological model. We choose a domain of the size of a typical coarse-resolution hydrological model (400×400 m) and compare a baseline simulation in which there is no subgrid heterogeneity within this domain to others in which subgrid heterogeneities are introduced. The chosen domain size is conservative, given that the typical resolutions in large-scale hydrological studies are on the order of 1 km^2 or more (e.g., Bierkens et al., 2015; Gudmundsson et al., 2012; Kauffeldt et al., 2016; Li et al., 2015). The focus is on headwater catchments, characterized by steep topography and small drainage areas, where groundwater flow is not dominant. Our main objectives are as follows: (1) we quantify and evaluate the effect of subgrid heterogeneity on a range of simulated hydrologic variables for different soil properties and climates. (2) We then focus on soil moisture subgrid heterogeneity and test a simple method for soil moisture redistribution in space based on the topographic index (e.g., Beven et al., 1995; Blöschl et al., 2009) as an option for soil moisture downscaling in coarse resolution models. (3) We analyze the potential impact of ignoring subgrid variability in soil moisture on slope stability computed with the infinite slope model, as this is an approach that has been suggested for operational landslide forecasting and warning systems (Schmidt et al., 2008; Wang et al., 2020).

2. Methods and Data

To understand how subgrid variability affects the different hydrological variables, we conduct a systematic analysis with 16 synthetic domains using the integrated hydrological model ParFlow-Common Land Model (ParFlow-CLM) and two different sets of meteorological forcing and two of soil properties, for a total of 64 simulations. Additionally, we use the output of the simulations to test the downscaling of soil saturation following the topographic wetness index approach and to assess the impact on slope stability. We introduce here the hydrological model, the domain configurations, and the boundary conditions (Section 2.1), the two sets of meteorological forcing and soil properties (Section 2.2), and then the methodology for the

Figure 1. (a) Conceptual workflow of the numerical experiments. The section in which the different components are introduced and described is indicated in the top left of each box. (b) Inputs of ParFlow-CLM, boundary conditions (BC), and water fluxes (surface and subsurface flow and evapotranspiration, ET). (c) Scheme of the two slopes: the main slope, in y -direction, constant in all simulations and the side slope, in x -direction, changing depending on the domain configuration.

downscaling of soil saturation (Section 2.3) and the assessment of slope stability (Section 2.4). The conceptual workflow is shown in Figure 1.

2.1. Hydrological Model and Synthetic Domains

The integrated land surface-subsurface model ParFlow-CLM (Kollet & Maxwell, 2008; Kuffour et al., 2019; Maxwell & Miller, 2005) is a physically based distributed hydrological model which solves the subsurface flow (3D Richard's equation) and overland flow (kinematic wave) simultaneously and is coupled with the CLM (Dai et al., 2003) interacts with ParFlow over the uppermost 10 soil layers and, given the soil moisture distribution obtained by ParFlow, calculates infiltration, evaporation, and root water uptake fluxes (water and energy budgets), feeding back to ParFlow the net water input to the soil.

Here, we apply ParFlow-CLM (PF) to study the effect of subgrid heterogeneities starting from a domain grid of size 400×400 m representative of a typical large-scale hydrological model, with four different subgrid geometries (Figure 2). All domains are discretized with a resolution of $20 \text{ m} \times 20 \text{ m} \times 0.2 \text{ m}$ cells, with 25 vertical soil layers. In the baseline simulation, the domain consists of one 5 m thick soil unit, with no heterogeneities within (top left, in Figure 2, no conv., soil only). The main slope gradient (in y -direction in Figures 1c and 2) is 11.31° (20%), for all of the domains, chosen as the 40th percentile of the gradient computed from the 200 m digital elevation model (DEM) for one of the two reference catchments (Napf, Switzerland). One of the variations we consider in the different domains is that of sloping terrain in the direction perpendicular to the main slope (x -direction or *side slope* in Figures 1c and 2). In the baseline domain, the

Figure 2. Setup of the different synthetic domains used for the numerical experiments. At the top left, one homogeneous domain (representative of the information content of a single cell in a large-scale hydrological model). From left to right, the side slope is incremented, creating v-shaped domains and a real slope. From top to bottom, the soil geometry is changed: one layer of soil, and one thin, thick, or depositional soil layer over bedrock. The red regions are modeled as soil and the blue ones as bedrock. The z-axis in the profile is exaggerated to facilitate the visualization.

side slope is flat (no conv.). Then we produced two v-shaped domains, by introducing symmetric side slopes with gradient 5.71° (10%, gentle conv.) and 21.80° (40%, steep conv.), respectively, the 20th and 40th percentile of the gradients computed from the 25 m DEM of Napf. And finally, we also generated a real slope profile, selecting a typical slope cross section from the 25 m DEM of the Napf catchment (real slope).

Additionally, we consider different soil geometries (in the vertical z-direction in Figure 2): one soil unit covering the entire depth (*soil only*), a 1 m soil unit (*thin soil*) or 4 m soil unit (*thick soil*), and a variable depth layer, where the soil layer increases in thickness approaching the center of the domain from the sides (*depositional soil*). The latter configuration represents a soil profile produced by soil formation and erosion along typical hillslopes (Roering, 2008). For all the configurations where the soil depth is smaller than 5 m, the remaining lower portion of the depth profile is modeled as bedrock (e.g., 1 m of bedrock below the 4 m of soil for the *thick soil* configuration or 4 m of bedrock below the 1 m of soil for the *thin soil* configuration). To make the different simulations comparable, we consider a homogeneous grassland vegetation cover for all of the domains.

For the downhill boundary, we impose a fix head boundary condition, 0.2 m below the bottom of the domain, while the lateral sides and the bottom of the domain are zero flux boundaries (as shown in Figure 1b). We choose these boundary conditions as representative of headwater catchments, where lateral groundwater contributions, such as in regional aquifer systems, are limited. While boundary conditions will affect simulated fluxes, keeping them the same in all simulations allows for objective comparisons between the different domain configurations.

2.2. Meteorological Forcing and Soil Properties

We choose two locations for the description of soil properties and meteorological forcing of ParFlow-CLM representative of two climates: a wet temperate climate in Napf, Switzerland (*wet temperate*), and a semiarid climate in Niwot Ridge, Colorado, USA (*semiarid*). For each of these sites, we select a Water Year (October–September) within the available data time frame as the one with landsliding activity in the proximity of the site, WY2014 (WY, October 2013–September 2014) for Napf and WY2013 for Niwot Ridge (October 2012–September 2013). Several studies focused on landsliding have been carried out both in the Napf region (e.g., Rickli & Graf, 2009; von Ruetten et al., 2014, 2011; Anagnostopoulos et al., 2015) and Colorado Front Range (e.g., Coe et al., 2014; Alvioli and Baum, 2016).

As far as climate is concerned, Napf is generally wetter, with a higher annual precipitation total (1,885 vs. 1,027 mm) as well as stronger hourly rainfall intensities (up to 30 vs. 10 mm/h), but generally milder, with a higher average temperature and a smaller range of fluctuations, with temperatures below 0°C only seldom occurring between November and March. In Niwot Ridge, temperature is below 0°C for most of the time between November and April, but the total shortwave radiation is higher than in Napf for the entire duration of the year and especially in winter, with a yearly total of 1.60 MWh/m^2 (1.14 MWh/m^2 in Napf). For both locations (climates), all the meteorological input required by ParFlow-CLM (see Figure 1b) is available at the hourly resolution.

Two sets of parameters are representative of the soils at each of the sites (Table 1), as reported by previous studies in the two areas. Napf soil is described as a sandy loam (Anagnostopoulos et al., 2015), while Niwot Ridge soil is a poorly sorted coarse sand with low fines content (Alvioli and Baum, 2016). The most notable difference in the parameterization of the two soils is in saturated hydraulic conductivity, which is a sensitive parameter for the hydrological model. For the Niwot Ridge soil (*high K*), it is one order of magnitude higher than in the Napf soil (*low K*). This results in much slower soil water fluxes in Napf. In all cases that

Table 1
Soil Parameters Used in ParFlow-CLM Simulations and in the Calculation of the Factor of Safety (FoS)

Parameter	Units	high K (CO)	low K (CH)
Hydraulic conductivity, K	m/h	0.10152	0.0152
Specific storage	1/m	0.2256	0.2256
Porosity	-	0.19	0.4
α (van Genuchten param.)	1/m	7.5	3.3
n (van Genuchten param.)	-	1.89	1.59
Residual water content	-	0.029	0.086
Saturation water content	-	0.19	0.4
Roughness (Manning's coefficient)	s/m ^{1/3}	0.02	0.02
Internal friction angle, ϕ	°	35	32
Cohesion, c	Pa	1500	2000
Saturated unit soil weight, γ	N/m ²	17,900	17,900

The parameters of the soil “high K (CO)” are representative of a region within the Front Range in Colorado, USA (Alvioli and Baum, 2016). The parameters of the soil “low K (CH)” are representative of the Napf region, in Switzerland (Anagnostopoulos et al., 2015). The bedrock is represented in the simulations with the same parameters as the corresponding soil, but 100 times smaller hydraulic conductivity.

have a soil unit thinner than the entire depth of the domain, to represent a strong hydraulic conductivity contrast with the underlying bedrock, we reduce K by a factor 100 in the bedrock unit, while all the other soil parameters are homogeneous with depth.

In the simulations, we store the hourly timeseries of the spatially distributed hydrological variables—ET, snow water equivalent, runoff—for every domain and the different combinations of soil properties and meteorological forcing. To remove the dependency from arbitrary initial conditions and reach hydrological equilibrium, we repeat the same year of meteorological forcing in a spin-up period until steady state is reached. We consider the spin-up successful when the change in storage over a water year is less than 0.01% of the total storage. Depending on the domain as well as the soil properties and the meteorological forcing, the number of repetitions required to reach steady state ranged between 3 and 23. All the results presented hereafter are obtained from the year following spin-up.

2.3. Downscaling of Soil Saturation

We use the Topographic Wetness Index (TWI) method (e.g., Beven et al., 1995) to redistribute (downscale) soil saturation in space. This method assumes that the local departure from average soil saturation conditions can be calculated from the local departure of the topographic wetness index $TWI = \ln\left(\frac{a}{\tan\theta}\right)$ from its spatial mean λ . The redistribution is applied to every soil column i in the domain (e.g., Schmidt et al., 2008):

$$S_{TWI,i}(t) = \bar{S}_{PF,noconv.}(t) + \frac{1}{fd_i} \left[\ln\left(\frac{a_i}{\tan\beta_i}\right) - \lambda \right] \quad (1)$$

where $S_{TWI,i}(t)$ is the TWI-redistributed local soil column saturation at time t , $\bar{S}_{PF,noconv.}(t)$ is the spatially averaged saturation simulated by ParFlow-CLM at time t calculated from the saturation field of the *no convergence* configuration, f is a scaling parameter (1/m), d_i is the local soil depth (m), a_i is the drainage area upstream of every soil column in the domain (m²), and β_i is the local slope angle (rad).

We redistribute soil saturation in space $S_{TWI,i}$ for all side slope geometries from the mean soil saturation for the simulated *no convergence* configuration in Equation 1 because this is the situation we would encounter if we ignored subgrid heterogeneity in topography in a coarse resolution model at the 400 × 400 m grid scale. The differences in redistributed $S_{TWI,i}$ and ParFlow-CLM simulated $S_{PF,i}$ for all side slope geometries give us the effect of subgrid heterogeneities and show the performance of the simple redistribution method by TWI compared to ParFlow-CLM.

From the distributed ParFlow-CLM saturation output, we compute the local saturation $S_{PF,i}$ by vertically averaging simulated saturation levels for all simulated soil layers in every soil column: either the top 5 layers, 1 m in the *thin soil* case, or top 20 layers, 4 m in the *thick soil* one. In this sense, the parameter f in Equation 1 is a scaling factor that accounts for the redistribution of soil water in unsaturated and saturated states in the soil with thickness z , and it does not describe transmissivity changes with depth as in the original definition of TWI (e.g., Sivapalan et al., 1987).

We estimate the scaling parameter f from Equation 1 by fitting the spread of the distributions of simulated soil saturation and the TWI, that is, we find f that equates the width of interquantile range of departures of soil saturation S_{PF} from its mean as estimated by ParFlow-CLM with the width of the interquantile range of the TWI departure from its mean:

$$1/f = \frac{\left(S_{PF,i}(t) - \overline{S_{PF}(t)}\right)_{0.8quantile} - \left(S_{PF,i}(t) - \overline{S_{PF}(t)}\right)_{0.2quantile}}{\left(TWI_i - \overline{TWI}\right)_{0.8quantile} - \left(TWI_i - \overline{TWI}\right)_{0.2quantile}} d_i \quad (2)$$

where $S_{PF,i}(t)$ is the value of vertically averaged saturation for each soil column i at time t and $\overline{S_{PF}(t)}$ its spatial average, TWI_i is the topographic wetness index for the soil column i , $\overline{TWI} = \lambda$ is the domain average, and d_i the soil depth (4m for the case considered). This step allows us to adjust the variability of saturation within the domain generated by the TWI to the one produced by ParFlow-CLM. We calculate the scaling factor f only using the TWI and ParFlow-CLM saturation values for the *thick soil* with *no convergence* setup, with *high K* soil and *semiarid* forcing, and we apply it to all the different domain setups.

We compare the mean saturation for each soil column as well as the linear correlation between the saturation field obtained from ParFlow-CLM and with TWI-redistribution to assess if and how much the TWI downscaling method improves the saturation estimates compared to the spatial mean, which is what would be available if subgrid heterogeneity within the domain was not considered.

2.4. Slope Stability Assessment

To illustrate the impact of ignoring subgrid variability beyond hydrological processes, we also estimate slope stability within the modeling domain as a function of soil water state. We choose this application because landslides tend to occur in headwater catchments at locations characterized by converging topographies. For this purpose, we use the common infinite slope approach (e.g., Baum et al., 2008; Iverson, 2000; Lu & Godt, 2008; Pack et al., 1998), assuming that the entire soil layer will fail along the main slope. To facilitate direct comparison between the simulated scenarios and avoid boundary effects, we calculate the Factor of Safety (FoS) using the pore pressure simulated at the center of the domain (center in x- and y-directions in Figure 2) at the base of the soil, which in most cases is at the soil-bedrock interface, if the soil unit covers the entire depth:

$$FoS(t) = \frac{c + [\gamma d - \gamma_w h] \cos^2 \beta \tan \phi}{\gamma d \sin \beta \cos \beta} \quad (3)$$

where h is the water pressure head (m), d is the soil depth (m), c is the soil cohesion (Pa), γ is the soil unit weight (N/m^2), γ_w is the specific weight of water (N/m^2), β is the slope angle (rad), and ϕ is the internal friction angle (rad). The soil depth depends on the soil geometry configurations in the domains. The slope is the same for all configurations (11.31°), as we assume failure to occur along the main slope. The pressure changes with time and is computed by ParFlow-CLM. All the other parameters are constant given the selected soil type (values summarized in Table 1).

3. Results

3.1. Effect of Subgrid Variability, Climate and Soil Properties on Hydrological Variables

We evaluate the effect of subgrid variability in topography and soil geometry (Figure 2) in terms of the resulting impacts on several key hydrologic fluxes and variables. These include total cumulative annual ET and cumulative annual surface runoff, considering only water leaving the domain as surface flow (Figure 3). We also evaluate the maximum depth of snow water equivalent (SWE) and its date, and the duration of snow-pack persistence (Figure 4).

Average annual ET shows some small differences among the soil geometry and subgrid topography configurations considered (Figure 3, upper panel). The *wet temperate* climate is characterized by higher annual precipitation and lower radiation inputs, compared to that of the *semiarid* climate. Higher soil saturation is reached in soil with lower hydraulic conductivity consistently in all simulations. The combination of climate (precipitation and radiation) and hydraulic conductivity can explain most of the differences in simulated ET. It is highest for soil characterized by lower hydraulic conductivity (*low K*) and *semiarid* forcing.

Figure 3. (a) Annual evapotranspiration and (b) runoff for all the different domain setups and combination of meteorological forcing (*semiarid* from Niwot Ridge, Colorado, or *wet temperate* from Napf, Switzerland).

The former increases water availability for evaporation, while the latter the energy input, both potentially leading to higher ET values. In higher hydraulic conductivity soil the differences between the two climates become smaller as water becomes limiting. Overall, ET is greater for the *semiarid* than the *wet temperate* climate for both soils.

Although soil properties and climate are controlling most of the trends in ET, subgrid variability in side slope and soil thickness also affect the water availability and in turn ET. Thinner soils (*thin soil* and *depositional soil*) lead to elevated saturation which increases soil water availability, therefore leading to elevated ET for all scenarios with thin soils. Additionally, for the *semiarid, low K* scenario with thinner soil geometries (*thin* and *depositional soil*), ET is higher for flat slopes (*no conv.*) than for those that have any form of side slope (*conv.*). In this case, the combination of thin soil and low hydraulic conductivity is the one that leads to slowest subsurface water flow and therefore highest soil moisture. For these cases, the absence of side slope and flow convergence toward the center of the domain favors ET, as water is more uniformly distributed over the domain, leaving a larger part of the domain close to field capacity.

All the different factors considered (climate, soil properties, soil geometry, and subgrid topography) have a notable impact on the annual surface runoff totals (Figure 3, lower panel). The introduction of any side

Figure 4. (a) Annual maximum Snow Water Equivalent (SWE), (b) date of maximum SWE, and (c) duration of snowpack for all the different domain setups and combination of meteorological forcing (*semiarid* from Niwot Ridge, Colorado or *wet temperate* from Napf, Switzerland).

Figure 5. An example of the timeseries of hourly (a) precipitation and (b) surface runoff for the setup with a thick soil unit with gentle convergence and all combinations of meteorological forcing (*semiarid* from Niwot Ridge, Colorado, or *wet temperate* from Napf, Switzerland) and soil properties (*low* and *high K*). The runoff plot has been cut at 5 mm/h to better observe variability at low flows, but peaks up to 21 mm/h were reached.

slope or flow convergence has the greatest impact on runoff. In general runoff is always increasing with side slope (in order of increasing runoff: *no convergence*, *gentle convergence*, *steep convergence*, and *real slope*), with greater differences for drier configurations (i.e., *high K* rather than *low K* soil and *semiarid* rather than *wet temperate* forcing). In some of the *no convergence* and *gentle convergence* cases, no surface runoff is generated throughout the entire simulated water year (e.g., *soil only* with *semiarid* forcing and *high K* soil). In general, as in the case of ET, thinner soils (*thin soil* and *depositional soil*) exhibit slightly higher runoff production than thicker soils (*soil only* and *thick soil*).

Finally, as expected, more water leaves the domain as surface runoff for the cases of *wet temperate* climate than for *semiarid* climate (higher precipitation and lower potential ET) and for lower hydraulic conductivity. Due to the small size of the domain considered, the runoff timeseries show a flashy intermittent behavior characterized by runoff peaks from the saturated fraction of the domain following intense rainfall (e.g., Figure 5). These responses are stronger (i.e., higher peaks) for wetter conditions either due to the setup (domain configuration, forcing, and soil properties) or the additional water input in the snowmelt season (Figure 5, March–April for *wet temperate* forcing and March–May for *semiarid* forcing).

Snow cover and snowmelt are important factors for soil moisture and runoff. The precipitation input is higher for the *wet temperate* than the *semiarid* forcing climate. On the other hand, in the latter, climate temperatures are generally lower and remain below 0°C for roughly 5 months. This results in lower melt rates, a much longer melting phase, and longer duration of the snowpack for the *semiarid* forcing than the *wet temperate* (Figure 4). In ParFlow-CLM, wetter soils are more conductive, which results in higher melting if the soil is warmer than 0°C, or lower if the soil is frozen. The soils in the *semiarid* climate are frozen for the entire duration of the snowpack, whereas in the *wet temperate* climate, although soil temperature constantly decreases during winter, it never reaches 0°C (Figure 6). The consequence is an opposite simulated behavior for the two climates: for the *semiarid* forcing it is the *low K* (generally wetter) soil that leads to higher insulation and therefore lower melt, longer duration of the snowpack, and highest SWE, while for the *wet temperate* forcing it is the *high K* (generally drier) soil that has the same effect. The same reasoning explains the comparison of thinner (generally wetter) and thicker soils (generally drier). The timing of the snow cover peak is slightly later for *semiarid* forcing than for the *wet temperate* forcing. For example, the

Figure 6. An example of the timeseries of hourly (a) Snow Water Equivalent (SWE), (b) temperature, and (c) soil moisture averaged in space within the first soil layer for the setup with one thick soil layer with gentle convergence and all combinations of meteorological forcing (*semiarid* from Niwot Ridge, Colorado or *wet temperate* from Napf, Switzerland) and soil properties (*low* and *high K*).

delay for the *semiarid* forcing with *low K*, is due to the lower melt and the second snow accumulation phase between April and May (Figure 6).

3.2. Downscaling of Soil Saturation

We use the topographic index approach to redistribute soil saturation from the spatial mean of the *no convergence* case, both for the *thin* and *thick soil* configurations. The results depend on the slope configuration considered as well as on the soil properties and climate, but in general, this computationally efficient downscaling method does reproduce the range of variability in soil moisture in space simulated by ParFlow-CLM reasonably well (Figure 7).

In the *no convergence* cases, for which the mean of the ParFlow-CLM saturation for that same domain configuration is used for the downscaling, the TWI downscaling method generates slightly higher values of saturation than ParFlow-CLM for the *high K* soils (*thick soil, high K, no conv.* and *thin soil, high K, no conv.* in Figure 7). This is because, in this flat topography, few cells have very high simulated saturation along the bottom boundary (identified as PF outliers in Figure 7) compared to the rest of the field, while the TWI index distributes saturation more gradually along the flow path, leading to a higher mean. This is particularly evident for the *thick soil, high K* cases with side slope, for which several high saturation outliers exist (gray crosses in Figure 7).

In all of the other configurations with side slope, the temporal mean of saturation is consistently overestimated with the TWI redistribution in space (in Figure 7 the boxplots for TWI are always shifted upwards). However, for those configurations, the errors in the estimation of local saturation are not only a consequence of the TWI index distribution, but also of the mean value that is downscaled ($\bar{S}_{PF, no conv.}(t)$ in Equation 1). In these configurations, the larger differences compared to the ParFlow-CLM saturation distributions are mostly due to differences in the average saturation. The presence of side slope generates runoff leading to smaller water storage in the soil

Figure 7. Boxplots of soil saturation obtained with the temporal mean of hourly values over one year of soil column (20×20 values) for the thick and thin soil configurations and both *high* and *low K* soils, with *semiarid* forcing. The blue boxplots are obtained with ParFlow-CLM saturation values (PF), the green redistributed with the Topographic Index method (TWI), and the red value is the mean spatial saturation of the flat domain ($\bar{S}_{PF, no conv.}$). The boxes extend between the 25th and 75th percentile, and the horizontal line indicates the median. Gray crosses represent outliers.

Figure 8. Scatterplot of Pearson correlation coefficient between ParFlow-CLM (PF) and TWI saturation fields against the median value of saturation estimated by ParFlow-CLM for the thin (left four plots) and thick (right four plots) soil geometries, *high* and *low K* (alternating in the columns), and *semiarid* and *wet temperate* forcing (alternating in the rows).

(lower domain saturation). While the TWI does reproduce the convergence of flow toward the center of the domain, it cannot compensate for the overestimation in mean saturation. Therefore, in cases in which the difference in the mean saturation for cases without and with convergence is large, then the error in estimated local TWI saturation is also large. This is particularly evident for the *steep conv.* and *real slope* cases with *high K* soil.

We also compare the actual values of saturation at the cell level simulated by ParFlow-CLM and redistributed by TWI across the entire domain by estimating their (linear) correlation and changes in time. The correlation coefficient is independent from the mean saturation used for the downscaling. We observe that the Pearson correlation coefficient is generally high (Figure 8), especially considering that without downscaling, mean saturation at the coarse grid scale would be used (value constant in space), which would result in correlation equal to zero. The cell-level correlation seems to increase with saturation in ParFlow-CLM simulations, that is, for all the generally wetter conditions: higher correlation (and saturation) for *low K* than *high K* soils, for *wet temperate* than *semiarid* forcing and for *thin* than *thick* soil units. As saturation increases, a larger number of soil columns becomes fully saturated and the TWI-redistribution affects a smaller part of the domain. Once the saturation reaches 1 and ParFlow-CLM generates saturated conditions over most of the domain, the TWI-redistribution fails and the correlation drops (visible especially for *thin* soils with *low K* in Figure 8). The same effect would be true for very low values of saturation, but these are never reached in these simulations with 1–4 m deep soil columns.

Particularly interesting are the cases with *real slope*. In fact, those have the lowest correlation coefficient between ParFlow-CLM and TWI-distributed soil saturation. This side slope profile highlights the biggest limitation of the TWI approach, which is driven by surface topography. For example, the TWI value for the small local depression almost at the center of the side slope profile (indicated by an arrow in Figure 9) is quite high due to the accumulated drainage area along this flow path and the small local slope. This creates a local high saturation value, which of course is much smaller in the saturation field generated by subsurface flow in ParFlow-CLM (Figure 9b). The opposite is true for the small ridge (to the left of the arrow in Figure 9), where the TWI estimated saturation is smaller than that of ParFlow-CLM due to the locally small drainage area. These microtopographic variations that affect TWI will exaggerate the extremes of TWI-redistributed saturation compared to real subsurface flow. While these are clear limitations of this downscaling methodology, it should again be stressed that the downscaled results (panel c in Figure 9) are

Figure 9. (a) The profile for the real slope domain configuration, snapshots of the saturation for the *thin soil, high K, real slope* configuration with semiarid forcing; (b) estimated by ParFlow-CLM; (c) following the TWI approach; and (d) the mean spatial saturation of the flat domain ($\bar{S}_{PF, noconv.}$), used for the TWI downscaling. The black arrow in the side slope profile indicates the critical cross section in which the TWI largely overestimates saturation.

certainly better than no redistribution (panel d in Figure 9), demonstrating the value of this computationally efficient additional step to account for subgrid variability.

3.3. Effect of Subgrid Variability on Slope Stability

All of the aspects we consider in the ParFlow-CLM simulations, that is, climate, soil properties, subgrid variability in soil geometries and side slopes, affect the amount and spatial redistribution of soil water within the domain and therefore pore water pressure head, which is the only dynamic component in the Factor of Safety calculations (Equation 3). Therefore, all the considerations previously made for the different hydrological fluxes in the presence of subgrid variability (Section 3.1) also apply for soil stability.

As expected, we find that overall the least stable cases (lowest FoS in the center of the domain) are those in which the domains are generally wetter: that is, the hydraulic conductivity (K) is lower, there is some concentration of flow (convergence/side slope), and/or the water input is higher and ET lower (*wet temperate* forcing rather than *semiarid* forcing). The strongest effect is that associated with soil parameters (Figure 10). For the majority of the cases considered, the soil column above the point of interest is basically constantly fully saturated and therefore the FoS is almost permanently at its lowest possible value.

It is interesting to focus on the few configurations for which some variability of the FoS can be observed over the year: the differences between the FoS values for the different topographies are very strong for thicker and more permeable soils (*soil only* and *thick soil*, with *high K* soil). This shows a clear trend of overestimation of stability (higher FoS) when the topography is smoothed partly (*gentle* vs. *steep convergence*) or completely (*no convergence* vs. *gentle* or *steep convergence*). The differences in the latter comparison are visible even for thinner soils (*thin* and *depositional soil* with *semiarid* forcing and *high K* soil).

An example of the timeseries of FoS together with precipitation and SWE is shown in Figure 11 for the *semiarid* climate and *high K* soil. For some configurations, the FoS is stable (at its minimum, corresponding to fully

saturated soil column) for the entire year. Nevertheless for the *no conv.* cases, as well as the thicker soils (*soil only* and barely noticeably also *thick soil*) with *gentle convergence* some variations over the year can be observed. The reduction in FoS is clearly related to the wetting of the soil by snowmelt (March–May) and rainfall (September). Here too, the convergent slopes produced consistently lower FoS than nonconvergent domains. This highlights the fact that neglecting subgrid variability in coarse scale hydrological models is likely to lead to underestimation of slope safety and therefore landslide risk. This is true even if in our chosen domain geometries the central cell never reached truly critical slope failure conditions $FoS = 1$.

4. Discussion

This work provides information on the potential errors associated with subgrid heterogeneities incurred when a regional hydrological model with coarse resolution is used to depict headwater hollows and catchments for the prediction of hydrological fluxes and water-related natural hazards, namely rapid runoff (debris flows/floods) and soil saturation leading to slope failure (landslides). It also provides insights on which of the possible sources of errors are more significant and whether they depend on the regional conditions (soil properties and climate). The results presented here highlight issues potentially affecting all large scale applications of hydrological models at coarse resolutions, especially those associated with natural hazard prediction. In particular, we show that in steep terrain there is an important role of hillslope-scale processes

Figure 10. Comparison of the Factor of Safety (FoS) ranges of values within 1 year of simulation. The results are shown for each domain configuration and combination of soil properties (*low* or *high K*) and climate (*semiarid* or *wet temperate*). The horizontal blue dashed lines indicate the lowest FoS that can be obtained in each domain assuming the entire soil column is saturated.

in conditioning the resulting subgrid fluxes (discharge, ET) and state variables (soil moisture, groundwater table, etc.) that would be incorrectly simulated for an individual cell of a coarse resolution model. Considering that these effects would be cumulative across a catchment, this work provides a warning for the calibration of coarse resolution models to integrated responses (e.g., river discharge) and potentially completely missing other important internal state variables (e.g., soil moisture, pore water pressure) that are critical for hazard assessment and land-atmosphere interactions (Gupta et al., 2008; Madsen, 2000).

We demonstrate some of the strongest effects of subgrid variability for the large differences between domains with only a main uniform slope and without side slope (*no convergence*) and those with some side slope indicating the importance of lateral surface and subsurface flow. This convergence of flow in space at the subgrid scale affects practically all components of the water balance, especially runoff, but also soil moisture and ET (Ghan et al., 1997; Kuo et al., 1999), with consequences for pore water pressure and slope stability. This is very important to take into account when designing regional models for the prediction of landslides (e.g., Krogli et al., 2018; Schmidt et al., 2008). In fact, while it has been previously shown that under certain conditions the timescale of vertical pore pressure propagation is far more rapid than lateral propagation (e.g., Iverson, 2000), which allows one dimensional event scale simulations, the results of continuous simulations in space and time here show that lateral flow becomes very important for the determination of realistic initial conditions for landsliding (e.g., Lanni et al., 2013; Mirus et al., 2007).

The results indicate that there is a nonlinear and nonsystematic influence of slope, hydraulic conductivity (soil properties), and soil depth in different climates on the subgrid variability in hydrology. For instance, the effect of hydraulic conductivity on the snowpack depends on the climate, with lower values favoring snowmelt in a *wet temperate* climate, while reducing it in a *semiarid* climate. The main conclusion that can be deduced from these simulations is that when using coarse resolution hydrological models, one should be aware that any concavity within the cells can lead locally to large underestimation of wetness and therefore

Figure 11. An example of the hourly timeseries of one meteorological forcing variable (precipitation) and the modeled Snow Water Equivalent (SWE), pore water pressure, and Factor of Safety (FoS). The properties of *high K* soil are used and semiarid climate (Niwot Ridge, Colorado). Here, the steep and gentle convergence scenarios are indistinguishable, and thus for clarity, only the steeply convergent scenario is shown.

pore water pressure and runoff. While it is clear that soil properties and climate will affect hydrological fluxes at the coarse grid scale, the consistent differences due to subgrid variability in soil and slope, for example, between no convergence and gentle/steep converge cases, with the latter being generally wetter locally (i.e., highest ET, higher runoff, and lower FoS), are less intuitive.

This nonlinear and nonsystematic influence is also confirmed by the results of the downscaling experiment in which we test a computationally inexpensive TWI downscaling method to reproduce ParFlow-CLM simulations of soil saturation. We are generally able to reproduce the spatial variability generated by ParFlow-CLM, as the range of variability is comparable and the correlation coefficient relatively high. Most of the errors in the estimation of local saturation are associated with the mean saturation value used for the downscaling, which is once again due to the large differences between the setups with and without side slope. The conclusion is that, in an operational setting with a resolution of 400 m, smoothing local topography would lead to a local under- or overestimation of the saturation (here mostly underestimation), which cannot be improved by the downscaling. It is likely these problems would affect more complex downscaling techniques (e.g., Ajami & Sharma, 2018) as well.

The downscaling results for the *real slope* setup also illustrate another limitation of the TWI downscaling approach that fails to reproduce the correct saturation in cases where subsurface flow is not driven by surface subgrid topography. This is an important limitation that might be relevant when strongly convergent and rough topographies are considered; such would typically be more complex than the v-shaped domains used here and more similar to the *real slope* setup, which indeed is based on an actual DEM cross section.

The continuous simulations of FoS values show that situations critical for landsliding (here low FoS) develop in time and space as a consequence of intense/prolonged precipitation (e.g., September in Figure 11), but also during and right after periods of rapid snowmelt (March–May in Figure 11). This is consistent with the common knowledge that antecedent wetness plays a significant role in the predisposition of hillslopes to landsliding (e.g., Bogaard & Greco, 2018; Crozier, 1999). For all the different cases set up here for this analysis, the minimum value is still well above the typical $\text{FoS} = 1$ threshold, which would suggest that for those configurations failure conditions will not be reached.

Finally, it should be stressed that the results shown here focus on only some of the issues associated with model resolution. In fact, typically the resolution of inputs and parameters also corresponds to the computational resolution, which is $20\text{ m} \times 20\text{ m} \times 0.2\text{ m}$ for all the different cases. So while we use the *soil only, no convergence* setup as representative of a coarse resolution model because it is homogeneous at subgrid scale, further errors are expected due to the fact that the chosen resolution of the model may also introduce artifacts into the analysis. Here, the focus was on the impact of subgrid heterogeneity, so we purposely considered all different domains with the same resolution. Thus, while it does not remove completely numerical effects associated with solving partial differential equations with a finite difference scheme, it allows us to carry out intercomparisons independent from resolution effects. Nevertheless, in the case of a large-scale hydrological model application to a real catchment, numerical effects could impact the results and interplay with the effect of subgrid heterogeneities. Additionally, the issue of heterogeneities in the forcing is not addressed in our experiments. While some of the meteorological inputs are expected to be relatively homogeneous over such a small domain, such as precipitation, others could vary even over short distances, such as wind, or also be affected by the exposure and presence of side slopes, such as radiation. Vegetation is a further element in the analysis that is considered homogeneous, but it too could affect the redistribution of soil moisture within the domain by differential root water uptake when spatially variable.

5. Conclusion

We carry out numerical investigations with ParFlow-CLM to quantify and explain the effect of subgrid heterogeneities within one hypothetical cell of a coarse resolution hydrological model. We consider subgrid soil geometry and topography, with different combinations of realistic soil properties and meteorological forcing. Our main findings are:

1. Trends in ET, snow dynamics, and runoff are most sensitive to soil properties and climate.
2. Large underestimation of runoff, over/underestimation of ET, locally over/underestimation of soil saturation, and overall overestimation of water storage in the soil are obtained when subgrid variability in topography is smoothed. These are consequences of removing the side slope and therefore the lateral flow convergence.
3. Soil thickness has a lesser impact on the simulated hydrological variables than the topography, but overestimation of soil depth will result in underestimation of runoff and ET, consistently for all climates and soil types.
4. The topographic wetness index method can reproduce the patterns simulated by ParFlow-CLM well as it introduces some subgrid spatial variability in the soil saturation estimate. However, it relies heavily on the mean saturation used for the downscaling, which is overestimated when the converging topography is smoothed. Furthermore, it fails when topography is not representative of subsurface flow paths.
5. The effects of subgrid variability on hydrological processes in turn influence slope stability, here computed by the infinite slope model. Here too, side sloping is found to be a most important factor, consistently leading to lower FoS estimates than nonconvergent domains for all climates and soil property combinations. The second important aspect is that of soil thickness. While generally thinner soils are less stable because they are easier to saturate, the maximum pore water pressure they can develop (soil column fully saturated) might not be enough to generate very low FoS values (slope failure).

The findings above are derived from a combination of subgrid topographies (main slopes and side slopes) for two typical soil types and climates. We also did not consider subgrid heterogeneities in vegetation and forcing, which could also impact the redistribution of moisture within the domain, and the computational resolution, which typically changes with the spatial resolution. While subgrid heterogeneities in lithology are unlikely at the scale considered, those in soil properties and vegetation would add further variability in space, require spatial data on soils that are currently unavailable and models that simulate ecohydrological plant water use. Despite these limitations, we are convinced that this numerical analysis allows us to generally conclude that in coarse scale hydrological models that ignore subgrid variability in topography and soil thickness, hydrological processes like runoff, soil saturation redistribution, and consequently slope instability can be grossly underestimated. Users of such models should be aware of these biases for which post-processing can only partially compensate (e.g., TWI downscaling), and consider ways to include subgrid effects in coarse scale hydrological predictions.

Data Availability Statement

The meteorological data from Napf were provided by the Swiss Federal Office of Meteorology and Climatology MeteoSwiss (available upon request at <https://gate.meteoswiss.ch/idaweb/>, last accessed 20 September 2018) and from Niwot Ridge by AmeriFlux (available at <https://ameriflux.lbl.gov/sites/siteinfo/US-NR1>, last accessed 08 March 2018). ParFlow-CLM version 3.3.0 was used in this research and downloaded from <https://github.com/parflow> (downloaded on 31 January 2018).

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