



Large-area land surface simulations in heterogeneous terrain driven by global data sets: application to mountain permafrost

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Abstract. Numerical simulations of land surface processes are important in order to perform landscape-scale assessments of earth systems. This task is problematic in complex terrain due to (i) high-resolution grids required to capture strong lateral variability, and (ii) lack of meteorological forcing data where they are required. In this study we test a topography and climate processor, which is designed for use with large-area land surface simulation, in complex and remote terrain. The scheme is driven entirely by globally available data sets. We simulate air temperature, ground surface temperature and snow depth and test the model with a large network of measurements in the Swiss Alps. We obtain root-mean-squared error (RMSE) values of 0.64 °C for air temperature, 0.67–1.34 °C for non-bedrock ground surface temperature, and 44.5 mm for snow depth, which is likely affected by poor input precipitation field. Due to this we trial a simple winter precipitation correction method based on melt dates of the snowpack. We present a test application of the scheme in the context of simulating mountain permafrost. The scheme produces a permafrost estimate of 2000 km², which compares well to published estimates. We suggest that this scheme represents a useful step in application of numerical models over large areas in heterogeneous terrain.

past and future states, an essential step for change detection of (near-)surface conditions (Eitzelmüller, 2013). Numerical approaches may also provide the means to simulate land surface variables where there are insufficient data for statistical method,s e.g. remote areas or future periods.

Landscapes that are heterogeneous in terms of e.g. topography, vegetation or redistribution of snow (e.g. Smith and Riseborough, 2002; Liston and Haehnel, 2007) provide a great challenge in this respect, as surface and subsurface conditions may vary on various, and often short, length scales, creating highly spatially differentiated surface–atmosphere interactions. This poses, in particular, a challenge to large-area simulations, which can be summarised as follows: (1) high-resolution grids are required to capture surface heterogeneity, which is often numerically prohibitive over large areas, and efficient methods are therefore required to make this task scalable; (2) there is often a lack of a representative forcing at the site or scale that it is required, particularly in remote regions.

Recent efforts in this respect include spatially explicit or distributed simulations; e.g. Jafarov et al. (2012) and Westermann et al. (2013) produced a transient run of the ground thermal state in Alaska to assess permafrost dynamics under IPCC change scenarios. Another meso-scale modelling effort, that of Gislén et al. (2013), provides an equilibrium model of permafrost distribution in Norway at a spatial resolution of 1 km². While representing major steps in application of numerical models over large areas, the grid resolution of 1–2 km is too coarse to simulate relevant spatial differentiation on fine scales, particularly under heterogeneous terrain. At site scales several studies have applied numerical models to investigate the ground thermal regime at specific

1 Introduction

Numerical simulation is an increasingly important tool for assessment of the energy and mass balance at the earth's surface for many fields of research and application (e.g. Wood et al., 2011; Barnett et al., 2005; Gruber, 2012). In addition, numerical methods allow for transient assessment of

permafrost sites (Scherler et al., 2010, 2014); however, in a few studies downscaled climate data have been used to force such a model (e.g. Marmy et al., 2013).

In global climate models, a spatially detailed representation of the sub-grid land surface still remains somewhat behind the implementation of the atmosphere, yet is recognised to be key in accurately simulating feedbacks to the atmosphere (Pitman, 2003), e.g. surface albedo–atmosphere exchanges in the energy balance (Betts, 2009). For example, land surface heterogeneity is often represented in tiled approaches (Koster and Suarez, 1992), where surface types are represented by a limited number of surface types (or even a single one). Energy and mass balance is then computed independently, and finally aggregated at grid level. Here too, methods capable of representing fine-scale land surface heterogeneity efficiently could be useful. Finally, methods exist (e.g. SAFRAN-Crocus scheme; Durand et al., 1993, 1999) which classify topography according to fixed classes based on terrain parameters and enable application of numerical models over large areas in a semi-distributed fashion.

Gubler et al. (2011) have shown that fine-scale variability of surface processes can be high in complex terrain – e.g. variation in soil moisture, ground cover and local shading – can cause differences of as much as 3 °C mean annual ground surface temperature (MAGST) within a 10 m × 10 m grid. This underscores the importance of scale-appropriate evaluation of models. There are many studies in the literature where models operating on grids of 10s–100s or, in extreme cases, 1000s of metres are evaluated by point-scale measurements, and this is known to pose a serious challenges to model evaluation (Randall et al., 2003; Li, 2005). However, methods that provide simulation results over large areas capable of exploiting distributed site-scale ground truth are rare.

In previous papers (Fiddes and Gruber, 2012, 2014), methods have been developed and tested which enable (i) physically based land surface models (LSMs) to be applied over large areas using a sub-grid scheme that samples land surface heterogeneity and (ii) a method that scales gridded climate data necessary to drive an LSM to the sub-grid using atmospheric profiles. The philosophy behind these approaches is to develop methods that depend only on globally available data sets to derive high-quality local results in heterogeneous and/or remote regions.

The main aim of this study is to establish this combined method as a proof of concept and perform an initial evaluation of its performance in the context of the ground thermal regime and specifically permafrost occurrence in the European Alps, as a test case. That said, the aim is not to provide a best-possible result for e.g. permafrost (as the example subject of this study) but to provide a demonstration of this method using simple data sets. It is well known that precipitation bias is a common problem when using climate model or reanalysis data (e.g. Dai, 2006; Boberg et al., 2008) and a key driver of the energy and mass balance at the land surface.

Therefore, an additional aim is to explore a simple method that may be useful in addressing precipitation bias using the parameter melt date (MD) of the snowpack. Specifically this paper will

1. conduct a test application of the combined schemes together with the LSM GEOTop (Endrizzi et al., 2014) to derive land surface/near-surface variables air temperature (TAIR), ground surface temperature (GST) and snow depth (SD) over a large area of the European Alps at a resolution of 30 m, and additionally a derived permafrost estimate;
2. evaluate the performance of the combined schemes against a large network of TAIR, GST and SD measurements in the Swiss Alps;
3. demonstrate a simple bias correction method for the precipitation field;
4. interpret results together with uncertainties in the model chain.

2 Methods

The model chain used in this study uses two previously described methods, (i) TopoSUB (Fiddes and Gruber, 2012, hereafter FG2012) and (ii) TopoSCALE (Fiddes and Gruber, 2014, hereafter FG2013), together with a numerical LSM, GEOTop (Endrizzi et al., 2014). A brief synopsis of the tools used is given here to enable full understanding of the current study, but for further details and results of testing of these tools please see the respective publications.

2.1 TopoSUB

TopoSUB is a scheme which samples land surface heterogeneity at high resolution (here, 30 m). Input predictors describing relevant dimensions of variability are clustered with a *K*-means algorithm to reduce computational units in a given simulation domain (here, 0.75° × 0.75°). A 1-D LSM is then applied to each sample. For example, in FG2012 we show that reduction of a domain from 10⁶ pixels to 258 samples yields comparable results to a full distributed 2-D baseline simulation. The main outcome is that the computational load is effectively reduced by a factor of 10⁴, with an acceptable reduction in the quality of results. The scheme transfers model results to high-resolution pixels by membership functions (crisp or fuzzy) for a spatialised mapping of simulation results or statistical descriptions of the sub-grid domain. Additionally, we have an optional informed-scaling training routine, which regresses model results against input predictors after a training run in order to adjust the weighting of each input according to its significance; in doing so, it improves the quality of the final result. Limitations to this fundamentally 1-D approach include the fact that lateral mass

and energy transfers can only be parameterised, not modelled explicitly. This approach allows for (1) modelling of processes at fine grid resolutions, (2) efficient statistical descriptions of sub-grid behaviour, (3) efficient aggregation of simulated variables to coarse grids and (4) comparing results and ground truth derived from similar scales.

2.2 TopoSCALE

TopoSCALE is a scheme which provides forcing to the LSM at fine scale using gridded climate data sets. It works on the assumption that vertical gradients are often more important than horizontal gradients in complex topography. Climate data sets are employed as they provide consistent fields required for LSM simulation in 3-D, therefore providing a detailed description of the atmospheric profile. In addition, they provide data with global coverage and so enable simulation in remote, data-poor regions. Finally, they provide the possibility of simulating future conditions. The basic principles of the scheme are as follows: (1) interpolate data available on pressure levels air temperature (TAIR), relative humidity (RH), wind speed (Ws) and wind direction (Wd) vertically above and below the target site to provide a scaling according to atmospheric conditions at each model timestep; (2) downwelling longwave radiation (LWin) is scaled according to TAIR, RH and sky emissivity; (3) topographic correction is made to downwelling radiation fields (SWin/LWin); and (4) lapse rate with elevation is applied to precipitation, P (optional disaggregation scheme based on climatology for site simulation only as this is spatially explicit). The final output is the time series of meteorological variables required to drive a numerical model at 3 h timestep. It is a flexible scheme that can be used to supply inputs to models in 1-D/2-D or lumped configurations. The scheme has been shown in FG2013 to improve the scaling of driving daily fields compared to reference methods such as fixed lapse rates.

2.3 Land surface model

The LSM used in this study, GEOTop, is a physically based model originally developed for hydrological research. It should be noted that this model is not an LSM in the conventional sense (e.g. Mosaic, CLM, NOAH; Koster and Suarez, 1992; Dai et al., 2003), as it has not been designed to feed back to the atmosphere. In addition this model has not been designed for global or hemispheric application. However, it couples the ground heat and water budgets, represents the energy exchange with the atmosphere, has a multilayer snowpack and represents the water and energy budget of the snow cover. GEOTop simulates the temporal evolution of the snow depth and its effect on ground temperature. It solves the heat conduction equation in one dimension and the Richards equation for water transport in one or three dimensions, describing water infiltration in the ground as well as freezing and thawing processes in the ground. We have used the ther-

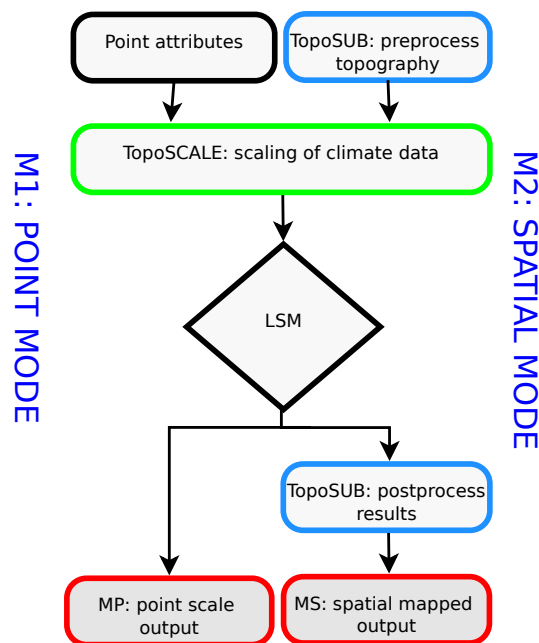


Figure 1. Overview of how the model chain of TopoSUB, TopoSCALE and LSM operate together. Two main modes of operation, (MP) point and (MS) spatial, are shown.

mal conductivity parameterisation given by Cosenza et al. (2003). It provides higher conductivities than Calonne et al. (2011), who show their parameterisation to be preferable to that of Sturm and Benson (1997), which provides rather low estimates. For densities below about 300 kg m^{-3} , the results of Löwe et al. (2013) are also higher than Calonne et al. (2011). We did not investigate in detail the effects of different parameterisations on soil surface temperature. Given the other uncertainties discussed in this paper, we do not expect it to be significant. GEOTop is therefore a suitable tool to model permafrost relevant variables such as snow and ground temperatures both at the surface and at depth. It can be applied in high mountain regions and allows accounting for topographic and other environmental variability. Further information is given by Bertoldi et al. (2006), Rigon et al. (2006), Endrizzi (2007) and Dall’Amico et al. (2011). Further details specifically relevant to this study are given in Sect. 3. A full description of the model is given in Endrizzi et al. (2014), and a description of model uncertainty and sensitivity is given by Gubler et al. (2013).

2.4 Model chain and modes

The model chain can be employed in two main configurations: point mode (MP) and spatial mode (MS) (Fig. 1). MS requires TopoSUB and TopoSCALE, while MP requires only TopoSCALE. In terms of output, MP simulates point-scale results, whilst MS simulates a spatially explicit mapped result from samples. The basic model chain employs

TopoSCALE to derive a forcing at simulation points or samples, depending upon the mode employed. The LSM simulates target variables at the computed points or sample centroids. TopoSUB is used in MS to pre-process topography and post-process results.

2.5 Snow correction method

Precipitation is highly variable in time and space, and fields computed by climate models often do not capture the frequency and/or intensity distribution of events correctly (Piani et al., 2009; Manders et al., 2012; Dai, 2006). Additionally, sub-grid topographic features may place large controls on the distribution of precipitation events (Leung and Ghan, 1998). Therefore, a method is required to correct magnitudes of precipitation inputs due to the important influence of this field on land surface processes. The method we test in this study relies on detection of the MD of the snowpack, a parameter which summarises both energy and mass inputs to the snowpack. We vary a parameter in the model which applies a multiplicative correction on precipitation inputs called snow correction factor (SCF). We vary this parameter over the range 0.5–3 in steps of 0.25 and run a simulation for each correction factor. MDs are computed according Schmid et al. (2012) for each simulation and observation site using GST (which avoids circularity). We fit the simulation MDs to observed MDs to obtain a correction factor for precipitation input. This method is based on cumulative winter precipitation and assumes summer and winter distributions of precipitation biases are similar, which is likely not the case. However, our primary aim is to address the thermal influence of the winter snowpack. The approach shown here could potentially be used together with satellite imagery in order to estimate snowfall bias based on MD. However, this paper evaluates the point-based performance of the new method without bias correction.

3 Data

3.1 Input data

All input data used in this experiment are available free of charge, globally. This does not imply, however, that data quality is consistent globally.

3.1.1 Driving climate

Driving climate data are obtained from the ERA-Interim (ERA-I) data set, which is an atmospheric reanalysis produced by the ECMWF (Dee et al., 2011). ERA-I provides meteorological data from 1 January 1979 and continues to be extended in near-real time. Gridded products include a large variety of 3-hourly (00:00, 03:00, 06:00, 09:00, 12:00, 15:00, 18:00 and 21:00 UTC) grid-surface fields (GRID) and 6-hourly (00:00, 06:00, 12:00, 18:00 UTC) upper-atmosphere

Table 1. Description of surface and sub-surface parameters used in this study. These are generic values of natural materials obtained from the literature.

Parameter	Unit	Bedrock	Debris	Vegetation
Residual water content	–	0	0.055	0.056
Saturated water content	–	0.05	0.374	0.431
Van Genuchten parameter, α	–	0.001	0.1	0.002
Van Genuchten parameter, n	–	1.2	2	2.4
Hydraulic conductivity	mm s ⁻¹	10 ⁻⁶	1	0.044

products available on 60 pressure levels (PLs) with the top of the atmosphere located at 1 mb. ERA-I relies on a 4-D-Var assimilation scheme which uses observations within the windows of 15:00 to 03:00 UTC and 03:00 to 15:00 UTC (on the next day) to initialise forecast simulations starting at 00:00 and 12:00 UTC, respectively. In order to allow sufficient spin-up, the first 9 h of the forecast simulations are not used. All fields used in this study were extracted on the ECMWF reduced Gaussian N128 grid (0.75° × 0.75°). Six PLs are used in this study covering the range of 1000–500 mb (1000, 925, 850, 775, 650, 500), corresponding to approximately an elevation range of 150–5500 m a.s.l.

3.1.2 Surface data

The DEM used in this study is the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model Version 2 (GDEM V2) (Tachikawa, 2011) available at approximately 30 m. Landcover was derived by a combined bedrock–debris classification which relies primarily on slope angle and a vegetation mask from a soil-adjusted vegetation index (SAVI) derived from Landsat Thermal Mapper/Enhanced Thermal Mapper (TM/ETM+) sensors. Full details together with description of uncertainty are given in Boeckli et al. (2012a). This resulted in three landcover classes, which also define sub-surface properties according to Gubler et al. (2013): (i) bedrock, (ii) coarse blocks and (iii) vegetation. Table 1 gives a description of sub-surface properties associated with each class.

3.2 Validation data sets

The validation data set covers a broad elevation range of 1560–3750 m a.s.l.; full range of slopes from flat to vertical rock walls; full range of aspects; and main Alpine surface cover types: Alpine meadows, coarse debris and bedrock (Fig. 3). The entire Alpine space of Switzerland is well sampled by the data sets (Fig. 2). Table 2 gives an overview of each data set.

3.2.1 SLF IMIS stations

The WSL-Institut für Schnee- und Lawinenforschung (SLF) Inter-cantonal Measurement and Information System (IMIS)

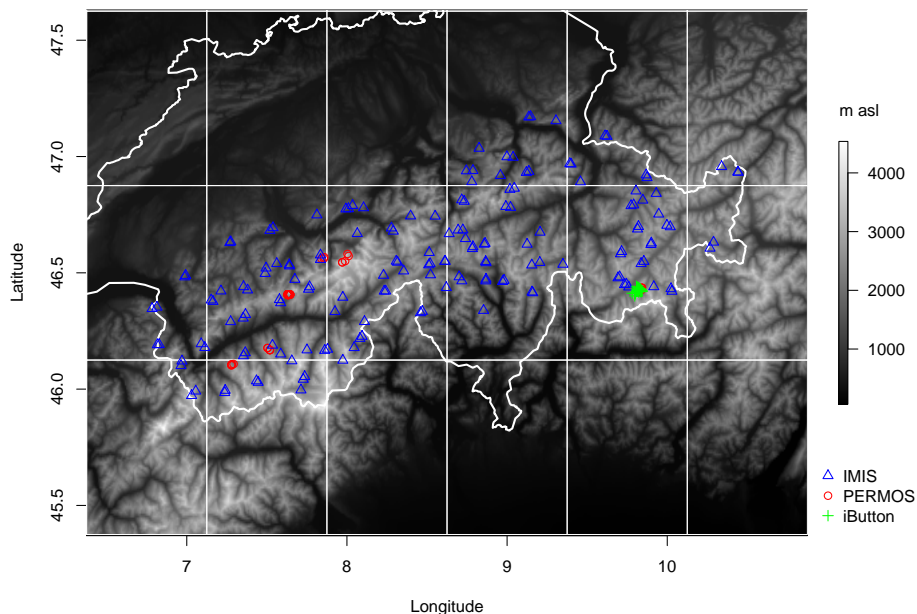


Figure 2. Experiment domain centred on the Swiss Alps together with evaluation data set locations. The ERA-I grid is overlaid in white.

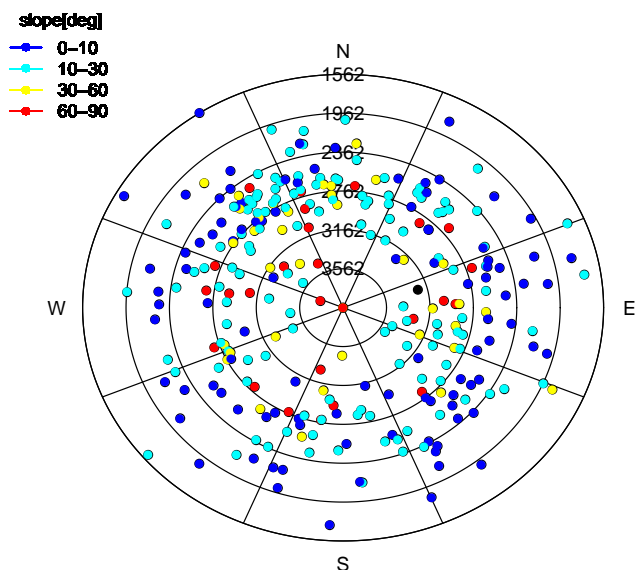


Figure 3. Polar plots describing topographic distribution of validation sites. Elevation range 1562–3750 m a.s.l.; slopes 0–> 90°; and all aspects are represented.

stations are used to evaluate TAIR, GST and SD. This network is biased towards high Alpine locations (there are few valley stations) but represents strong topographical heterogeneity, in terms of elevation, slope and aspect. The network elevation range is 1562–3341 m a.s.l. This data set is quite well behaved in that generally sites represent mainly elevation gradients. The data set used covers years 1996–2011;

GST is measured with a white temperature probe resting on the ground surface. It does not contain MAGST below 0°.

3.2.2 Data loggers

The data logger data set comprises two individual data sets and is used to evaluate GST only. Sensors measure GST a few centimetres below the terrain surface to avoid radiation effects. The dataset PERMOS data set (Swiss Permafrost Monitoring Network, <http://www.permos.ch>) contains data loggers of various types covering years 1995–2012 (ongoing) distributed throughout the Swiss Alps and managed by a number of institutions in Switzerland. The data set is not homogeneous but has been compiled using consistent methods. This data set covers a great diversity of locations but is biased towards permafrost monitoring sites and therefore clustered around MAGST of 0°C. In the analysis, PERMOS data are split into two groups: (a) PERMOS1: predominantly coarse debris; (b) PERMOS2: bedrock (mainly steep rock walls). The second logger data set, iBUTTONS, originates from a single study (Gubler et al., 2011; Schmid et al., 2012). It covers years 2010–2011 in a single region in the Engadin. While broader climatic heterogeneity is not represented by this data set, it does cover strong topographic variability. The data set is arranged as 10 m × 10 m “footprints” each containing 10 data loggers. In this study footprint mean values are used.

3.2.3 Data quality control

Observations outside acceptable limits were removed automatically by applying physically plausible thresholds to all

Table 2. Description of evaluation data sets used in this study.

Data set	Stations/ sites	Type	Variables	Period	Coverage (ERA boxes)
IMIS	81	Station	GST/TAIR/SD	1996–2011	12
PERMOS	77	Logger	GST	1995–2012 (variable)	4
iButtons	40	Logger	GST	2010–2011	1

data sets. Non-changing values beyond prescribed time limits were screened from wind direction data. These checks follow the methods of Meek and Hatfield (1994). Thresholds of a maximum of 10 % missing data in any given year qualified that year as a valid MAGST value. As data sets and sites within data sets differ in number of valid MAGST years (as defined above), validation values are computed as the mean of all available MAGST years and compared to the mean of the same modelled years.

4 Simulation experiments

The simulation domain covers an area of approximately 500 km × 250 km, centred over the Swiss Alps (Fig. 2). The domain contains 18 coarse-grid ERA-I boxes which supply the driving climate data. We simulate results for both MP and MS modes. TopoSUB is run at 200 sample resolution on each coarse-grid unit. The simulation period is 1984–2011. Spin-up is performed over 50 years (10 times, 1979–1983 period). This is necessary to obtain soil temperatures at depth that reflect atmospheric conditions and are independent of their initial value. The LSM runs on an hourly timestep. LSM model parameters are fixed in all simulations as a mean value of prior distributions defined in Gubler et al. (2013). We compute mean annual air temperature (MAAT), MAGST and mean annual snow depth (MASD). Focus is placed on mean annual values as we are primarily interested in analysing the performance of the spatial prediction of the scheme. In computing a permafrost estimate, we define a permafrost pixel as one in which the maximum daily ground temperature at 10 m depth (GT_{10}) over the entire observation period time is $\leq 0^\circ\text{C}$. Results are analysed statistically using the root-mean-squared error (RMSE), correlation coefficient (CORR) and mean bias (BIAS), defined as

$$\text{BIAS} = \overline{\text{mod} - \text{obs}}. \quad (1)$$

5 Results

5.1 Evaluation: simulated variables

Figure 4 gives MP and MS simulated results validated against measurement sites for MAGST, MAAT and MASD.

MAGST results are validated against IMIS, PERMOS and iBUTTON data sets. The scheme most successfully simulates IMIS sites with low error and bias; however, there is cold (warm) bias at cold (warm) sites. The iBUTTON data cover the largest range of MAGST and demonstrate good performance of the scheme in cold (i.e. $\text{MAGST} < 0$) locations. Both iBUTTON and PERMOS site validation shows the ability of the scheme to capture results influenced by the fine-scale variability of the topography (Fig. 3). PERMOS1 sites (non-bedrock) are reproduced with greater success than PERMOS2 sites (steep bedrock). MP gives improved results for IMIS and PERMOS2, whereas the converse is true for iBUTTON and PERMOS1. Over all data sets an RMSE of 1.29 is obtained for MS and 1.21 for MP. However, these figures should be interpreted with caution as there is an implicit weighting based on available data points, which are unlikely to be representative of the distribution of underlying surfaces in the simulation domain.

All MAGST results display some degree of positive bias, with the exception of PERMOS2 data. This is likely due to a negatively biased snowpack. This fits with PERMOS2 being the exception as locations of steep rockwalls and therefore no snowpack. Underestimated snowpacks may have various and opposing effects on the ground thermal regime, e.g. greater cooling in winter or greater warming in late spring with earlier melt. The balance of these effects depends on their relative magnitude. This issue is further explored in Sect. 5.2.

MAAT is well modelled at IMIS stations with low error and a bias of only 0.18°C , although a counteracting slight cold (warm) bias at warm (cold) sites is visible in the data. MS and MP give statistically identical results. MASD is not captured well due to large biases in driving precipitation fields. The bias becomes more pronounced at higher values of SD. A slight improvement is seen in MP over MS. Overall, MP generally shows an improvement over MS in reproducing observations, which would be expected as the spatial uncertainty introduced by TopoSUB is removed. However the difference is generally quite small (most significant difference is MAGST IMIS), and this is encouraging in that it seems MS does not introduce significant uncertainty over MP simulation. Figure 5 gives a visual impression of MS simulated MAGST results as a transect through the experiment domain.

A simple classification of results according to permafrost and no permafrost based on $\text{MAGST} > 0^\circ\text{C}$ and

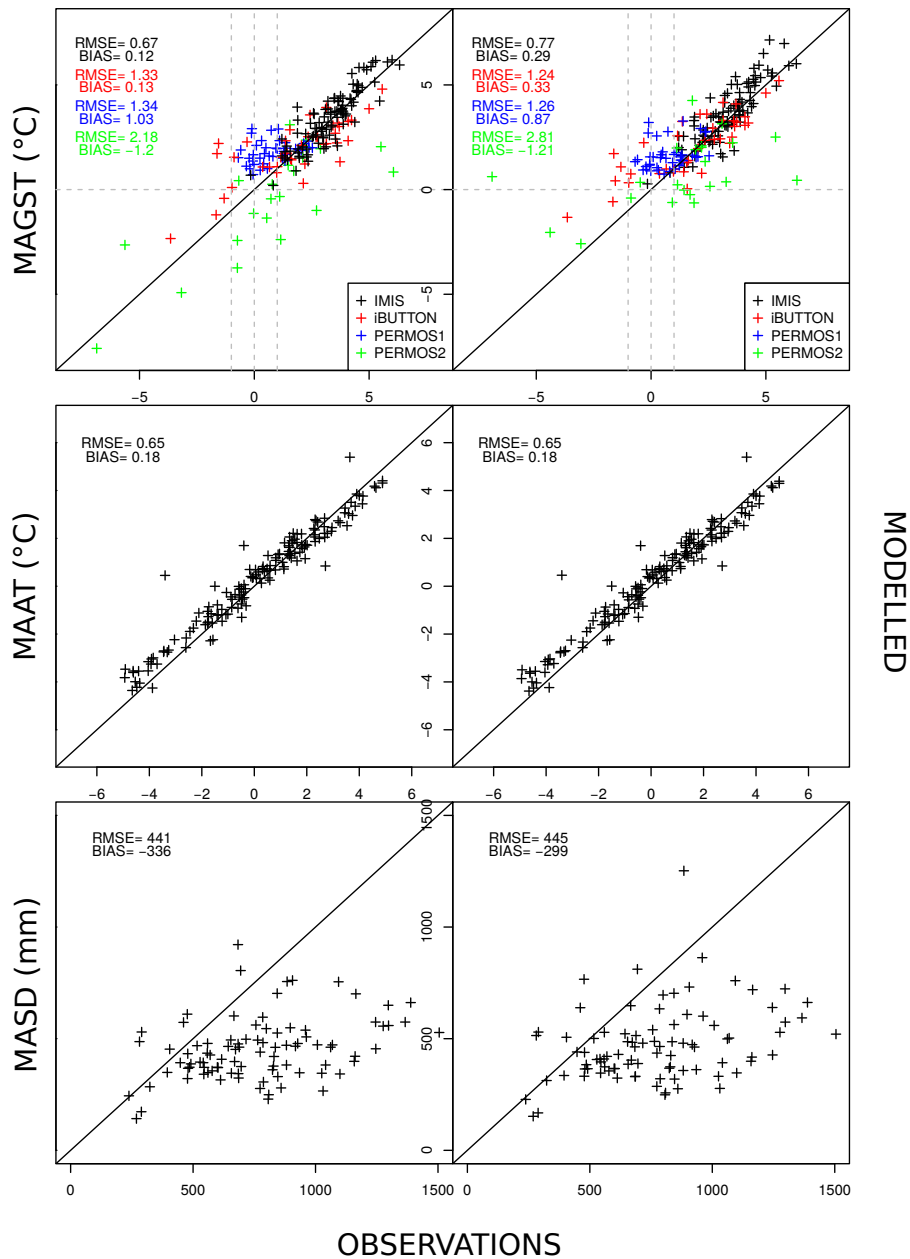


Figure 4. A comparison of MP and MS results. Modelled MAGST, MAAT and MASD evaluated against IMIS sites (2006–2011) together with statistics. Sensitive thresholds of 0 and ± 1 °C are added to aid interpretation.

MAGST < 0 °C, respectively, shows that the model does not perform very well for PERMOS1 data. However, this data set is strongly clustered around 0 °C, and therefore small uncertainties lead to misclassification. In addition, strong bias due to likely underestimated snowpack skews the simulated results positively.

5.2 Snow bias correction method

Figure 6 illustrates the snow bias correction (SBC) method with an example from a high-snowfall region (Val Bedretto)

where underestimated snow depth drives warm bias in summer (cold bias in winter due to inadequate insulation of simulated snowpack). The SBC successfully corrects simulated snow depths and as a consequence the ground thermal regime. A broader evaluation is given by Fig. 7, which shows ground surface temperature (a) without and (b) with SBC at all available IMIS stations (64). The plots give data by season, with winter mean ground surface temperature (MGST, blue), summer MGST (red) and MAGST (green) shown. Negative bias is seen in winter, whereas a positive bias is

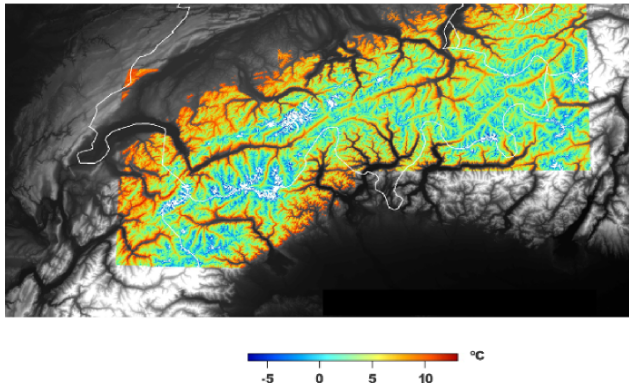


Figure 5. A visual impression of MS spatialised results: a section of a large-area simulation of MAGST with glacier mask for areas above 1000 m a.s.l. (UTM zone 32° N). Switzerland's southwestern border is overlaid for orientation.

visible in summer. Annually the positive bias dominates due to the greater magnitude of values. The effect of correcting snow depth via the SBC method has more effect on summer MGST than winter MGST. This is explained by ensuring the correct end of snowpack date therefore averting strongly positive GST too early in summer. This agrees with the findings of Marmy et al. (2013), who found that snow duration rather than maximum snow height was the most important factor controlling simulated ground temperatures at a high Alpine permafrost site. MASD (c) without and (d) with SBC evaluated at the same stations. This shows the ability of the method to correct MASD, albeit while retaining a systematic bias. This could be due to the fact that SWE is reproduced accurately but parameters governing density of the snowpack or wind erosion are not correct. However, without SWE evaluation data at these stations, this is difficult to confirm.

Additionally, in permafrost areas basal temperatures of the snowpack may vary much more than in non-permafrost areas (such as those given by the IMIS stations). Therefore underestimation of the snowpack may have even stronger effect on model bias.

5.3 Test application: permafrost estimate

In this study we produced an estimate of 1974.9 km² permafrost within Switzerland based on the stated definition. Figure 8 gives a visual comparison of permafrost extent computed by this study with a state-of-the-art statistical model (Boeckli et al., 2012b) derived from Alpine specific data sets. The current method compares well in terms of spatial patterns with results of Boeckli et al. (2012b). Comparison of model results, despite differences in the definition of permafrost area and in observation periods, is intended to demonstrate the similarity of patterns resulting from both approaches (cf. face validity, Rykiel, 1996). Boeckli et al. (2012b) is based on climate normals 1961–1990 whereas the current estimate covers the period 1984–2011. The method

Table 3. Comparison of PE (km² × 10³) obtained by this study compared to other methods in the literature.

Author	Value	Method	Relevance
This study	1.97	numerical	global
Gruber (2012)	0.7–2.5	statistical	global
Boeckli et al. (2012a)	2.2	statistical	regional
Keller et al. (1998)	1.7–2.5	statistical	regional

we have shown benefits from the simplicity of definition in actually simulating permafrost (i.e. ground < 0 °C for more than two years), although depth of simulation remains an arguable point. In addition, Table 3 shows that the current study produces an estimate that fits a range of key estimates from the literature, well.

5.4 Macroclimatic distribution of error

Figure 9 shows the distribution of bias for all IMIS stations for TAIR, GST and SD at the macroclimatic scale. The purpose was to investigate whether there are any significant biases or sign changes of bias at the mountain range scale. Such biases would largely be a result of how well the driving climate is simulated in different topo-climatic settings, e.g. north or south slope of the Alps, inner-Alpine regions or west to east. TAIR bias is well distributed in sign and generally small in magnitude. There is no clear pattern in error distribution, although the north slope seems most well modelled. GST bias is well distributed in magnitude but positively biased (as shown in Fig. 8). Again north slope seems to be modelled most successfully. SD bias is very negative and error magnitude seems to fit magnitudes of precipitation i.e. greater north and south of the main Alpine ridge and less in inner-Alpine regions (Frei and Schaer, 1998). However, stations on the north-slope of the main Alpine chain appear to be modelled well. Overall, there is no clear evidence of topo-climatic gradients in error patterns at the mountain range scale.

However, Fig. 9 is supporting evidence that generally negatively biased snowpack (too shallow) is most likely driving a positively biased MAGST (too warm) at least at the IMIS stations given in this figure. In addition, air temperature seems to be excluded as a driver of bias in MAGST as it displays no obvious bias pattern.

6 Discussion

6.1 Model chain uncertainty

In order to place these results in context we provide a semi-quantitative analysis of uncertainty through the model chain. The main sources of uncertainty we identify are: (1) bias in driving fields, (2) error in scaling approach, (3) uncertainty in

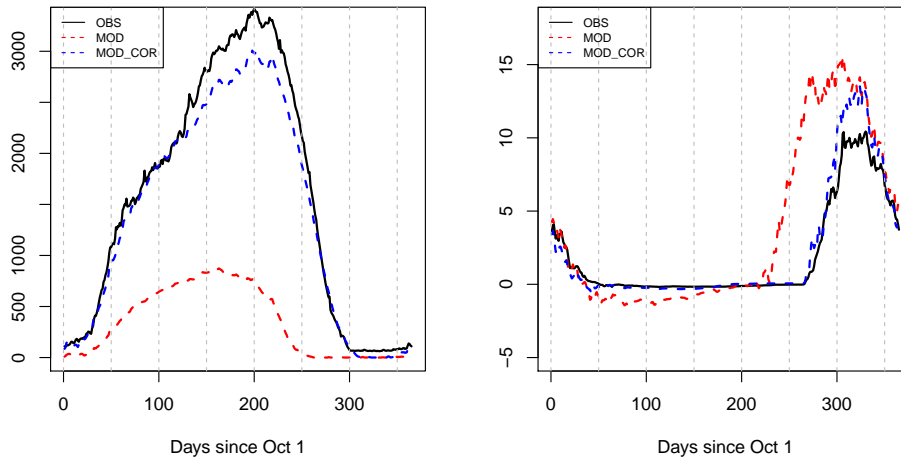


Figure 6. Evolution of SD and GST at a high-snowfall IMIS site (Val Bedretto); linkage between GST and SD is very clear. Correction of SD using the SBC method improves GST estimate.

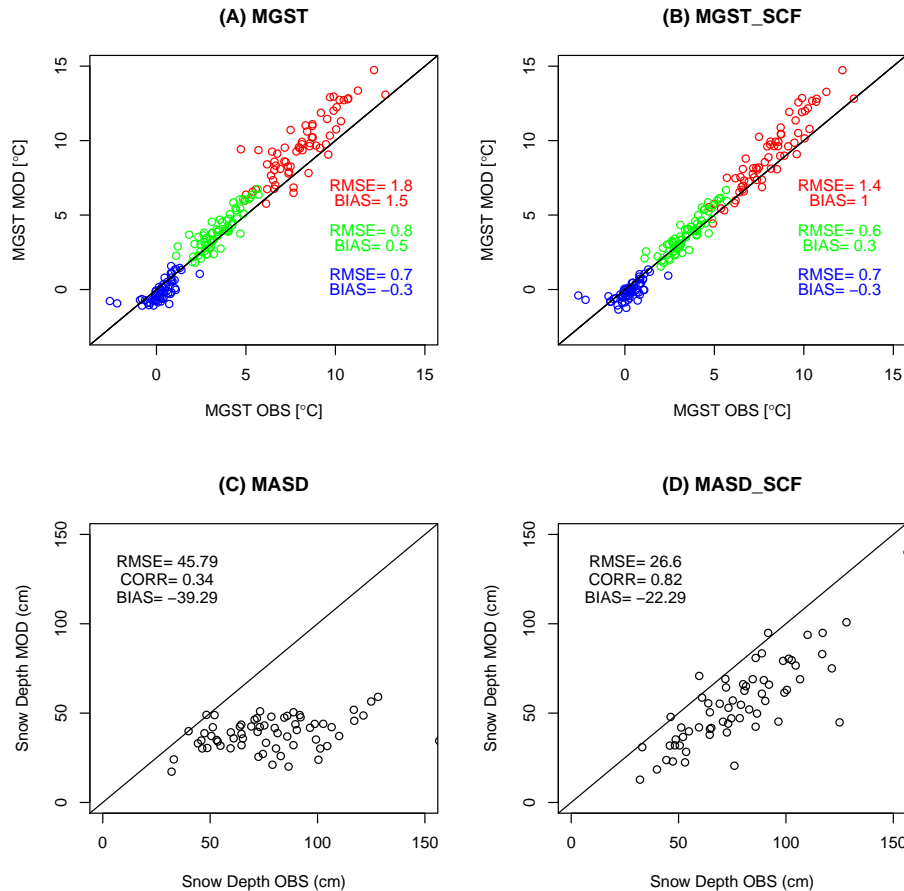


Figure 7. Ground surface temperature (a) without and (b) with SBC method evaluated at all available IMIS stations (64). Winter (blue) and summer (red) MGST, and MAGST (green) are shown. Negative bias is seen in winter and positive bias in summer. Annually the positive bias dominates due to greater magnitude of values. MASD (c) without and (d) with SBC method evaluated at the same stations. This shows the ability of the method to correct MASD, albeit while retaining a systematic bias.

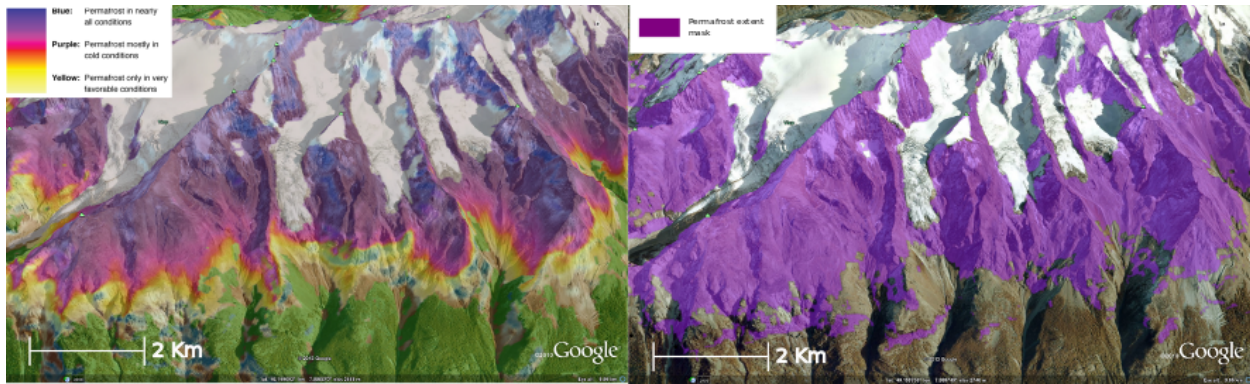


Figure 8. Visual comparison of permafrost extent computed by (a) this study (MS setup) and (b) a state-of-the-art statistical model (Boeckli et al., 2012b). Comparison of model results, despite differences in the definition of permafrost area and in observation periods, is intended to demonstrate the similarity of patterns resulting from both approaches.

the lumped scheme, (4) LSM uncertainties (parameters and processes) and, (5) surface data based uncertainties (scale discussed separately).

1. Uncertainty in the driving fields can be due to bias, spatial/temporal issues or model physics and parameterisations. This issue was explored in FG2013 and reasonable to good results were reported for the variables tested. The exception being precipitation. Additionally, reanalysis data sets are expected to vary spatially and temporally with density of observations assimilated. Bias in driving precipitation is a commonly reported problem in atmospheric models (e.g. Dai, 2006; Boberg et al., 2008), and we have attempted to address this issue with the correction method detailed in this study. Two notes of caution are worth mentioning with respect to this method: (a) this method is only valid currently at site scale, and (b) it relies on GST measurements. However, the approach shown here could potentially be used together with satellite imagery in order to estimate snowpack bias based on MD to enable scalability of the method. However this is beyond the scope of this paper. Other uncertainties in modelling snow precipitation lie in the definition of the snow/rain threshold; the fact that errors are cumulative over a season; and also that significant inputs are relatively infrequent, discrete events, which means that missing an event can have a large impact on season totals. Bias associated with snow-based precipitation may have strong impacts on the ground thermal regime due to the thermal properties of the snowpack, duration of snowpack or even cooling effects of very shallow snowpacks where the albedo effect may dominate. In this study the snowpack tends to be negatively biased (too shallow), leading to often negatively biased winter temperatures (too cold, possibly exacerbated by choice of snow thermal conductivity parameterisation) due to lack of adequate insulation, and positively biased (too warm) summer temperatures, due

to early melt of spring snowpack (Fig. 7). Out of these seasonal effects the summer warm bias dominates on average due to higher magnitude of values.

2. In discussing uncertainty in the scaling approach (TopoSCALE), we focus on TAIR as this is the only driving variable evaluated in this study due to its importance in driving the ground thermal regime. Other driving fields (including TAIR) were previously evaluated in FG2013. Frei (2014) reports a TAIR RMSE of 1.5 °C in the Alps using a sophisticated interpolation technique of station data. While these are daily values and cannot be compared directly to an RMSE of 0.64 as obtained in this study, in FG2013 we show that TopoSCALE is able to achieve an RMSE of 1.93 on daily TAIR values. To place this in context, the method of Frei (2014) interpolates station data to model non-linearities in the vertical thermal profile together with a distance-weighting scheme to account for terrain effects. Given this, TopoSCALE compares quite favourably given that only vertical profiles are modelled explicitly. In addition there are possibly advantages in the gridded ERA data set over interpolated station data in terms of representing larger-scale, synoptic conditions. It should be noted that TAIR at the majority of stations is modelled at considerably lower RMSE but the overall value is affected by four key outliers (RMSE is sensitive to outliers), which degrade the overall result (Figs. 4 and 9).
3. Uncertainty of the sub-grid scheme (TopoSUB) has two main sources: (1) the resolution of the base DEM and (2) the description of surface cover. The resolution of the DEM defines the range of parameter space, irrespective of number of samples computed. For example, the base DEM of 30 m in this study produces in several cases a steepest sample of under 60°, whereas in reality vertical slopes exist. This has an effect on both mass and energy balance computed at such sites. In this study,

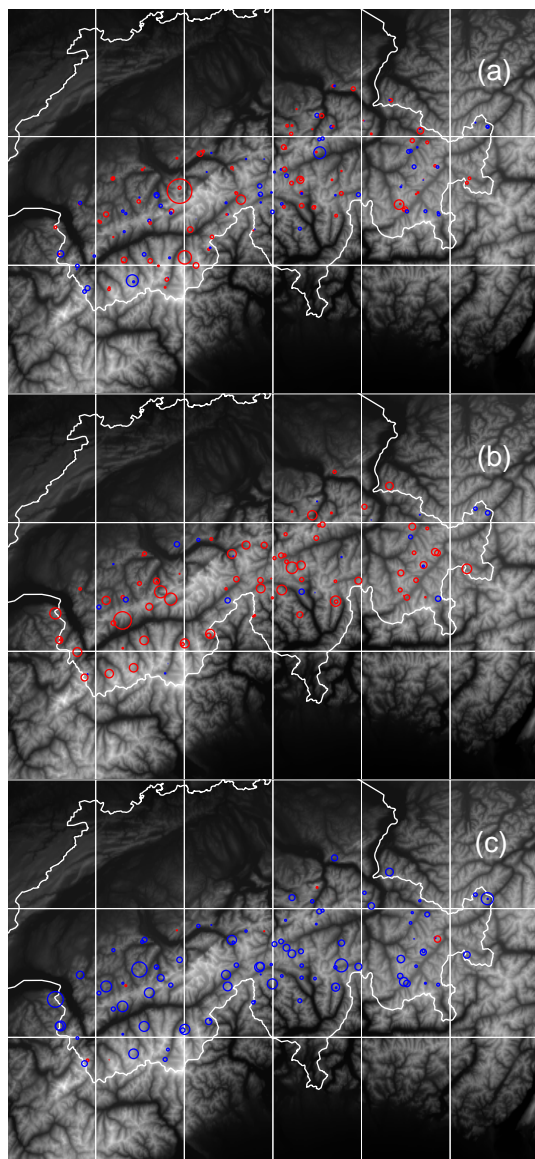


Figure 9. Distribution of bias in (a) TAIR, (b) GST and (c) SD at the macroclimatic scale. Blue indicates negative bias (model colder/less); red indicates positive bias (model warmer/more). Size of circle indicates the relative magnitude. Sites correspond to all IMIS stations included in the analysis.

surface cover is prescribed as an average value of surface characteristics within a TopoSUB sample, which are derived from a simple landcover data set. Landcover could however be used as a predictor in sample formation if this was deemed to be important, e.g. vegetation mosaics that significantly affect soil moisture, wind drift or energy balance at the surface. While surface cover is often a function of topographic predictors in the study domain, samples with complex surface characteristics – e.g. vegetation, boulder and bedrock matrix – will exhibit a degree of uncertainty due to the fact that all

members are modelled as the modal surface type. Due to the significance of surface (and prescribed sub-surface) characteristics in simulating surface (sub-surface) processes, this may constitute an important source of uncertainty.

4. Uncertainties due to the LSM have three main source: (i) process description (or omission), (ii) parameterisation of processes not explicitly modelled and (iii) values given to sensitive parameters. This topic has been well discussed in the literature (e.g. Gupta et al., 2005; Beven, 1995), and so here we focus on parameter values that are sensitive and therefore have a large influence on the final result. Parameter values were fixed and taken from a distribution described by Gubler et al. (2013). The exception to this is sub-surface properties (Table 1) which vary as a function of surface type. Gubler et al. (2013) provide a thorough analysis of sensitivities and uncertainties related to parameter values used in the model GEOTop, and their analysis is likely applicable to many other LSMs that have similar process description to GEOTop. In this study the authors found a total parametric uncertainty based on intensive Monte Carlo simulation of 0.1–0.5 for clay silt and rock and 0.1–0.8 for peat sand and gravel – the higher values being related to higher hydraulic conductivity of these surface classes. Therefore a portion of the error statistics given in Fig. 4 could be explained by LSM uncertainty alone.

While addressing all these sources of uncertainty within the analysis is beyond the scope of the paper, an important outcome of this work is that through the improved efficiency of simulation by several orders of magnitude, intensive simulation-based uncertainty analysis starts to become feasible.

6.2 Scale issues

While scale issues are a central topic of this work in scaling between atmospheric forcing and surface simulation, another important aspect of scale mismatch arises in validation. Evaluation exercises are often carried out in the literature where model results representing cells with side lengths of 10s–100s or, in extreme cases, 1000s of metres are compared to point-scale measurements. In this study the PERMOS data set is point scale in both measurements and topographic properties upon which modelled results are based, as these properties have been measured locally and not extracted from the DEM. The IMIS data set is comprised of point-scale measurements. The iButton measurements are aggregated to a footprint mean, representing a 10 m pixel. Modelled results of both data sets are based on properties derived from a 10 m DEM. While this seems a reasonable comparison, Gubler et al. (2011) demonstrated large differences in surface conditions within such a scale domain. Smoothing of slope angles by DEM resolution, localised shading or

snow drifting at a measurement point may cause large differences in measured and modelled conditions. Additionally, as stated above, there is a limitation based on resolution of base DEM (30 m) which under-represents steep slopes in TopoSUB sampling.

6.3 Important limitations

Key limitations are discussed in terms of (a) TopoSCALE and (b) TopoSUB. TopoSCALE based limitations primarily originate from the horizontal resolution of driving fields. In this study ERA-I fields at $0.75^\circ \times 0.75^\circ$ are used. This resolution is far too coarse to represent sub-grid effects such as valley temperature inversions. In addition, topographic precipitation barriers are unresolved in regions like the Mattertal (SW Switzerland) which produce important rain shadows. Finally, spatial patterns of sub-grid effects such as shallow (mainly cumulus) convective precipitation, which is important in simulating correct precipitation intensities, only start to become resolved at resolutions of around 1 km (e.g. Kendon et al., 2012). In the case of ERA-I this is because shallow convection is parameterised by a bulk mass flux scheme, as described by Tiedtke (1989), which cannot resolve the level of spatial differentiation that is present in the measurements. This process is particularly significant in spring and summer months, as surface heating occurs during a typical diurnal cycle, driving convective mass fluxes. An outlook in this respect is that the presented scheme is readily scalable to higher-resolution driving climate data that will likely come into the public domain in the next few years.

Another key limitation of the TopoSCALE scheme is that boundary effects are not included in the scaling of atmospheric profiles that represent the free atmosphere. It was shown in FG2013 that the diurnal amplitude of fields such as TAIR and shortwave (SW) radiation was not as great as surface-affected measurements within the boundary layer. This may have important implications for processes which are driven by strong daily amplitudes, such as spring melt of the snowpack.

TopoSUB-based limitations are largely derived from the scale of the base DEM on which sampling is based (as previously discussed), together with the description of surface cover. However, an important limitation comes from the inherent 1-D structure of samples as simulation units. This means that all lateral processes can only be parameterised and not modelled explicitly. For example, in computing horizon angles that are important for cast-shadow calculations (Dubayah and Rich, 1995), we apply a mean horizon angle derived from the sky-view factor and local slope. This has obvious problems when the horizon is highly asymmetric; e.g. consider a steep, south-facing mountain slope overlooking a plain. In this situation the horizon angle would be artificially raised in the southerly direction to a mean level, therefore reducing radiation inputs and consequently introducing a cold bias. This effect may also give biases in

terms of reduced radiation in westerly directions under convective systems (e.g. Marty et al., 2002) or under strongly anisotropic local horizons. Another example of neglected 2-D effects is illustrated well by the PERMOS2 results (steep rock walls, Fig. 4). The results here are negatively biased, indicating that part of the energy balance is missing or poorly described. Missing or inadequately described physical processes is a well-known and common characteristic of most physical models (Arneth et al., 2012; Beven, 1995); however, as testing of the physical model GEOTop is not the focus of this study, we provide only a limited discussion on this topic. GEOTop computes the emissivity (LW) and albedo (SW) of its hypothetical surroundings as identical to that of the point itself – in this case a steep rock wall. This will reduce the SW radiation reflected from surrounding terrain, which can be a significant energy input to steep rock walls when a winter snowpack is present. From a mass balance perspective we do not model redistribution of snow by wind or avalanche. This has an important effect on the surface energy balance where melt dates can be several weeks later due to heavy accumulations at bases of avalanche slopes (Harris et al., 2009) or earlier on wind-eroded slopes (Bernhardt et al., 2010). This sub-grid effect can be parameterised by computing multiple cases for increased/decreased snow cover, but corresponding results will be difficult to spatialise. We model the loss of snow on steep slopes as a function of slope angle; however this is not a mass-conservation method as the removed mass is not redistributed.

6.4 Snowpack issues

The winter snowpack is extremely important in controlling the ground thermal regime (cf. Smith, 1975; Goodrich, 1982; Ling and Zhang, 2003; Zhang et al., 1996; Zhang, 2005b). Therefore, here we summarise the main issues with respect to this paper together with a brief assessment of the modelling approach used.

Precipitation is often the most difficult model driver to estimate both in quantity and timing, whether originating from a model or extrapolated from a nearby station. This challenge is increased in the case of winter precipitation, which is often harder to measure (gauge undercatch, satellite insensitivity) or model (solid/liquid thresholds, densities etc.). In our study the use of output from an atmospheric model (even re-analysed) has been shown to have inherent biases. This can be clearly seen in how precipitation is distributed (cf. Fiddes and Gruber (2014), Figs. 7 and 8), for example in the absence of high-intensity precipitation events which contribute strongly to build-up of the winter snowpack. Additionally, errors accumulate over the winter season, which can be a challenging characteristic of the modelled seasonal snowpack.

All our results display some degree of positive bias in MAGST with the exception of steep rock wall sites, indicating the importance of the snowpack (and driving precipitation) as a controlling variable. We have shown that correction

of the snowpack can be extremely important in successfully modelling the ground thermal regime. Underestimated snowpacks may have various and opposing effects on ground temperatures, e.g. greater cooling in winter due to albedo effects or greater warming in late spring with earlier melt of a shallow snowpack. The balance of these effects over an annual cycle depends upon their relative magnitude. In our study region we have shown that a shallow snowpack is likely driving positively biased MAGST. However, at a seasonal scale we see negatively biased winter temperatures due to radiative cooling and higher thermal conductivities (generally cooling atmosphere) and positively biased spring/summer temperatures due to earlier melt of snowpack and exposure to atmosphere (generally warming). Negative biases in winter are not necessarily insignificant and may have process-relevant effects, but they are often masked in this study by positive summer biases. In addition these opposing biases can cause a cancelling effect of errors at annual timescales. How these results scale out to other geographical regions very much depends upon the topo-climatic conditions. However, some generally applicable conclusions may be drawn: (1) biased snowpacks can be a common feature of model simulations due to bias in driving precipitation field, (2) correction of snowpack bias is often important to address bias in the underlying ground thermal regime and (3) determining the sign of the effect of a biased snowpack upon ground temperatures is complex and likely varies strongly with location and season.

The approach taken in this study offers a straightforward correction, which can compliment the downscaling strategy in its simplicity. In this sense, the primary aim is to correct major biases in the water balance and therefore the magnitude of resulting biases in the ground's energy balance. However, as this correction is used only on input precipitation, it assumes that this is the dominating bias. It does not address possible biases in temperature (or other variables influencing snowpack evolution, e.g. wind) or biases due to snowpack-related model parameters, such as thermal conductivities.

6.5 Applications and outlook

In this study we provide a large-scale permafrost model estimate as a test case. However, the scheme is generic in that it is able to generate surface fields of any variable the LSM is able to simulate. The scheme can be used to simulate high-resolution maps of current conditions as well as recent dynamics which can be used to generate estimates of near-future trajectories of change. In longer-term planning applications the scheme, when driven by suitable climate model data, can be used to produce scenarios of site-specific future conditions. A core strength of the scheme is computation reduction, which means that multiple repeat simulations are more likely to be possible. This can be utilised by producing a range of outcomes that consider significant uncertainties in the model chain and therefore a range of scenarios

that should be considered in a given study. Such scenarios could be interpreted together with site-specific knowledge to provide an improved quality of result, or a range of outcomes to be planned for in terms of uncertainty related to future conditions or other unknowns. In terms of model evaluation the scheme has two important contributions: it provides model data at an appropriate scale for validation measurements (e.g. site of measurement); secondly, by utilising an LSM, the scheme can generate a wide range of variables, in order to maximise use of all available evaluation data and therefore provide more robust evaluations.

With respect to this permafrost application (but also relevant to other land surface variables), it is important to remember that we currently have a strong environmental change and we assume permafrost thaw in many areas; therefore it is not so much only the classification of permafrost vs. non-permafrost that we are interested in, i.e. a classic distribution map, but also the ability to describe the evolution over time or, in other words, map a process. Much of the inherent uncertainty (including whether there is permafrost in the first place) will have to be accepted and estimated. For this, our scheme provides a way to reduce the computational effort of a thorough uncertainty analysis.

7 Conclusions

This study has shown that the presented scheme is able to simulate GST and TAIR reasonably well over large areas in heterogeneous terrain, using global data sets. We have presented a simple method that enables correction of winter precipitation inputs and thus greatly improves simulation of SD, where data are available. As a test application, an estimate of permafrost distribution in Switzerland has been computed with the scheme, which is comparable to published statistical model results. However, the scheme described in this study is additionally capable of producing transient simulations; results in remote areas; and many more useful variables besides the simple variable of distribution, such as changing subsurface properties (e.g. ground ice loss). This underscores a key strength of the scheme: through efficiency gains, it allows for application of LSMs at high resolutions over large areas with transient simulation possible. This opens a number of new possibilities in the field of land surface change assessments in heterogeneous environments. In addition it allows model results to be validated at an appropriate scale by a wide range of measurement types due to the comprehensive set of physically consistent outputs that are generated. We summarise the main contributions and insights of this work as the following:

- the presented scheme works well in large-area simulation of the tested variables due to an efficient sub-grid sampling of surface heterogeneity and scaling of driving climate;

- simple bias correction of winter precipitation may be possible based on the melt date of the snowpack;
- the scheme produces an estimate of permafrost area in the Swiss Alps that is comparable to statistical methods;
- all inputs are derived from global data sets, suggesting that consistent application globally in heterogeneous and/or remote terrain is possible.

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