Using earth observation data to evaluate a land surface model in three Siberian catchments

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In this paper, we analyse the ability of the JULES (Joint UK Land Environment Simulator) model to simulate the physical conditions in the terrestrial Arctic using satellite-based earth observation data products. Catchment-average seasonal surface temperatures and snow cover are constructed over the largest river basins of the Eurasian Arctic (the Ob, Lena and Yenisei) and compared with the modelled values. The results indicate that the modelled snow cover decreases too quickly in spring in all studied areas, and that the modelled surface temperature of snow-free areas is too high. There are several causes of uncertainty in both the model outputs and the earth observation products, and care has to be taken to ensure consistent use and sampling of the data. The results indicate that earth observation products provide important information that can assist in the diagnosis of problems in a land-surface model.

Introduction

The Arctic is expected to warm considerably over the next century, with temperature-increase estimates varying between 4 and 7 K by 2100 (ACIA 2004). Arctic regions store a large proportion of the world's terrestrial carbon, with estimated total soil carbon of 1400–1850 Gt (McGuire *et al*. 2009), although considerable uncertainty remains in these values (Tarnocai *et al*. 2009). As the Arctic warms, these stocks of carbon in the soil are likely to become available for decomposition, adding to the carbon dioxide (CO_2) burden of the atmosphere. At the same time, the warmer climate will lengthen the growing season which will result in more vegetation growth, which will soak up some of that CO_2. Part of the reason for the strong response of the Arctic to climate change is because it experiences non-linear warming due to the snow cover: when the snow is present, it keeps the region cool by reflecting approximately 80% of the incoming sunshine, while as soon as it melts, the reflection drops to around 10%. The role that the Arctic will play in global climate in future depends on complex couplings between the carbon, energy and water dynamics of the region. Further, the balance between the Arctic being a sink or source of carbon and its role in the radiation budget depends on the length of the season when the land is snow-free and the soil is not frozen (Betts 2000). Predicting changes in these aspects of land–atmosphere exchange relies largely on models.

Most models predict an increase in carbon sequestration in the Arctic region in a future warmer climate (e.g. Schaphoff *et al*. 2006, Sitch *et al*. 2007), but there is large divergence between

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the predictions for the Arctic (Sitch *et al*. 2008). In this study, we focus on the land-surface model used in the UK Met Office climate prediction model, the Joint UK Land Environment Simulator (JULES; Best *et al*. 2011, Clark *et al*. 2011). JULES models the carbon, water and energy interactions between the land surface and the atmosphere, including snow, soil and vegetation dynamics. Previously, JULES has been tested globally against a suite of datasets (Blyth *et al*. 2011) using offline runs in which JULES is driven by observed near-surface meteorology. Four datasets distributed around the globe were used to test the model: surface water and carbon dioxide fluxes at ten locations, atmospheric carbon dioxide concentration at four locations, and river flow and area-average greenness index in 7 large river basins. These tests were aimed at giving an overview of the model performance in terms of regional and seasonal fluxes of water and carbon. One of the conclusions of that study was that the model simulated an earlier spring response in high northern latitudes than was observed, based on the comparison with the surface flux data and atmospheric CO_2 concentrations.

The observed and modelled fluxes of water and CO_2 at Hyytiälä in southern Finland over an evergreen forest were reported in Blyth *et al*. (2011). The model was forced with locally-observed meteorological data and the Leaf Area Index was considered to be constant, which is a reasonable assumption for evergreen forest, so differences in the seasonal fluxes are largely due to soil and photosynthesis processes, rather than phenology or driving data. In that study, it was clear that in the spring both the evaporation and the photosynthesis are overestimated. In addition, Blyth *et al*. (2011) compared the modelled and observed mean-monthly atmospheric CO_2 concentrations at Barrow in Alaska. Also in this case, there was an early modelled decrease in atmospheric CO_2 due to the greater draw-down of CO_2 from the vegetation in the spring in the northern latitudes, which tallied with the early modelled increase in CO_2 uptake demonstrated by the comparison with the flux data.

These tests indicated that the model is responding to spring too soon. However, the difficulty of diagnosing the cause with just these datasets is apparent: Is it a physiological phenom-enon (e.g. a poor parameterisation of an aspect of physiology) or a physical one (e.g. poor representation of the thermal state of the landscape)? According to observational studies (Tanja *et al*. 2003 and Sevanto *et al*. 2006), the threshold for the onset of photosynthesis in spring is that the air temperatures need to reach a 5-day average of above 3–4 °C. This can occur without the soil thawing and can cause the trees to be damaged as a result. However, in the model, the plants will not begin to transpire or photosynthesise until at least the snow has melted and the soil is warm enough for the soil water to be liquid. Irrespective of this difference in the representation of the onset of photosynthesis, an error in the simulation of snow cover and/or soil temperature will always lead to an error in the spring response. Following this line of thought, in this paper we expand the analysis to include more physically-based datasets in an attempt to better understand the problem and make progress towards being able to identify the cause of the early spring in the model. Furthermore, the extra datasets we use are satellite-based Earth Observation (EO) products, which are a type of data that were not used in the earlier study. We chose to use the EO data that describe the snow cover and surface temperature, as described below. The EO data bring new possibilities (e.g. global coverage) but with characteristics that need to be understood before a successful comparison can be made (e.g. temporal and spatial coverage). The work presented here is an initial study and further effort is needed to refine the method. However, it illustrates an approach that might be adopted if this kind of distributed data is to be used to test large-scale, distributed models.

Material and methods

Description of the model

The model used in this exercise is JULES ver. 2.2, which is the land-surface model used within the Hadley Centre climate model (The HadGEM2 Development Team 2011). JULES is described in Best *et al*. (2011) and Clark *et al*. (2011). It is a community model, and it is distributed via the website www.jchmr.org/jules, which contains
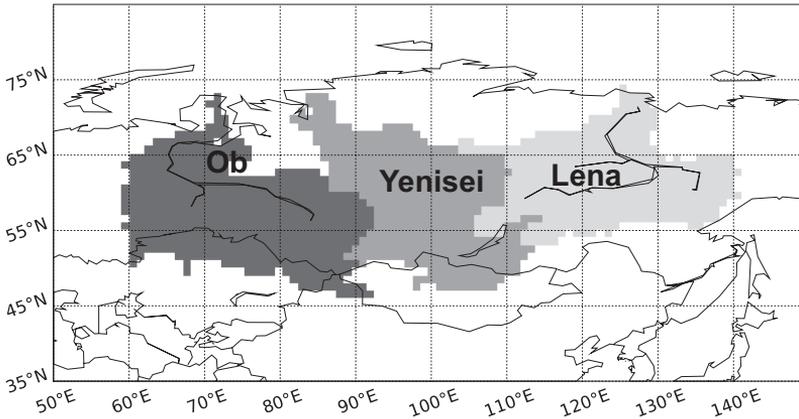
Fig. 1. Catchment areas used in this study.

further information about the model. JULES is a mechanistic model of the land surface including representations of photosynthesis and evaporation, soil and snow physics as well as plant phenology and soil microbial activity. The model is driven by prescribed near-surface meteorology and runs with a typical timestep length of 1 hour or less. In the standard configuration used here, JULES represents the land using nine land cover types: five plant functional types, and four non-vegetation types. Sub-grid scale heterogeneity of land cover is represented using a "tile" approach in which fluxes from each surface type are calculated separately and the total found by weighting each contribution by the fractional cover of each land type. Each surface type has its own surface (or "skin") temperature that is used in the calculation of fluxes. The soil hydraulic and thermal properties are specified for each grid box.

Snow is represented using a multi-layer approach in which the temperature, frozen and liquid water content, grain size and density of each layer are simulated. The evolving snow grain size represents aging of the snow after each snowfall and gives a time-varying snow albedo. The total albedo is also a function of snow depth and vegetation height, with shallow snow having less effect on the albedo of trees because of protruding vegetation. Each tile in JULES has a separate snowpack.

Study area

To obtain an overview of the performance of

the model, we use the river basin as the unit for this model-data comparison. Using a catchment as the unit for averaging allows the simulated water balance to be compared with observed river flows (e.g. Blyth *et al*. 2011), although river flow results are not presented here. The three largest river basins in Siberia were chosen for this study: the Ob, the Yenisei and the Lena (*see* Fig. 1). The areas of these basins (defined on the 1° model grid) are approximately 3.1, 2.6 and 2.3 million km², respectively.

Model runs

JULES was run on a grid with a resolution of 1° in latitude and longitude, using meteorological drivers from Sheffield *et al*. (2006). The model was run from 1982 to 2008, with the last 7 years used in the analysis as this is when the Earth Observation data are available. The model was run with a prescribed land cover map which was derived using the UK Met Office's data processing utility (the Central Ancillary Program, http://cms.ncas.ac.uk/CAP_INTERFACE/cap_general.php). The soil dataset was derived by Dharssi *et al*. (2009) and has hydraulic parameters for the Van Genuchten parameterisation of soil hydraulics, based on six soil types globally.

Earth observation products

We chose to use the EO datasets from MODIS as they overlap with the time interval of the

meteorological data available to drive JULES, are widely used and are readily available. The following sections describe the datasets used and the steps required to convert the MODIS data into fields that can be compared directly with the model. All analysis considered the period 2002–2008.

Snow cover data

For assessment of modelled snow cover, we used the MODIS/Terra Monthly L3 Global 0.05Deg (MOD10CM) dataset (Hall *et al*. 2006a). The data are based on a snow mapping algorithm that employs a Normalized Difference Snow Index (NDSI) and a regression equation to give the Snow-Covered Area (SCA) of each pixel (Riggs *et al*. 2006). There are fewer data for the extreme north of the study area during winter, when lack of daylight prevents data acquisition. Monthly average snow cover is calculated from the daily global product. The product has a geographic projection with a spatial resolution of 0.05°. Hall and Riggs (2007) discussed several studies of the accuracy of the MODIS snow products, including the MOD10_L2 swath product from which all other products are ultimately derived. They concluded that the absolute accuracy was generally greater than 93%, depending on the land cover, with the greatest problem being that of snow/cloud discrimination. Lower accuracy is found in forested areas and complex terrain, and there is much higher accuracy in agricultural areas. Simic *et al*. (2004) compared MODIS snow cover maps with observations from mete-orological stations in Canada and found the poorest agreement for areas of evergreen forest, where MODIS tended to overestimate the snow cover. Over evergreen forests the agreement was between 80% and 90%. In terms of the Eurasian domain considered in the present study, this sug-gests that the errors in the MODIS data will be of the order of 5% in regions of open, short vegeta-tion such as the Tundra in the north of the study catchments, and 10%–20% in the evergreen for-ests that cover much of the study area.

For the present study, the data were regridded to the 1° model grid by a simple averaging of all values. A value was given to a 1° area when at least 50% of the 0.05° pixels had data that were flagged as being of good quality. The results for the three basins for the first half of the year (Fig. 2a) show that the 95% confidence limits of the mean monthly values over the 7 years decrease in the mid-summer and mid-winter as the snow cover approaches 0% and 100%, respectively. All the basins are completely or almost completely snow-covered in January. Snow in the Ob basin largely melts in April and May, while in the Yenisei and Lena the melt is slightly later with a maximum rate in May.

Land-surface temperature data

The EO land-surface temperature (LST) data used for this comparison were the MODIS/Aqua Land Surface Temperature/Emissivity Daily L3 Global 0.05 Deg CMG collection 5 dataset (MYD11C1) (Wan 2008). Assessments by Coll *et al*. (2009) and Wan and Li (2008) found that the MODIS LST product was, in most cases, within 1 K of ground truth data over homogenous areas in clear skies. The errors were found to be slightly higher in areas of bare soil and heteroge-neous sites due to variations in the emissivity.

The product has a geographic projection with a spatial resolution of 0.05°, which is much finer than the model resolution of 1°. Therefore, it was possible to remove the low quality pixels and still get good coverage. The quality assessment was made as follows:

- Only pixels flagged as "good quality, not necessary to examine detailed QA" in the QA layer were used. Cloud cover in the region means that only approximately 50% of the pixels can be used (Hachem *et al*. 2009).
- To reduce the biases reported at higher view angles by Ghent *et al*. (2010), only pixels with the view angle < 30° were used.

In addition to this quality control, we studied the land-surface temperature only of snow-free areas so as to investigate the simulation of soil thawing and heating processes after the snow has melted. Using the MODIS daily snow product (MOD10C1, Hall *et al*. 2006b), we defined a 1° grid box to be 'snow free' if more than 70% of the
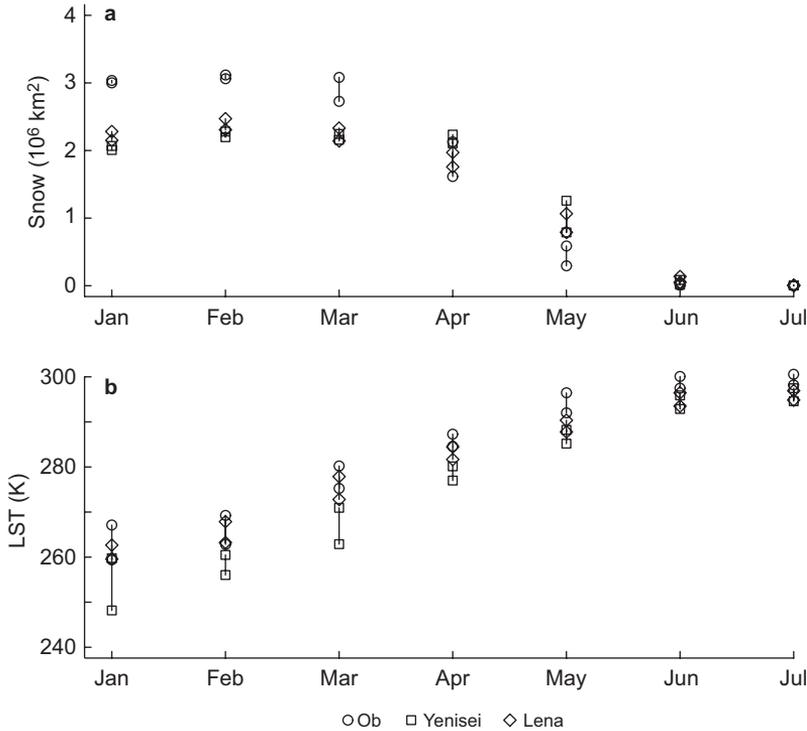
Fig. 2. (**a**) Monthly snow-covered area, and (**b**) snow-free land surface temperature from MODIS for the three basins in 2002–2008. Ob (circle), Yenisei (square) and Lena (diamond). Vertical lines span the 95% confidence limits of the mean-monthly values over the period.

pixels were snow free. Our results were not very sensitive to the threshold percentage as long as it was at least 70%. Pixels with snow were removed.

The data were also averaged in time to give the monthly mean temperature. Here, the issue is that surface temperature varies considerably on sub-daily time scales, while the MODIS data represent instantaneous values at the time of the satellite overpass, which was from midnight to 10:00 local time. Given that air temperature varies strongly at a sub-diurnal timescale, it is important to know how the sampling is distributed in time, as this potentially affects the comparison with the model. Analysis of the data showed that the distribution of overpass times was approximately Gaussian, with 70% of the samples taken from 05:00 to 07:00, and no systematic bias through the season. Hence, all available samples were used to calculate the average, with no adjustment for time of day. Finally the product was aggregated up to 1° by taking the mean of the snow-free LST data values, and then averaged over the river basins.

The 95% confidence limits of the mean monthly snow-free morning land-surface tem-

perature (Fig. 2b) for the three basins do not vary substantially through the season. Note that this snow-free LST is averaged over an increasingly large area as the melt season progresses, starting from rather small areas with little or no snow early in the year. For March (or April in the Lena) and later months, a considerable area was free from snow and the averages included much larger numbers of data.

Comparison of model with earth observation products

Processing of model outputs

As noted above, JULES models the snow cover separately in each of up to nine land-cover tiles in a grid box. For the calculation of Snow Covered Area (SCA), a tile was considered snow-covered when the mass of snow was greater than a small (effectively zero) threshold. Results are not very sensitive to this choice of threshold. The tile SCA is thus 0 or 1, consistent with the treatment within JULES in which snow is considered to form a
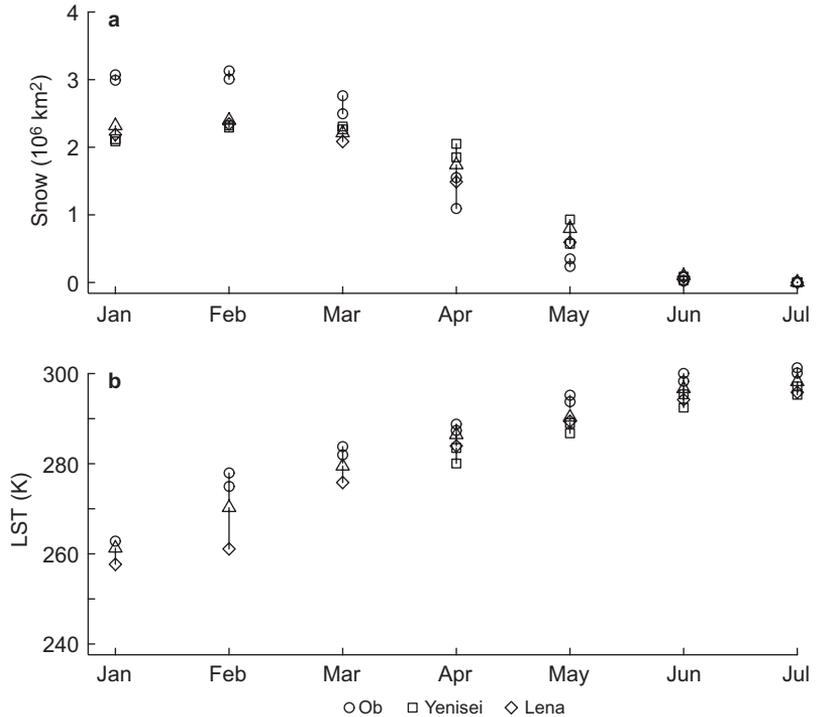
Fig. 3. (**a**) Mean monthly snow-covered area, and (**b**) snow-free land surface temperature from the JULES model for the three basins in 2002–2008. Vertical lines span the 95% confidence limits of the mean-monthly values over the period. There are no snow-free LST data when the snow cover is complete or nearly so.

layer of uniform depth across the tile. The grid-box SCA was calculated as the sum of the areas of snow-covered tiles. The model assumption of spatially homogeneous snow cover within a tile is likely to result in a larger SCA, as in reality the snow cover over a region with heterogeneous topography or vegetation cover will often be patchy. In comparison, the much higher resolution MODIS product is able to capture much more of this variability. We also note that the MODIS SCA is calculated via a rather different algorithm, based on the use of the NDSI and a regression (Riggs *et al*. 2006). It is not possible to use the same algorithm for the model, as the model does not have the detailed spectral reflectance information used by the NDSI.

As LST varies strongly with time of day, we had to sample the model LST so as to be consistent with the time distribution of the MODIS LST. We investigated the effect of sampling the model LST at different times within the range of MODIS overpass times (midnight to 10:00) and concluded that our results were not very sensitive to the choice of time. For all subsequent analysis we used the modelled LST for 05:00, which was close to the mean MODIS overpass time. To calculate the modelled, snow-free LST we used a similar criterion as was used for the MODIS data, namely a 1° gridbox was considered to be snow-free if the modelled SCA was at most 30% of the area.

The seasonal variation of the resulting modelled mean monthly SCA and snow-free LST for the three basins (Fig. 3) show that they broadly agree with the observations (Fig. 2).

Comparison of modelled and observed spring snow cover

The difference in SCA between the model and the EO data for the spring months (Fig. 4a), in terms of mean-monthly averages over seven years varies across the seven months. The difference was calculated for all times and locations when MODIS data were available (e.g. excluding very high latitudes in mid-winter), so the same locations are considered for both JULES and MODIS. As expected, the difference between the model and the observed snow covered area is smallest in mid-winter and summer, when there is extensive or no snow cover, respectively. JULES
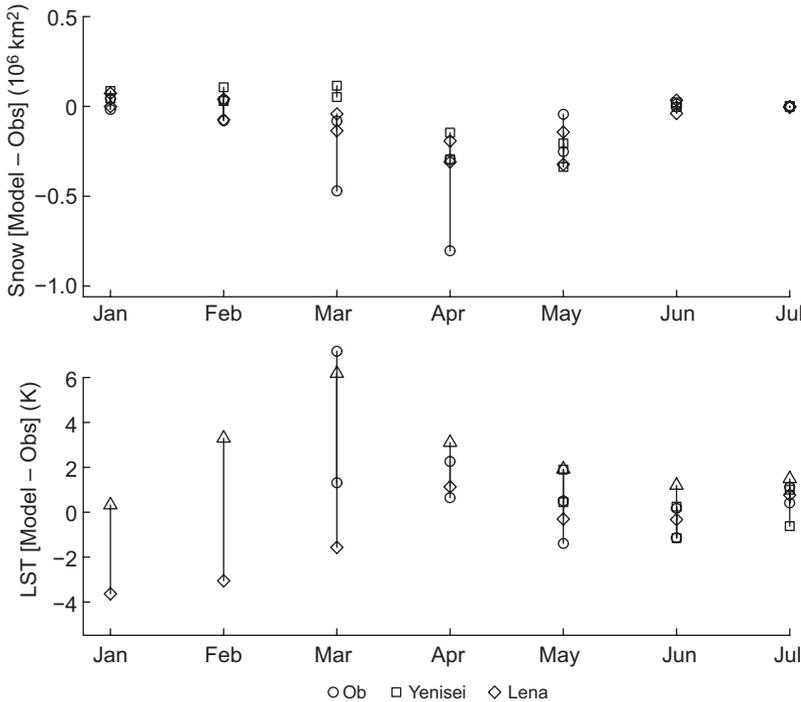
Fig. 4. (**a**) Differences between the modelled and MODIS snow-covered area, and (**b**) snow-free land surface temperature. Vertical lines span the 95% confidence limits of the difference of the mean-monthly values over the period.

persistently gives insufficient SCA in spring, and excessive SCA in autumn (not shown); that is, there is a slight phase-shift such that the model leads the observations. In spring, this suggests that snow melts too quickly in JULES. This signal is found in all three basins and has a consistent spatial pattern within each basin and between months (not shown), with the error in each month being focussed in a zonal band where snow is melting. The average difference for March to May, expressed as a percentage of the MODIS value, is 18%, 11% and 8% for the Ob, Yenisei and Lena basins, respectively.

The early modelled snowmelt is evidence of an error in the model physics which could result in the early spring response found by Blyth *et al.* (2011), as melting of the snow is an important precursor to thawing of the ground and plant transpiration.

Comparison of modelled and observed spring snow-free land-surface temperature

The difference between the modelled and MODIS land surface temperatures for all the

snow-free pixels (Fig. 4b) also caries across the seven months. The difference was calculated for all times and locations when the ground was considered snow-free in both the MODIS and JULES data, before the catchment average was taken, so the same locations are considered for both MODIS and JULES.

During the spring months, the modelled temperatures are generally higher than suggested by the MODIS observations, with differences of several K, followed by smaller errors later in the year. The number of snow-free points is rather small before April–May, so the large temperature differences earlier in the year are based on few points and possibly less reliable. The largest warm biases are generally found around the time when snow is melting, with a warm bias of 1.3 K for the Ob in April, and 0.9 and 1.4 K in May for the Yenisei and Lena, respectively. However, whereas the errors in snow cover were much more homogeneous over space and persistent in time (as summarised in the averages in Fig. 4), the signal was much less clear for snow-free LST which had areas of warm and cold bias in most months (not shown), and a less clear signal in the averages shown in Fig. 4b. However, Fig. 4b does show a warm bias on average over large

areas of Siberia during the spring, after the snow has melted. Many biological processes are very sensitive to temperature and a warm bias in the model would tend to result in larger fluxes of moisture and CO_2. Again this is evidence in support of there being errors in the model physics (rather than physiology) which could result in the early spring response found by Blyth *et al.* (2011).

The interpretation of these features of the snow-free LST data is rather complicated. As both the model and MODIS are free of snow at these locations, a higher model LST would be consistent with the model having been snow-free for longer (the analysis of snow cover showed early melt in the model) so the accumulated heating is greater, and/or the rate of heating of the land surface being too large in the model. Further analysis would be required to attempt to quantify the relative contributions of these effects.

Possible sources of error

The difference between the model and the observed snow-covered and snow-free land-surface temperatures is likely the result of a combination of errors in both the model and the data.

As discussed earlier, the MODIS snow-covered area product can have an error of 10%–20% over evergreen forest (Simic *et al.* 2004) and has an overall error of approximately 7% (Hall and Riggs 2007). This is considerable when compared with the size of the model bias e.g. March–May average differences of 8%–18% (Fig. 4). Note, however, that Simic *et al.* (2004) reported that MODIS tended to underestimate the snow cover in forest, in contrast to our results (Fig. 4) which show larger cover in MODIS, so if anything the model bias might even be larger than suggested by our study. Our preliminary analysis does not suggest a clear relationship between the model error and the land cover type, rather the dominant relationship is between areas of melting snow and model error. However, there is also evidence that the MODIS-estimated SCA appears to be less reliable during snowmelt (Simic *et al.* 2004). Areas of thin and/or ephemeral snow (both of which are likely to be more

common during the melt period) are difficult to measure accurately using MODIS (Hall and Riggs 2007). Note, however, that larger disagreement between model and EO data during melt is not surprising, as this is the time of transition between two more-easily modelled states (snow-covered in winter and snow-free in summer). MODIS estimates are also poorer in complex terrain, such as mountainous regions, but again our results did not show a clear relationship to terrain as measured by the 1° gridbox elevation. In summary, although the overall accuracy of MODIS SCA estimates is relatively high, there are substantial uncertainties that vary with both time and location.

Similarly, there are uncertainties associated with the MODIS LST data (e.g. Ghent *et al.* 2010). Our own analysis can add to these, for example a higher threshold snow-coverage below which we define a 1° gridbox as snow-free (30% used here; *see* section 'Land-surface temperature data') will result in greater contamination by snow pixels and a lower LST estimate — although we did not detect any great sensitivity to this particular threshold. The choice of threshold involves a balance between the desire for conservative analysis (e.g. perfectly snow-free pixels) with the need to leave sufficient data for meaningful analysis. Finally, we note that the MODIS LST by definition tend to sample sunny days, while the model diagnostic we used here was the LST averaged over all sky conditions, which would tend to be lower than for sunny days. This does not affect our conclusions, as sampling only sunny days in the model would tend to further increase the warm bias seen in this study (Fig. 4b).

There are also several sources of uncertainty in the modelled results, introduced by both the model structure and the input data. JULES contains parameterisations of several processes and necessarily makes many simplifying assumptions regarding each 1° gridbox. For example, the model configuration used here contains no representation of subgrid variability of soil temperature and moisture, whereas in reality this will vary over complex terrain or patchy snow. Similarly the near-surface air temperature is assumed to be constant across the gridbox, but will vary in reality. These are errors introduced by the

structure of the model. Other errors arise from the input data. A key input is the prescribed meteorological data — e.g. the data from Sheffield *et al.* (1996) used here — but for remote regions, such as Siberia, these are based on a sparse network of observations. Precipitation data in this region are highly uncertain (e.g. Sereze *et al.* 2005, Tian and Peters-Lidard 2010). Another important input is the map of land cover types. There are several land-cover datasets that can be used, each of which has to be mapped onto the land cover types used in JULES, and differences in the datasets and the mapping can have considerable impact on the model results. Similarly, models are sensitive to the prescription of subsurface thermal characteristics (e.g. Hall *et al.* 2003), which is a major challenge for large-scale applications. Particularly relevant for the area studied here are the rather different thermal and hydraulic properties of organic soils when compared with those of mineral soils (e.g. Letts *et al.* 2000) and the challenge of simulating infiltration into partly-frozen soils (e.g. Niu and Yang 2006). These and others are areas of active research in the JULES and broader land surface communities and it is beyond the scope of the current study to quantify the uncertainty introduced.

The analysis procedures used in this paper involved several thresholds (e.g. minimum allowed data capture rate for a 1° grid, largest allowed view angle for MODIS LST). Although the detailed quantitative results presented here inevitably show some sensitivity to the chosen values of these parameters, the qualitative results were more robust and held over a wide range of reasonable values.

Conclusions

This study showed that Earth Observation data can be used as part of the process of assessing the performance of a global land surface model. By comparing the seasonal variation of snow-covered and snow-free land-surface temperatures over three large regions, it was possible to identify some key differences between the modelled and observed physical state of the spring in northern latitudes: the modelled snow cover is disappearing too early and the modelled surface temperatures following the disappearance of the snow are too high.

The use of the EO data provided further insight into the model than was possible in the earlier analysis by Blyth *et al.* (2011) based on surface-based measurements. The results here are consistent with those of the earlier study that showed that, when compared with the data from southern Finland, JULES placed the start of transpiration and photosynthesis too early in the spring. The fact that the current study has shown that the snow melts too soon over large areas of Siberia strongly suggests that errors in the simulation of snow processes are at least partly to blame for the early vegetation activity. The springtime melting of snow is an essential precondition that then allows the soil surface to thaw and vegetation to transpire. A further advantage of using EO products is that the global coverage and multi-year time series of the MODIS data showed that the model biases in snow cover were persistent between years and spatially extensive. This spatial coverage in particular is impossible when using only surface-based data.

The errors in modelled snow-covered area and LST might or might not be linked, but the more complicated spatial patterns of LST error in comparison with the large-scale coherent signal in snow cover suggest that any link is complicated by other factors. This does not matter for our main goal, which was to look for evidence of errors in the representation of physical processes which could lead to too much vegetation activity in spring. Both the signals found here (early melting of snow and high temperatures over snow-free land) would tend to give enhanced vegetation activity, regardless of whether or how they are linked. The findings of this study do not rule out the possibility that further errors in the parameterization of physiological processes also contribute to the model errors in spring, but this study could not address those issues.

Although early snowmelt suggests that this might be the starting point for subsequent soil thaw and vegetation activity, the EO-based evidence presented here does not allow for the identification of direct causality. There are other EO-based datasets that could be used in future work and that would fill in some of the current gaps in our understanding, particularly of the post-snow-

melt period. Estimates of Snow Water Equivalent (SWE), such as from the GlobSnow project, will be used to identify whether the early disappearance of snow cover is at least partly related to insufficient accumulation of snow. Microwave-based estimates of soil moisture (which can also be used to identify when the soil surface thaws) might be useful in the analysis of the post-snow-melt period when the vegetation becomes active. Closer analysis of the time series of LST, combined with soil moisture estimates, might shed light on the processes of surface heating and thaw once the snow has receded. This is an area of particular interest, given the importance shown by Lawrence *et al.* (2011) of the realistic representation of the thermal and hydraulic characteristics of organic soils, such as are commonly found in Siberia. Errors in soil heating could exacerbate the early warming that is initially driven by early snowmelt. This study has considered averages over large intervals in time and space, which are essential tools to reduce the complexity of large datasets, but future work will likely need to consider finer details of the data as we attempt to add to our understanding of the physical and physiological processes involved.

Earth observation products are an important resource for the evaluation of large-scale land surface models. The results presented here are of particular relevance to the JULES model but, equally importantly, we have outlined a methodology that allowed us to gain more insight than was possible using more traditional, site-based observations. Careful consideration has to be given to the nature of the EO product and to the processing of both EO and model data.

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