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# Future European temperature change uncertainties reduced by using land heat flux observations

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[1] The variability of European summer climate is expected to increase in the next century due to increasing levels of atmospheric greenhouse gases, likely resulting in more frequent and more extreme droughts and heatwaves. However, climate models diverge on the magnitude of these processes, due to land-surface coupling processes which are difficult to simulate, and poorly constrained by observations. Here we use gridded observation-based sensible heat fluxes to constrain climate change predictions from an ensemble of 15 regional climate models. Land heat flux observations suggest that temperature projections may be underestimated by up to 1 K regionally in Central to Northern Europe, while slightly overestimated over the Mediterranean and Balkan regions. The use of observation-based heat flux data allows significant reductions in uncertainty as expressed by the model ensemble spread of temperature for the 2071-2100 period. Maximal reduction is obtained over France and the Balkan with values locally reaching 40%. Citation: Stegehuis, A. I., A. J. Teuling, P. Ciais, R. Vautard, and M. Jung (2013), Future European temperature change uncertainties reduced by using land heat flux observations, Geophys. Res. Lett., 40, 2242-2245, doi:10.1002/grl.50404.

#### 1. Introduction

[2] The greenhouse gases forced increase in radiative forcing causes global warming. However, not all regions of the globe are expected to warm at the same rate. Europe is a sensitive region where natural climate variability is large, and land-atmosphere coupling is important in large parts of the continent. In Central-Western Europe, a projected increase in summer temperature and temperature variability [Schär et al., 2004; Seneviratne et al. 2006; Fischer et al. 2007] has been attributed to an increase in this coupling. In this study, we hypothesize that any summer anomaly in the partitioning of the land surface energy balance in the current climate will be amplified on average under (drier) future summer climate conditions. It follows that information to reduce uncertainty on the land surface energy balance partitioning in the current climate may help to constrain future climate projections [Fischer et al. 2012]. This type

of approach (see *Hall and Qu* [2006]) is topical because the magnitude of land surface feedback processes is uncertain and differs considerably between climate models because the parameterization of these models are diverse, and rather poorly constrained. Most commonly, model ensemble means and spread are used to quantify model ensemble predictions of future climate variables.

[3] A method that leads to local reduction in uncertainty in the future by using present-day observations and models was proposed by Hall and Qu [2006]. They linked empirically the seasonal cycle of present-day snow albedo feedback to the magnitude of this feedback in the future. Following a similar rationale, Boberg and Christensen [2012] showed that inter-climate models' future summer temperature predictions over Europe were related to the present-day temperature bias of models, and this property was used to constrain temperature predictions in regions with dry and warm climate such as the Mediterranean. Quesada et al. [2012] reduced uncertainty in future European summer climate projections by the CMIP3 global climate model (GCM) ensemble by selecting a subset of models that best represent the current relationships between spring precipitation and summer temperature. They found that the CMIP3 models underpredict summer temperatures in Central Europe. However, constraining future projections using surface heat fluxes observations (latent or sensible) has not been done, and yet these fluxes controlling land-atmosphere feedbacks were identified to be a main source of model spread and uncertainty [De Noblet-Ducoudré et al., 2012].

[4] A method to improve future projections based upon heat flux measurements requires long-term observations, which are generally not available; the FLUXNET network of sites where latent and sensible heat is measured online only contains rather few multi-annual time series. Here we used a recent gridded observation-based dataset of sensible heat fluxes (hereafter H) based on the time and space extrapolation of point-scale FLUXNET observations by machine-learning algorithm [*Jung et al.*, 2009]. The purpose of this study is to investigate the use of the Jung *et al* observation-based land sensible heat flux dataset for selecting the most realistic climate models among an ensemble of future regional climate model (RCM) projections over Europe.

#### 2. Data and Methods

[5] 15 RCMs of the FP6 ENSEMBLES project are used [*Hewitt and Griggs*, 2004; *van der Linden and Mitchell*, 2009]. The RCMs are driven by GCMs used for the 4<sup>th</sup> IPCC assessment report for the A1B scenario. We use only those RCMs that were run for the period 1961–2099 or longer. All model outputs are provided on a 25 km spatial

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**Figure 1.** Spatial distribution of the Pearson correlation coefficient between simulated summer sensible heat flux  $(W m^{-2})$  and simulated temperature change (K) of 15 RCMs, defined by the difference in average air temperature between future and present-day periods. The black dot represents the grid point center location for Figure 2.

resolution, but in this study, they have been projected onto a common 50 km resolution grid using bilinear interpolation to be compared to the observational-based data. Monthly mean model output are extracted for sensible heat flux at surface (Wm<sup>-2</sup>) and 2-m mean temperature (K). The following GCMs are used from the institutes (in parentheses) HadCM3Q16 (C4I), ARPEGE (CNRM, DMI), ECHAM5-r3 (DMI, ICTP, KNMI, MPI, SMHI), BCM (DMI, SMHI), HadCM3Q0 (ETHZ, HC), HadCM3Q3 (HC, SMHI), and HadCM3Q16 (HC).

[6] We used observationally derived gridded sensible heat fluxes [*Jung et al.*, 2011] (hereafter MTE-H). This data product was obtained by applying a machine learning algorithm Model Tree Ensemble to estimate global monthly heat fluxes from 1982 to 2008 on a resolution of  $0.5^{\circ}$  (for a detailed description of the data product and underlying

methodology, see *Jung et al.*, [2009]). The spread (standard deviation,  $\sigma_{\rm H}$ ), between ensemble members being taken as a measure of uncertainty on observation-derived H. The advantage of using H instead of latent heat flux is that (1) H is more directly linked with air temperature, and (2) the measurement method by the eddy covariance technique is more direct than for latent heat fluxes [*Wilson et al.*, 2002].

[7] The spread of simulated summer temperature change ( $\Delta T$ , difference between 2071–2100 and 1971–2000) is rather large in the FP6 ENSEMBLES ensemble of RCMs. We will refer to this spread as the a priori spread (i.e., before adding information from flux observations). If a tight correlation exists between RCM-modeled  $\Delta T$  and H (1971–2000) (Figure 1), then a better (a posteriori) estimate of  $\Delta T$  could be obtained through the linear regression  $\Delta T = \alpha H + \beta$  at every grid point. The a posteriori uncertainty of  $\Delta T$  then depends on the uncertainty of the observation ( $\sigma_H$ ), the goodness-of-fit of the regression ( $\alpha$ ) (Figure 2a). The a posteriori uncertainty of  $\Delta T$ , given  $\sigma_H$ , is given by (see Appendix A):

$$\sigma_{\Delta T|H} = \sqrt{\sigma_{res}^2 + \alpha^2 \sigma_H^2} \tag{1}$$

[8] Note that adding information on H (predictor) will only result in a reduction of the a priori uncertainty if the observational uncertainty  $\sigma_H$  is (much) smaller than the spread of RCM-modeled H. The a posteriori uncertainty of  $\Delta T$  in equation (1) can be reduced by taking the standard error of the prediction of this correlation (see Appendix A). Where correlation is low, uncertainty reduction will only be minor. This also applies for a larger uncertainty in the observation-derived H data product (Figure 2b).



**Figure 2.** (a) Simulated summer sensible heat flux  $(W m^{-2})$  versus simulated air temperature change ( $\Delta T$  in K) in summer for the grid box indicated in Figure 1. Vertical lines indicate the MTE-H (solid) observation derived estimate, plus and minus one standard deviation (dashed). The gray area indicates the prediction interval for  $\Delta T$  ( $\sigma_{\Delta T|H}$ ) that is compatible with the MTE-H observations. The red lines show the linear regression between RCM-modeled  $\Delta T$  and H (thick solid) and the 1- $\sigma$  prediction interval (dashed). (b) Estimated prior and posterior normal distributions with modeled mean and SD; SD of  $\Delta T$  a priori (solid), SD of  $\Delta T$  given a perfect H observation (dotted), and SD of  $\Delta T$  a posteriori given uncertain H observations ( $\sigma_{\Delta T|H}$ ) (dashed).



**Figure 3.** (a) Mean predicted summer temperature change ( $\Delta T$  in K) of 15 RCMs, i.e., a priori simulations, (b) predicted temperature change that is compatible with observed sensible heat flux, i.e., a posteriori, and (c) the estimated RCM model  $\Delta T$  bias, diagnosed from the difference between b and a (K). Hashed areas indicate a significant difference between observation-based H and modeled H. (d) Standard deviation of mean temperature change of 15 RCMs a priori, (e) standard error of predicted temperature change based on the subset of RCM models that are compatible with present-day sensible heat flux, i.e., a posteriori, and (f) the relative change of  $\Delta T$  ( $\sigma$  difference between d and e in percentage).

#### 3. Results

[9] We found that there is a significant positive correlation between simulated average summer H in the current climate and mean summer  $\Delta T$  (Figure 1) which reflects the existence of a physical link between summer H and near-surface temperature change. Positive values are found over most of Europe, with exception of the Iberian Peninsula (Figure 1). The strongest positive correlations are found over central France and Hungary, regions which were also highlighted as strong coupling regions in other studies on soil moisturetemperature coupling [e.g., *Seneviratne et al.*, 2006]. The low correlation over the Iberian Peninsula might indicate different controls than land-atmosphere coupling behind model differences in this region.

[10] In general, the RCM-modeled  $\Delta T$  (Figure 3a), is close to  $\Delta T$  constrained by MTE-H (Figure 3b), leading us to diagnose only a small temperature bias when using MTE-H to restrain temperature change. Over central Europe and the southern part of Scandinavia, we found a positive  $\Delta T$ bias (Figure 3c), locally up to 1 K, suggesting an underestimation of modeled H with regard to MTE-H. Over the southeastern part of Europe, however, we found a negative bias, suggesting that models have somewhat unrealistic drying, resulting into too low latent heat emissions (soil moisture limitations) and too high H [*Stegehuis et al.*, 2012; *Boberg and Christensen*, 2012]. This is confirmed by subtracting mean simulated H from the observation based MTE-H (figure not shown). Areas with significant difference ( $\alpha = 0.1$ ) between the two are indicated in Figure 3c.

[11] The ensemble spread of simulated temperature change is largest over France and the Balkan (Figure 3d), which are two regions with predicted high interannual variability of summer temperature due to a strong soil moisture-temperature coupling [*Seneviratne et al.*, 2006; *Hirschi et al.*, 2011]. Also, in these regions, the correlation between present-day H and temperature change was highest (suggesting a strong coupling, indirectly explained by soil

moisture limitations on evapotranspiration), thus resulting in a smaller standard error of the prediction (Figure 3e). The difference between the a priori and a posteriori, the uncertainty reduction of temperature change predictions, is displayed in Figure 3 f. As can be seen, uncertainty (RCM model spread) is reduced by up to 40% in regions with highest correlations, by using H observations to constrain ensemble projections. This approach is only possible because we had access to an ensemble of RCM results with marked differences in model skills to reproduce presentday H, allowing to establish a strong positive relationship between H and temperature change, like in Figure 2.

#### 4. Concluding Remarks

[12] In this study, we proposed an approach to constrain summer temperature change predictions by using the existing correlation between simulated present-day H and temperature change in combination with present-day H observation-based gridded datasets over Europe. The fact that the uncertainty in observed H is smaller than the range spanned by the regional models output made it possible to reduce regional uncertainty of future climate change predictions. We chose to use sensible rather than latent heat flux as a predictor of future temperature change in the present study, because of the uncertainty between different observationbased data products [*Mueller et al.*, 2011].

[13] Our results indicate that in Central and Northern Europe, the ENSEMBLES RCM projections underestimate future temperature change, but that they overestimate it in Mediterranean regions. In contrast, *Fischer et al.* [2012] found that an ensemble constrained by observed present-day interannual summer variability predicts *lower* temperature change over Central Europe than the ensemble of all models. While this could be caused by an overestimation of MTE-H, a 40% lower MTE-H would be required to obtain a similar reduction in  $\Delta T$ . Using reanalysis data from ERA-interim

[*Dee et al.*, 2011] instead of MTE-H as a reference dataset results in an overestimation of  $\Delta T$  in Central to Northern Europe (like in *Fischer et al.* [2012]) of the ensemble of all models, and an underestimation over France (similar to MTE-H), the Balkan, and the Mediterranean regions, with on average twice the magnitude of MTE-H (not shown). Using our method with interannual summer variability instead of H results in a similar difference between a priori and a posteriori  $\Delta T$  as found in *Fischer et al.* [2012], indicating that the difference is caused by the selection of datasets and not methodology. The apparent inconsistency can be explained by the fact that the relations used are statistical rather than physical, since correlation does not guarantee causality.

[14] In the case of MTE-H constraint, the reduction of uncertainty in regional temperature change predictions has a heterogeneous amplitude. In regions where surface fluxes form a loose constraint on projections, other variables might be used. In addition to snow cover [Hall and Qu, 2006], temperature-precipitation relationships [Quesada et al., 2012], or summer temperature variability [Fischer et al., 2012], we hypothesize that other variables such as convective precipitation, soil moisture, moisture convergence, wind speed and direction, and indices of weather regimes that influence the transport of heat from North Africa can be used. In future studies, a multi-linear empirical regression approach could be developed where the target variable (temperature change) is empirically related to these different predictors. Since our study highlights the impact of land surface conditions on European summer temperatures, one key implication is that land cover and land cover change must be better accounted for by RCMs for robust predictions of the future summer climate in Europe.

#### Appendix A

[15] The results of the regression between H and  $\Delta T$  can be written as:

$$E[\Delta T|H] = \alpha H + \beta \tag{A1}$$

[16] With the residual standard deviation independent of *H*:

$$E[(\Delta T - \alpha H - \beta)^2 | H] = \sigma_{res}^2$$
(A2)

[17] Let:

$$E[H] = \mu_H \tag{A3}$$

and

$$E\left[\left(H-\mu_H\right)^2\right] = \sigma_H^2 \tag{A4}$$

and denote the a posteriori expectations of  $\Delta T$  by:

$$E[\Delta T|\mu_H] = \mu_{\Delta T|H}$$
(A5)  
$$E\left[\left(\Delta T - \mu_H\right)^2\right]$$
(A6)

$$\sigma_{\Delta T|H}^{2} = E\left[\left(\Delta T - \mu_{\Delta T|H}\right)^{2}\right]$$
(A6)

[18] With:

$$\mu_{\Delta T|H} = \alpha \mu_H + \beta \tag{A7}$$

[19] In rewriting (A6), the cross-term cancels out because  $E[\Delta T - \alpha H - \beta | H] = 0$ 

[20] The conditional expectation  $E[(\Delta T - E[\Delta T])^2|H] = \sigma_{\Delta T|H}$ then becomes:

$$\sigma_{\Delta T|H} = \sqrt{\sigma_{res}^2 + \alpha^2 \sigma_H^2} \tag{A8}$$

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