BLENDING IN SITU AND SATELLITE DATA FOR MONITORING LAND AIR TEMPERATURES

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Abstract

Land surface air temperatures have traditionally been monitored through in situ observations at meteorological stations. While the station network is extensive, many land masses, such as much of the African continent, are poorly observed. Moreover, there are issues in upscaling the point station observations to local and regional scales that can be compared with models. In this study, the potential for using satellite observations to improve the spatial coverage and representation of land air temperature data sets is explored. A simple linear model is constructed that estimates air temperature from satellite-observed land surface 'skin' temperature, solar zenith angle, and land elevation. Evaluation of the model with independent in situ station air temperatures in Europe demonstrates that the accuracy of the retrieved satellite air temperatures is comparable to the target accuracy of satellite land surface 'skin' temperature retrievals (1-3 K) in this region.

INTRODUCTION

A number of gridded land near-surface air temperature (T_{air}) data sets are now available to the scientific user community. These data sets have many applications, such as validation and initiation of forecast and climate models, near-real-time monitoring of temperatures, and quantifying climate change (Alexander et al., 2006; Feng et al., 2004). In general, these data sets are based on observations from the in situ station network, which undergo extensive interpolation to produce the final gridded data sets (e.g. Caesar et al., 2006). For areas that are well observed by the network, this approach has been shown to produce meaningful data sets with acceptable uncertainties. However, in data-sparse areas, interpolation is not feasible, leading to large spatial gaps in the data record. Unfortunately, many of these gaps are in regions such as Africa and high latitudes, where the effects of climate change are likely to be most acute and therefore where observations are most needed (Figure 1).

In this study, the potential for using satellite surface temperature data to supplement the in situ station data is explored. Satellites provide the opportunity to acquire consistent, near-spatially complete land surface temperature (LST) data sets. Observations are made over a swath that is comprised of a grid of pixels, typically ranging in size from one to several km across. LST can be estimated for each pixel, providing a grid of temperature data where each pixel represents an areal average over the area nominally contained within the pixel. However, there are several important limitations of these data. Firstly, the satellite LST data are derived from top of atmosphere (TOA) radiances, rather than direct measurements of surface temperature. The retrieval algorithms must correct for the effects of the atmosphere and non-unity of surface emissivity. Since these effects are extremely variable in both space and time, this process is often a source of errors in the LST data; current algorithms typically retrieve LST with an accuracy of 1-3 K. Secondly, the satellite LST data correspond to the temperature of the Earth's surface, often referred to as the 'skin' temperature. This quantity may differ considerably from the overlying T_{air} required by users and observed by traditional in situ meteorological stations (Figure 2). Lastly, depending on the observation wavelengths of the satellite TOA radiance data, LST data may not be available in the presence of cloud (infrared wavelengths) and/or precipitation (infrared and microwave wavelengths), leading to gaps in the data.

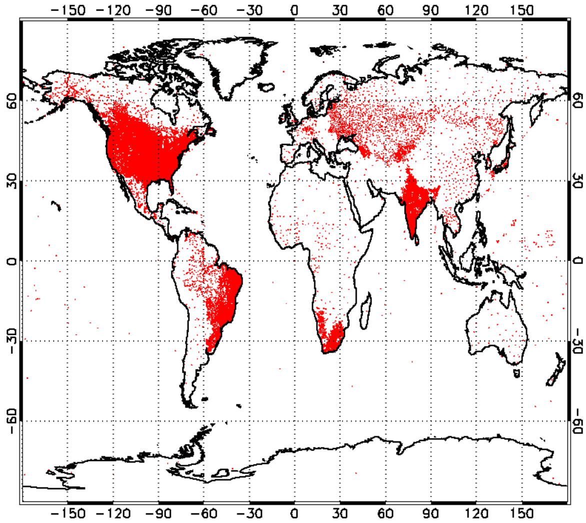

Figure 1: **Location of Global Historical Network-Daily (National Climatic Data Center dataset) stations (red dots).**

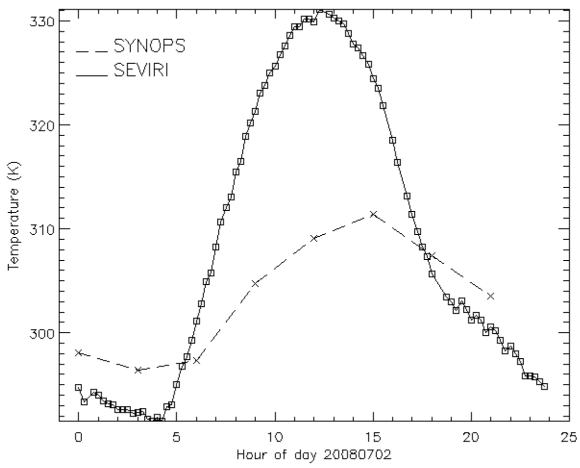

Figure 2: **Diurnal cycle observed by SEVIRI and in situ station WMO number 60735 (35 40N, 10 06E – Tunisia).**

There are a number of operational satellite LST products available to users. Most of these are from sensors operating in the infrared, for example the Along-Track Scanning Radiometer (ATSR: ERS-1, ERS2, Envisat platforms; polar-orbiting), MODerate resolution Imaging Spectroradiometer (MODIS: Terra and Aqua Platforms; polar-orbiting) and Spinning Enhanced Visible and Infrared Imager (SEVIRI: MSG; Geostationary orbit). Data from polar-orbiting sensors generally have higher spatial resolution than the geostationary datasets and provide global coverage, perhaps once or twice daily. Geostationary data sets provide more frequent observations, usually every 15-30 minutes for the more modern sensors, but are limited to certain regions of the globe. For example, SEVIRI observes Europe and Africa, and parts of South America.

In this study, a method of estimating T_{air} using satellite data is presented. The satellite T_{air} are then combined with observed station data to provide a blended T_{air} data set that offers improved coverage and representation relative to data sets based on station data alone. Results are reported for the months of January and July 2007 over Europe.

DEVELOPMENT OF THE AIR TEMPERATURE MODEL

A number of articles in the peer-reviewed literature describe efforts to estimate T_{air} in the absence of station observations. The approach adopted here is inspired by previous work reported by Cristóbal et al. (2008) and Ninyerola et al. (2007), who construct multiple linear regression algorithms to estimate

T_{air} over the Iberian Peninsula using Geographical Information Systems (GIS) data (Cristóbal et al, 2008; Ninyerola et al., 2007) and remotely-sensed data (Cristóbal et al, 2008)

In this study, various parameters, including satellite LST, are regressed against observed station T_{air} to generate a multiple-linear regression algorithm of the form:

$$T_{air}=\beta_0+\beta_1.x_1+\beta_2.x_2+\ldots+\beta_n.x_n \qquad (1)$$

where β_n are the regression coefficients and x_n are the predictor variables (e.g. satellite LST). The station data used are a subset of the Integrated Surface Daily (ISD), a National Climatic Data Center (NCDC) product that provides sub-daily (e.g. hourly, 3-hourly, 6-hourly) observations of a number of meteorological parameters, including T_{air}. These data have been quality controlled at the Met Office (personal communication: Peter Thorne and Kate Willett). Separate analyses have been carried out for January and July 2007, where all data from each month have been pooled into the same regression. Stations with valid data number approximately 400 in each month over the European region of interest. These have been sub divided into a separate training and validation data set, based on the number of observations at each station and their locations (Figure 3).

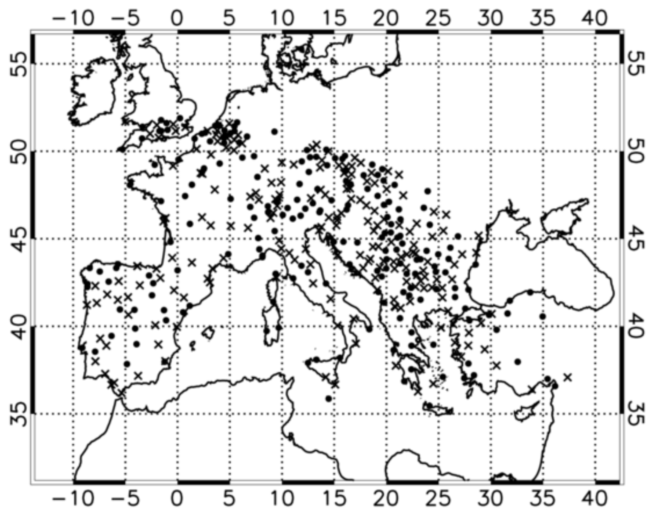

Figure 3: **Location of ISD stations used in the study for the July analysis. Both model training stations (•) and validation (x) stations are shown.**

A number of satellite, model and GIS predictor variables were tested in the regression. In each case, the variables were normalised by the mean and standard deviation. The satellite variables included LST, fraction of green vegetation and albedo from SEVIRI, all of which were obtained from the Land Surface Analysis Satellite Application Facility (LSA-SAF; see LSA-SAF product user manuals available from http://landsaf.meteo.pt/ for further details of data sets). GIS variables included elevation, latitude, distance from coast and solar zenith angle (SZA). Additionally, operational model wind speed data from the European Centre for Medium Range Weather Forecasting (ECMWF) were included. Each variable was collocated with the station locations. The collocated SEVIRI data were for the pixel nominally containing the station latitude and longitude. Owing to the use of satellite data parameters that are derived from infrared and visible observations, the analysis was only performed using cloud-free observations. Cloudy observations were identified both through interpretation of the satellite cloud masks, and cloud observations in the station data set. Although a total of seven predictor variables were tested, only three were selected for the final regression equation: LST, elevation and SZA. The selection process involved correlating the predictor variables with T_{air} and then successively adding each variable into the regression in order of decreasing magnitude of the correlation coefficient. An assessment of the impact of the predictor variable was made based on the relative magnitude of the corresponding regression coefficient, its standard error, and the resulting t and p values, together with the improvement to the multiple linear correlation coefficient (r_{multi}).

Table 1 shows the model parameters and statistics for each of the test months. The results for each month are quite different, although in both cases, LST has the strongest impact in the regression.

Variable	Mean	StDev	Regression Coefficient	Standard Error	T Value	P Value	Correlation r
January (r_{multi} = 0.84)							
Offset	-	-	4.827	-	-	-	-
Height	309.8 m	398.1 m	-0.7566	0.0129	-58.524	0.000	-0.278
SZA	115.0 º	31.0 º	0.6184	0.0153	40.498	0.000	-0.349
LST	277.0 K	6.3 K	4.6349	0.0154	300.274	0.000	0.819
July (r_{multi} = 0.88)							
Offset	-	-	24.455	-	-	-	-
Height	271.2 m	369.3 m	-0.8228	0.0079	-103.897	0.000	-0.332
SZA	77.0 º	31.4 º	2.2329	0.0129	173.619	0.000	-0.540
LST	298.8 K	10.1 K	7.5655	0.0131	576.787	0.000	0.848

Table 1: **Model parameters. Columns 'mean' and 'StDev' .**

Figure 4 shows the analysis of the January model residuals (modelled T_{air} minus true T_{air} from the training data set), the distribution of which is well approximated by a Gaussian function. This indicates that the model is providing a good fit with little structure in the residuals. Very similar results are obtained for the July model (not shown).

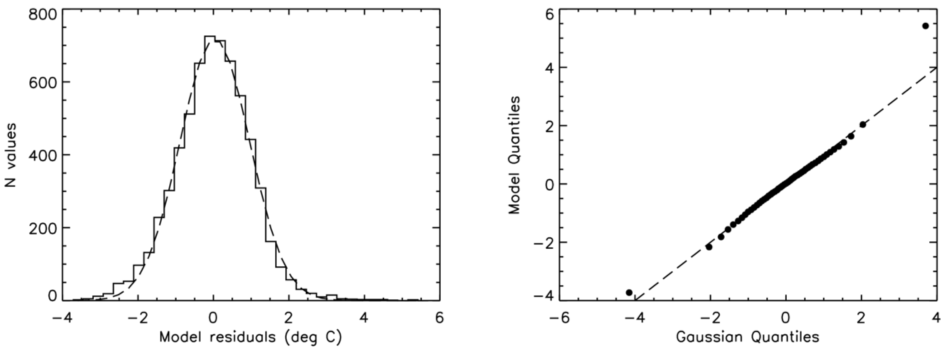

Figure 4: **Distribution of model residuals overlaid with fitted Gaussian function (left) and quantile-quantile plot (right) for January model analysis.**

VALIDATION OF THE AIR TEMPERATURE MODEL

Independent validation of the model has been performed by evaluating the model using the validation subset of stations. Considering all data, for all observation times, the bias and standard deviation are -0.2 and 3.0 K, respectively for the January model, and 0.0 and 3.3 K for the July model. This accuracy is similar to that of satellite LST retrievals in general, and is therefore an encouraging result. However, looking at the model T_{air} in more detail highlights some issues with the model. Figure 5 shows an example where the model T_{air} agree quite well with the station data throughout the diurnal cycle. Figures 6 and 7 show examples of discrepancies in the agreement, the former through most of the daylight hours and the latter during the afternoon. An offset between the timing of the peaks of the model and true T_{air} cycles occurs quite frequently because the LST diurnal cycle typically peaks before T_{air}.

Breaking the results down into the three main diurnal phases (night, morning, afternoon) also shows some interesting results (Figure 8). Results for night time model T_{air} are significantly better than the results for both morning and afternoon. The largest bias and standard deviation in the results is obtained for the afternoon comparisons (e.g. -0.5 and 4.2 K (n=2158) for July model compared with 0.7 and 3.7 K (morning, n=3281) and -0.1 and 2.9 K (night, n=12273)).

Figure 9 shows the spatial pattern of the mean bias and standard deviation for each of the validation stations. While there is no clear geographical pattern, analysis of the results as a function of land type does suggest that model accuracy depends somewhat on the surface characteristics. Table 2 shows the mean station bias for each of the main land types within the study region, as defined by the European Space Agency GlobCover data set, a state-of-the-art global land use map at 300m resolution (Arino et al., 2008). For example, both the January and July models appear to have lower accuracy for the closed broadleaf deciduous forest compared with other biomes.

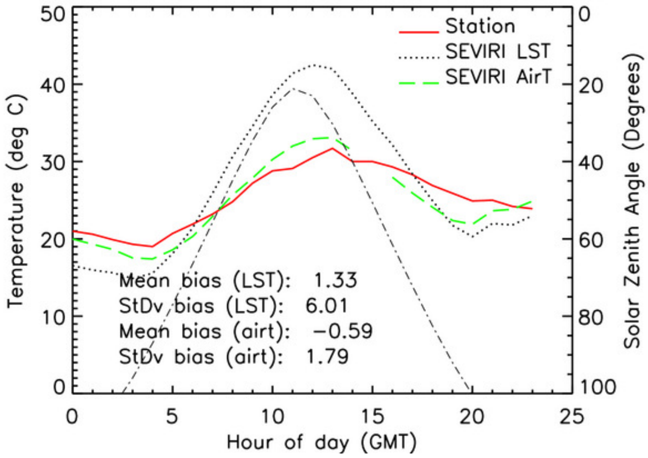

Figure 5: **Example of model performing reasonably well. WMO station 161790 (Italy), date 17 July 2007, GlobCover classification 'rainfed croplands', elevation 574 m. The black dot-dash lines shows the SZA (right-hand axis).**

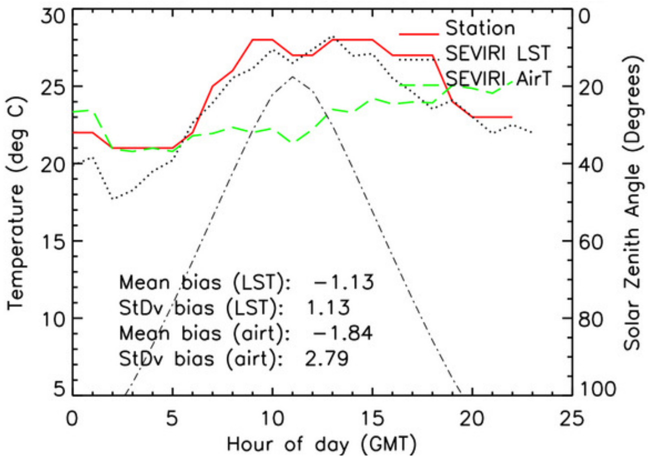

Figure 6: **Example of model performing badly. WMO station 163100 (Italy), date 09 July 2007, GlobCover classification 'sparse vegetation', elevation 185 m. The black dot-dash lines shows the SZA (right-hand axis).**

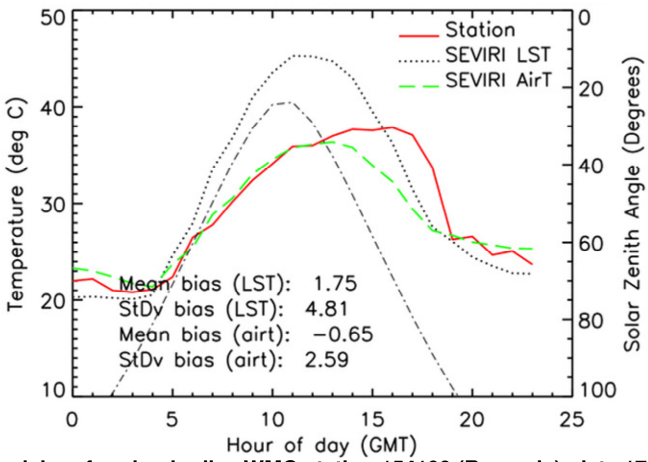

Figure 7: **Example of model performing badly. WMO station 154100 (Romania), date 17 July 2007, GlobCover classification 'rainfed croplands, elevation 185 m. The black dot-dash lines shows the SZA (right-hand axis).**

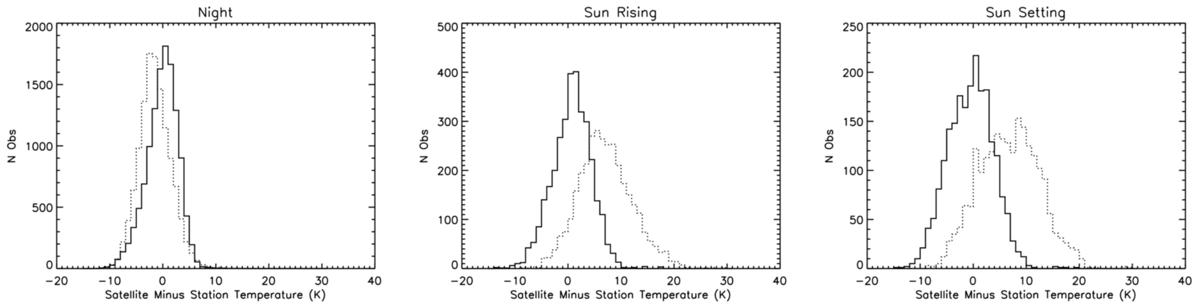

Figure 8: **July validation histograms (other minus station) for night (left), morning (centre) and afternoon (right). In each panel both the comparison between the T_{air} model (solid) and original SEVIRI LST (dotted) is shown.**

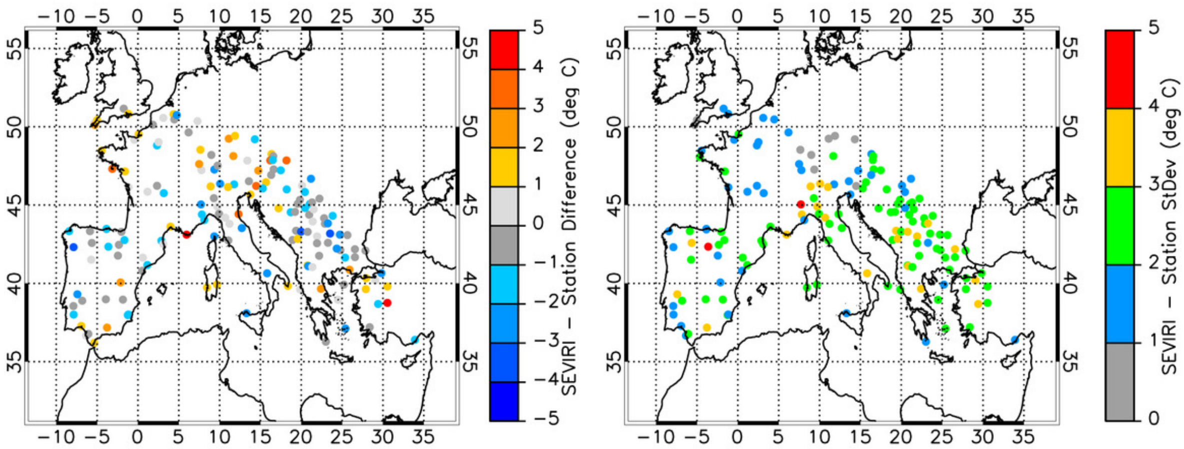

Figure 9: **Spatial distribution of mean bias (left) and standard deviation (right) for January model performance at validation stations.**

GlobCover Biome	January			July		
	N Stns	Bias (K)	StDev (K)	N Stns	Bias (K)	StDev (K)
Rainfed croplands (14)	38	-0.1	2.7	60	-0.1	3.0
Mosaic Cropland / Vegetation (20)	20	-0.1	2.9	28	-0.8	3.4
Closed broad. decid. forest (50)	24	-1.2	3.3	32	0.5	3.9
Sparse Veg (150)	19	0.3	2.8	21	-0.2	3.2
Artificial/Urban (190)	26	-0.2	2.7	25	1.0	2.8

Table 2: **Model performance for principal biomes/land use types.**

BLENDING IN SITU AND SATELLITE AIR TEMPERATURES

Previous sections have described the construction and validation of a simple model to estimate T_{air} in the absence of station observations. Here, the model T_{air} are combined with available station data to provide a gridded data set that should have improved spatial representation over one derived from station data alone.

The data are blended using optimal interpolation, which has been employed very successfully for blending satellite and in situ sea surface temperatures (Kawai et al., 2006; Reynolds & Smith, 1994; Reynolds et al., 2002; Reynolds et al., 2007). Before blending, the station data and model T_{air} are gridded separately to 1 degrees resolution. Land station air temperatures are typically gridded as anomalies, rather than actual air temperatures, to avoid problems that may occur as a result of averaging or interpolating over different elevations and terrains. Following this approach, the model data are also converted to air temperature anomalies by subtracting a suitable climatology. Ideally, one would use a climatology derived using the model data themselves. However, as the SEVIRI LST data are only available from 2007 (potentially 2003, but these data are not yet available from the LSA-SAF), a Climate Research Unit (CRU) one-degree 1961-1990 monthly climatology is used, temporally interpolated to daily resolution (CRU CL 1.0: New et al., 1999). Figure 10 shows an example of the blending process for maximum T_{air} on 29 July 2007. Also shown for comparison is HadGHCND, a gridded maximum and minimum daily station data set, for the same day (Caesar et al., 2006). Broadly speaking, the two data sets show similar characteristics and anomalies of similar magnitude, giving confidence in the approach described in this article. However, there are some noticeable differences, for example in northern France.

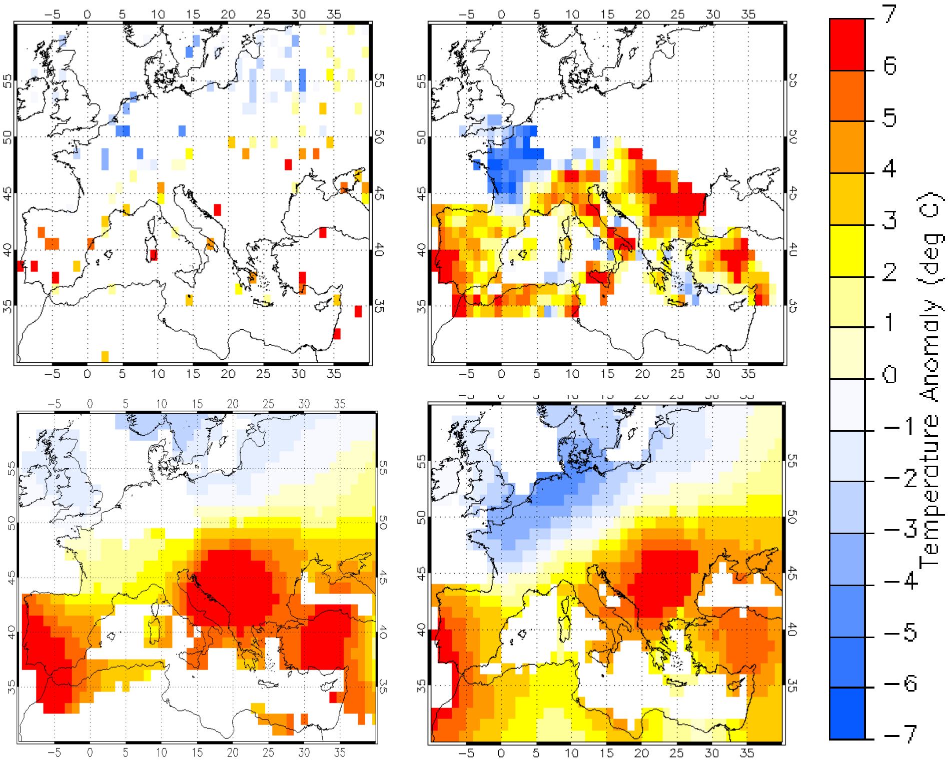

Figure 10: **Example of gridded station (top left), gridded model (top right) and blended station-model (bottom right) maximum T_{air} for 29 July 2007. Also shown is the corresponding HadGHCND data for comparison (bottom left). All data are shown with a spatial resolution of 1 degree.**

CONCLUSIONS

Land air temperatures have traditionally been monitored through the in situ station network. However, the sparsity of the network in some regions leads to gaps in the observation data sets. A simple model has been presented that can provide estimates of air temperature where there are no station data. The model requires three parameters: LST (e.g. observed from satellites), elevation and SZA. Assessed through independent in situ validation, the model has an overall bias and standard deviation of approximately 0 and 3 K, respectively. However, performance at night is significantly better than during the day, with the lowest accuracies achieved during the afternoon. The performance of the model also seems to demonstrate some dependence on land type biome. Some of the observed 'noise' in the validation results is an inherent aspect of the validation process, which is comparing a model quantity that represents a spatial average over several km, with 'point' in situ observations. Nevertheless, much of the noise is a result of inaccuracies in the model and future work will focus on reducing time- and biome-dependent biases.

The model air temperatures can be combined with available in situ observations. As an example of how this can be achieved, station and model-derived air temperatures have been blended over Europe using optimal interpolation for one day in July 2007. The result is a realistic air temperature map that compares well with the HadGHCND data for the same day. This suggests that the approach proposed here could be applied to other regions where station data are more sparse or non-existent, in order to produce a more spatially complete and representative data set than by using station data alone.

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