Supplemental Material

A multi-resolution air temperature model for France from MODIS and Landsat thermal data

Ian Hough; Allan C Just, Bin Zhou; Michael Dorman; Johanna Lepeule; Itai Kloog

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Appendix A. Statistical methods for stages 1 and 2

Stage 1: predicting 1 km T_a from LST

In stage 1 we predict T_a for all 1 km grid cells and days where MODIS 1 km LST is available. Our method is similar to that used in Kloog et al. (2017) with the addition of some explanatory variables and nesting of daily random effects within climatic regions. We start by associating each weather station T_a observation with the nearest 1 km grid cell for which LST is available on the day of the observation, up to a maximum distance of 1.5 km. The number of T_a observations matched with LST varies by year (**Table S3** – **Table S5**); the average is about 354 thousand for T_{min}, 205 thousand for T_{mean}, and 324 thousand for T_{max}. We use these to calibrate a mixed model with the equation:

$$\begin{aligned} \mathrm{T}_{\mathrm{a}ij} = {} & (\alpha + \mu_{jk}) + (\beta_1 + \upsilon_{jk}) \times \mathrm{LST}_{ij} + \beta_2 \times \mathrm{Emissivity}_{ij} + \beta_3 \times \mathrm{NDVI}_{im} \\ & + \sum_{l=1}^{4} \beta_{4l} \times \mathrm{Land\ Cover}_{ily} + \beta_5 \times \mathrm{Elevation}_i + \beta_6 \times \mathrm{Population}_i + \varepsilon_{ij} \end{aligned} \qquad \text{Eq. 1}$$

where Ta_{ij} is the observed ambient temperature associated with 1 km grid cell *i* on day *j*; α is a fixed intercept and μ_{jk} is a random intercept on day *j* for the climatic region *k* that contains cell *i*; β_1 is a fixed coefficient for LST and ν_{jk} is a random coefficient for LST on day *j* for the climatic region *k* that contains cell *i*; LST_{ij} is the MODIS 1 km land surface temperature of cell *i* on day *j*. β_2–β_6 are fixed coefficients of the other explanatory variables; $Emissivity_{ij}$ is the emissivity of cell *i* on day *j*; $NDVI_{im}$ is the MODIS NDVI of cell *i* in the month *m* that contains day *j*; β_l is a fixed slope for each of the *l* land cover groups and $Land\ Cover_{ily}$ is the fraction of cell *i* occupied by land cover group *l* in the CLC inventory year *y* closest to day *j*; $Elevation_i$ is the mean elevation of cell *i*; $Population_i$ is the population of cell *i*; and ε_{ij} is the error for cell *i* on day *j*. Specifically, we use the R package lme4 (Bates et al., 2015) to estimate a single value for the fixed intercept α and each fixed coefficient β_1– β_6 as well as a value in each climatic region on each day for the random intercept μ and the random coefficient ν using maximum likelihood. The random intercept and coefficient allow the relationship between LST and T_a to vary by day and between climatic regions, improving model fit. We then apply backwards stepwise regression, removing predictors that do not reduce the Akaike information criterion (AIC) by at least 5, and refit the final model using restricted maximum likelihood. We repeat this process for each of the four LST measures (Aqua daytime, Aqua nighttime, Terra daytime, and Terra nighttime) and select the model with the lowest 10-fold cross-validated RMSE. We use the final stage 1 model to predict T_a for all 1 km grid cell-days with LST.

Stage 2: predicting 1 km T_a where LST is unavailable

In stage 2 we predict T_a for the 1 km grid cell-days where LST was not available (usually due to cloud cover). We start by using inverse distance weighting to interpolate daily observed T_a from all weather stations across continental France. We then use all 1 km cell-days with LST to calibrate a mixed model with the equation:

$$\mathrm{T}_{\mathrm{ap\_s1}ij} = (\alpha + \mu_i) + (\beta + \upsilon_i) \times \mathrm{T}_{\mathrm{IDW}ij} + \varepsilon_{ij} \qquad \text{Eq. 2}$$

where T_{ap_s1ij} is the stage 1 predicted T_a of 1 km grid cell *i* on day *j*; α and β are the fixed intercept and slope, respectively; μ_i and ν_i are the random intercept and slope, respectively, for cell *i*; T_{IDWij} is the inverse distance weighted T_a of cell *i* on day *j*; and ε_{ij} is the error for cell *i* on day *j*. The random intercept and slope allow the relationship between T_{IDW} and T_{ap_s1} to vary between grid cells, improving model fit. We use the calibrated model to predict T_a for 1 km grid cell-days where LST is unavailable. We combine the predictions from stage 1 and stage 2 to get daily 1 km predicted T_a (T_{ap_1km}) across the entire study domain.

Table S1. Daily T_a observed at included weather stations during the 17-year study period

	N	Min	Mean	Max	SD*
T_{min}	13 464 964	-31.2	6.8	30.3	6.5
T_{mean}	7 888 798	-28.2	11.3	34.4	7.1
T_{max}	13 464 848	-26.0	16.5	44.1	8.3

* SD = standard deviation

Table S2. Aggregations of Corine Land Cover (CLC) classes used in this study

Aggregated category	CLC codes	CLC class descriptions
Artificial	1	Artificial areas
Vegetation	2	Agricultural areas
	3.1	Forests
	3.2	Shrubs and/or herbaceous vegetation associations
Bare	3.3	Open spaces with little or no vegetation
Water	4	Wetlands
	5	Water bodies

Table S3. Stage 1 T_{min} model performance (predicting daily 1 km T_{min} from LST): 10-fold cross-validated performance by year; overall, spatial, and temporal components.

T_{min}			Overall			Spatial			Temporal		
Year	LST*	N†	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE
2000	TN	299	0.87	1.92	1.47	0.86	1.54	1.14	0.88	1.65	1.27
2001	TN	332	0.92	1.88	1.43	0.91	1.50	1.10	0.93	1.65	1.25
2002	TN	323	0.88	1.99	1.52	0.87	1.57	1.15	0.89	1.74	1.33
2003	AN	405	0.94	1.88	1.41	0.91	1.67	1.21	0.96	1.50	1.10
2004	AN	367	0.92	1.86	1.40	0.90	1.59	1.16	0.94	1.53	1.12
2005	AN	398	0.94	1.89	1.42	0.91	1.65	1.20	0.95	1.53	1.12
2006	AN	365	0.94	1.84	1.38	0.91	1.58	1.15	0.95	1.49	1.09
2007	AN	385	0.91	1.88	1.41	0.89	1.60	1.17	0.93	1.52	1.11
2008	AN	358	0.91	1.85	1.39	0.89	1.56	1.15	0.93	1.50	1.10
2009	AN	386	0.93	1.86	1.41	0.90	1.63	1.20	0.95	1.49	1.09
2010	AN	347	0.93	1.84	1.38	0.92	1.60	1.18	0.95	1.48	1.08
2011	AN	392	0.90	1.95	1.48	0.87	1.67	1.24	0.92	1.54	1.13
2012	AN	362	0.93	1.92	1.45	0.91	1.61	1.19	0.95	1.56	1.15
2013	AN	322	0.93	1.87	1.39	0.91	1.56	1.15	0.94	1.53	1.11
2014	AN	324	0.89	1.82	1.37	0.88	1.52	1.12	0.92	1.46	1.07
2015	AN	336	0.91	1.95	1.47	0.88	1.68	1.24	0.93	1.57	1.14
2016	AN	316	0.91	1.94	1.45	0.88	1.66	1.22	0.93	1.55	1.13

* LST = source of LST; TN = Terra night; AN = Aqua night

† N = thousands of observations used to fit model

Table S4. Stage 1 T_{mean} model performance (predicting daily 1 km T_{mean} from LST): 10-fold cross-validated performance by year; overall, spatial, and temporal components.

T_{mean}			Overall			Spatial			Temporal		
Year	LST*	N†	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE
2000	TN	153	0.96	1.20	0.87	0.94	1.14	0.80	0.96	1.00	0.73
2001	TN	173	0.97	1.24	0.90	0.96	1.13	0.79	0.98	1.06	0.77
2002	TN	171	0.96	1.25	0.90	0.94	1.17	0.80	0.96	1.08	0.78
2003	TN	204	0.98	1.27	0.94	0.96	1.19	0.84	0.98	1.10	0.81
2004	TN	196	0.97	1.27	0.92	0.95	1.16	0.81	0.97	1.12	0.80
2005	TN	222	0.97	1.26	0.92	0.96	1.13	0.79	0.98	1.11	0.80
2006	TN	205	0.97	1.29	0.93	0.96	1.17	0.82	0.98	1.13	0.81
2007	TN	225	0.96	1.28	0.93	0.94	1.20	0.82	0.97	1.11	0.80
2008	TN	215	0.96	1.27	0.92	0.94	1.17	0.83	0.97	1.09	0.79
2009	TN	232	0.97	1.28	0.93	0.96	1.19	0.85	0.98	1.08	0.79
2010	TN	209	0.97	1.25	0.90	0.96	1.19	0.84	0.98	1.04	0.76
2011	TN	239	0.96	1.35	0.99	0.94	1.19	0.84	0.96	1.16	0.85
2012	TN	224	0.97	1.35	0.98	0.96	1.22	0.86	0.97	1.16	0.85
2013	TN	203	0.97	1.37	0.98	0.95	1.22	0.86	0.97	1.18	0.84
2014	TN	201	0.96	1.24	0.90	0.94	1.13	0.80	0.96	1.05	0.76
2015	TN	215	0.96	1.36	0.99	0.95	1.22	0.87	0.97	1.18	0.86
2016	TN	205	0.96	1.38	1.00	0.94	1.26	0.90	0.97	1.19	0.86

* LST = source of LST; TN = Terra night

† N = thousands of observations used to fit model

Table S5. Stage 1 T_{max} model performance (predicting daily 1 km T_{max} from LST): 10-fold cross-validated performance by year; overall, spatial, and temporal components.

T_{max}			Overall			Spatial			Temporal		
Year	LST*	N†	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE
2000	TD	265	0.94	1.78	1.33	0.90	1.56	1.13	0.95	1.38	1.02
2001	TD	319	0.96	1.80	1.34	0.92	1.54	1.12	0.97	1.46	1.07
2002	TD	314	0.94	1.83	1.37	0.90	1.56	1.14	0.95	1.46	1.08
2003	TD	379	0.97	1.84	1.37	0.94	1.59	1.16	0.97	1.49	1.10
2004	TD	334	0.95	1.79	1.33	0.93	1.51	1.09	0.97	1.45	1.06
2005	TD	358	0.96	1.77	1.32	0.94	1.52	1.09	0.97	1.44	1.06
2006	TD	337	0.96	1.86	1.38	0.92	1.59	1.16	0.97	1.52	1.11
2007	TD	353	0.95	1.79	1.34	0.91	1.55	1.11	0.96	1.45	1.07
2008	TD	318	0.95	1.77	1.32	0.91	1.52	1.11	0.96	1.41	1.04
2009	TD	341	0.96	1.83	1.37	0.92	1.58	1.15	0.97	1.44	1.06
2010	TD	308	0.96	1.77	1.32	0.93	1.56	1.13	0.97	1.38	1.01
2011	TD	358	0.94	1.82	1.37	0.91	1.62	1.18	0.96	1.45	1.07
2012	TD	332	0.96	1.83	1.37	0.92	1.61	1.18	0.97	1.46	1.08
2013	TD	291	0.96	1.86	1.38	0.92	1.62	1.17	0.97	1.49	1.09
2014	TD	300	0.94	1.73	1.29	0.91	1.51	1.11	0.95	1.36	1.01
2015	TD	315	0.95	1.86	1.39	0.91	1.61	1.18	0.96	1.51	1.12
2016	TD	290	0.95	1.82	1.36	0.91	1.60	1.17	0.96	1.47	1.08

* LST = source of LST; TD = Terra day
† N = thousands of observations used to fit model

Table S6. Stage 4 model performance (predicting daily 200 m residuals with an ensemble): 10-fold cross-validated performance by year.

	R_{Tmin}				R_{Tmean}				R_{Tmax}			
	N*	R^2	RMSE	MAE	N*	R^2	RMSE	MAE	N*	R^2	RMSE	MAE
2000	842	0.88	0.47	0.30	425	0.80	0.36	0.22	842	0.87	0.46	0.26
2001	834	0.85	0.49	0.32	427	0.75	0.41	0.25	834	0.83	0.52	0.31
2002	829	0.87	0.50	0.33	431	0.77	0.39	0.24	829	0.85	0.51	0.30
2003	824	0.78	0.66	0.43	431	0.79	0.42	0.28	824	0.84	0.54	0.34
2004	829	0.77	0.64	0.40	447	0.91	0.25	0.16	829	0.83	0.53	0.31
2005	825	0.75	0.70	0.44	467	0.75	0.44	0.28	825	0.85	0.50	0.31
2006	815	0.74	0.68	0.41	471	0.76	0.42	0.27	815	0.84	0.53	0.33
2007	817	0.79	0.64	0.41	480	0.77	0.42	0.28	817	0.83	0.53	0.32
2008	810	0.78	0.63	0.39	486	0.77	0.42	0.27	810	0.84	0.50	0.30
2009	803	0.78	0.66	0.42	488	0.79	0.42	0.28	803	0.85	0.52	0.32
2010	801	0.77	0.65	0.39	490	0.77	0.41	0.25	801	0.86	0.49	0.29
2011	793	0.80	0.67	0.43	487	0.79	0.43	0.29	793	0.84	0.54	0.34
2012	776	0.78	0.66	0.42	482	0.80	0.43	0.28	776	0.84	0.54	0.33
2013	748	0.76	0.65	0.40	476	0.85	0.35	0.22	748	0.87	0.48	0.29
2014	733	0.80	0.60	0.38	470	0.78	0.40	0.25	733	0.83	0.52	0.31
2015	709	0.79	0.66	0.43	461	0.77	0.45	0.29	709	0.86	0.52	0.33
2016	692	0.78	0.67	0.42	458	0.78	0.43	0.28	692	0.84	0.52	0.32

* N = thousands of observations used to fit model

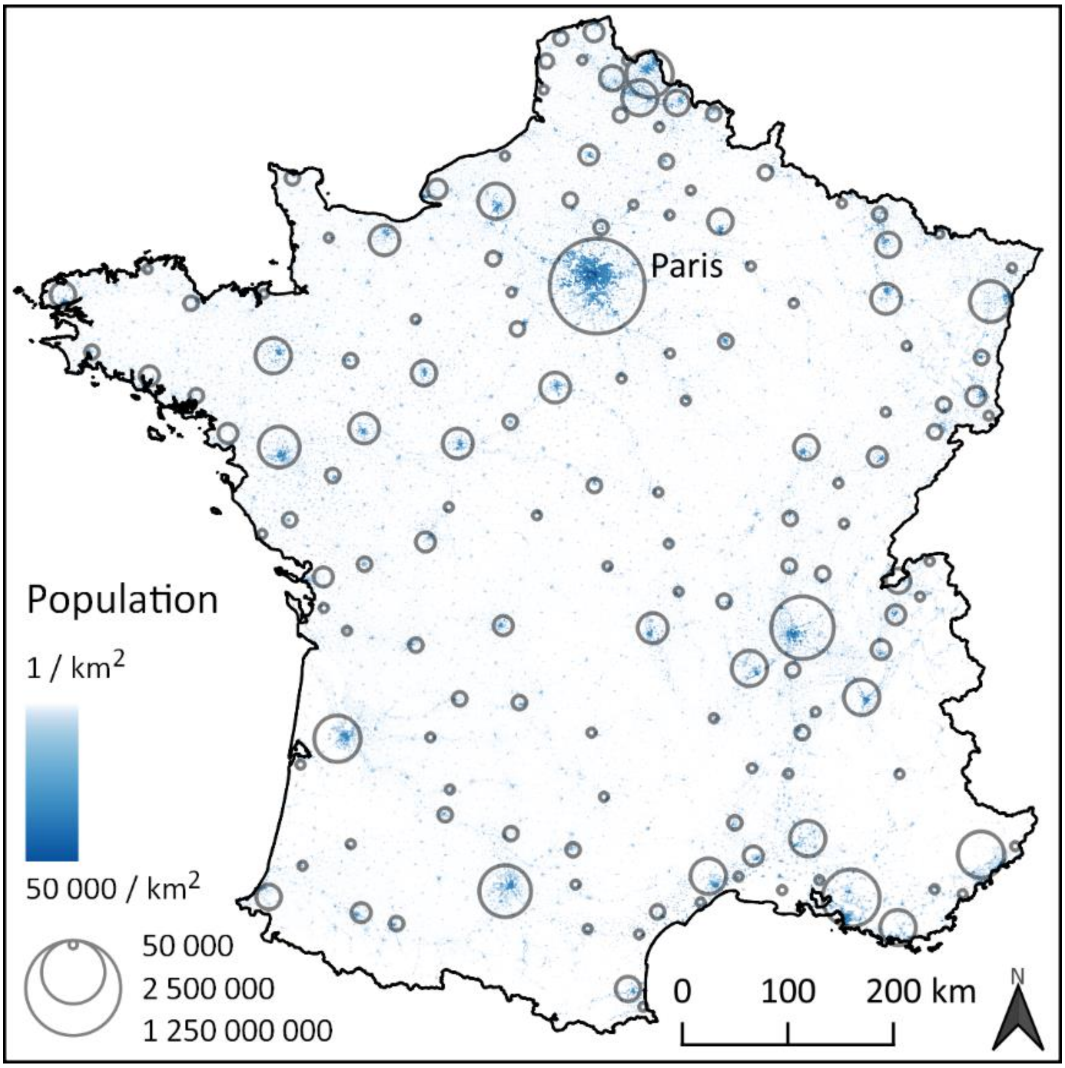

Fig. S1. Population density of France and urban areas with at least 50 000 residents.

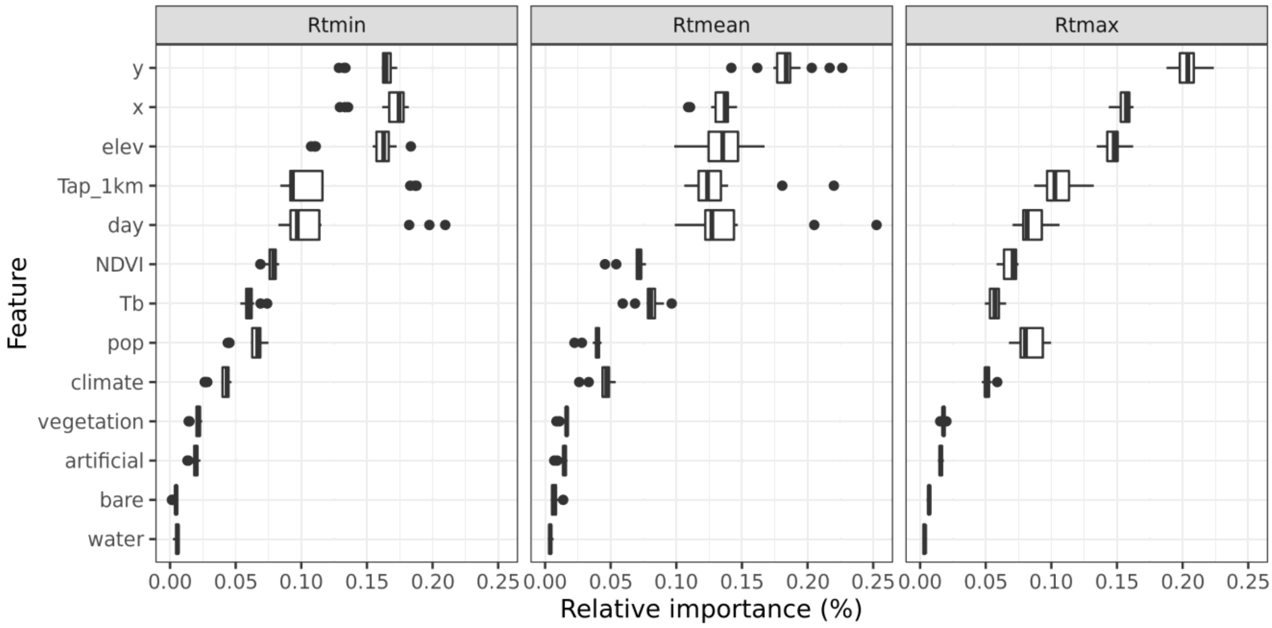

Fig. S2. Relative importance (%) of the predictors in the stage 3 random forest model (predicting 200 m residual). Each box shows the distribution for the different model years (2000 – 2016).

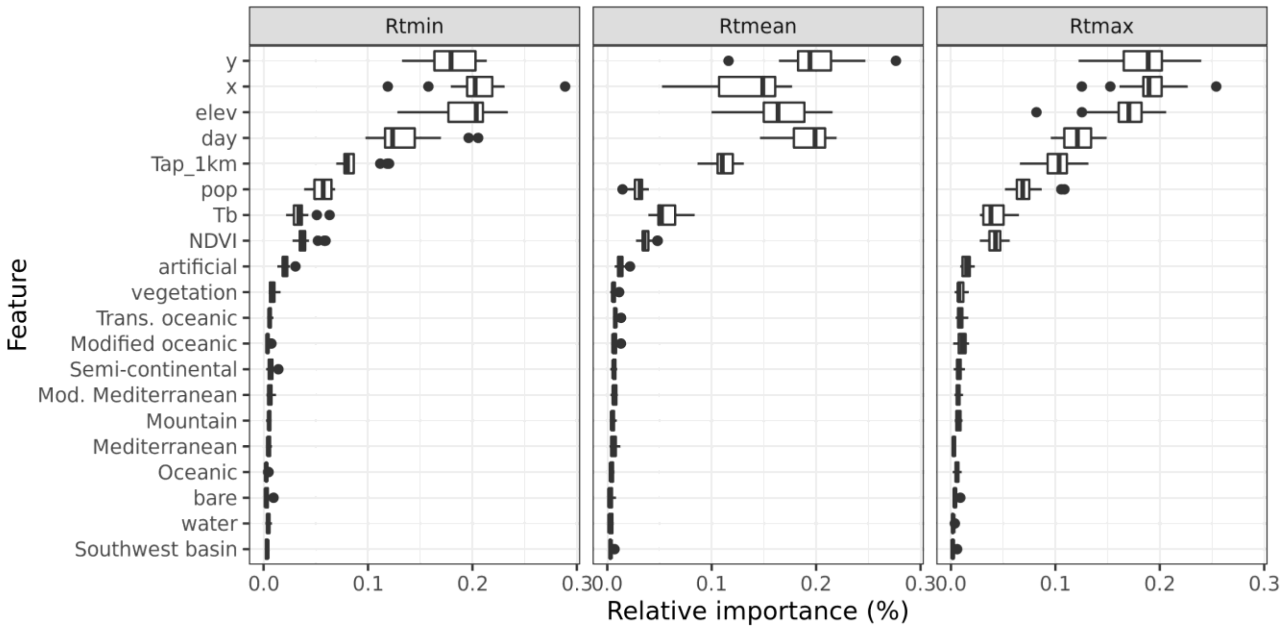

Fig. S3. Relative importance (%) of the predictors in the stage 3 XGBoost model (predicting 200 m residual). Each box shows the distribution for the different model years (2000 – 2016).

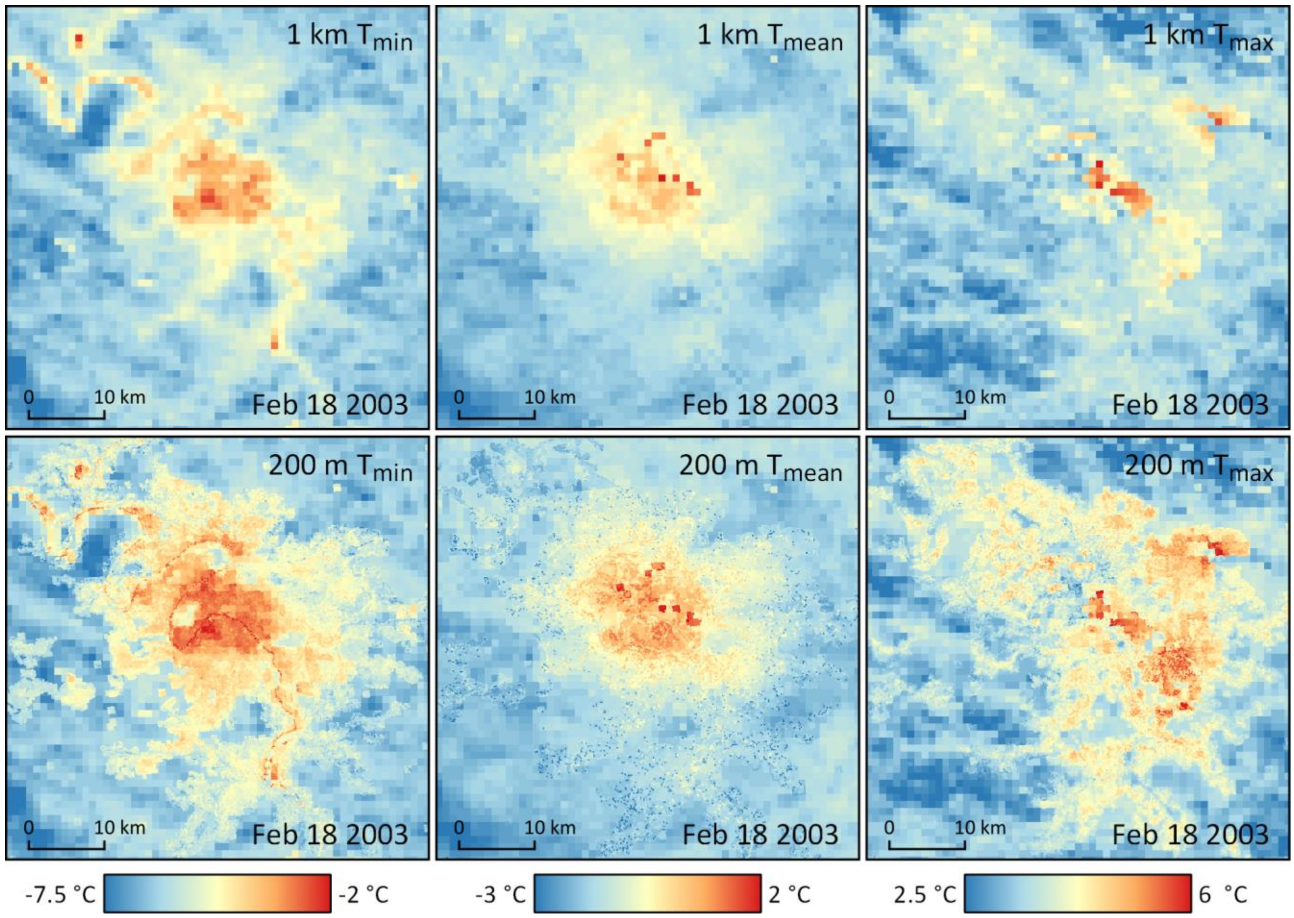

Fig. S4. Predicted 1 km T_a from the stage 2 model alone (top row) and with predicted 200 m T_{min} from the stage 4 model overlaid (bottom row) on Feb 18, 2003 over the Paris metropolitan area.

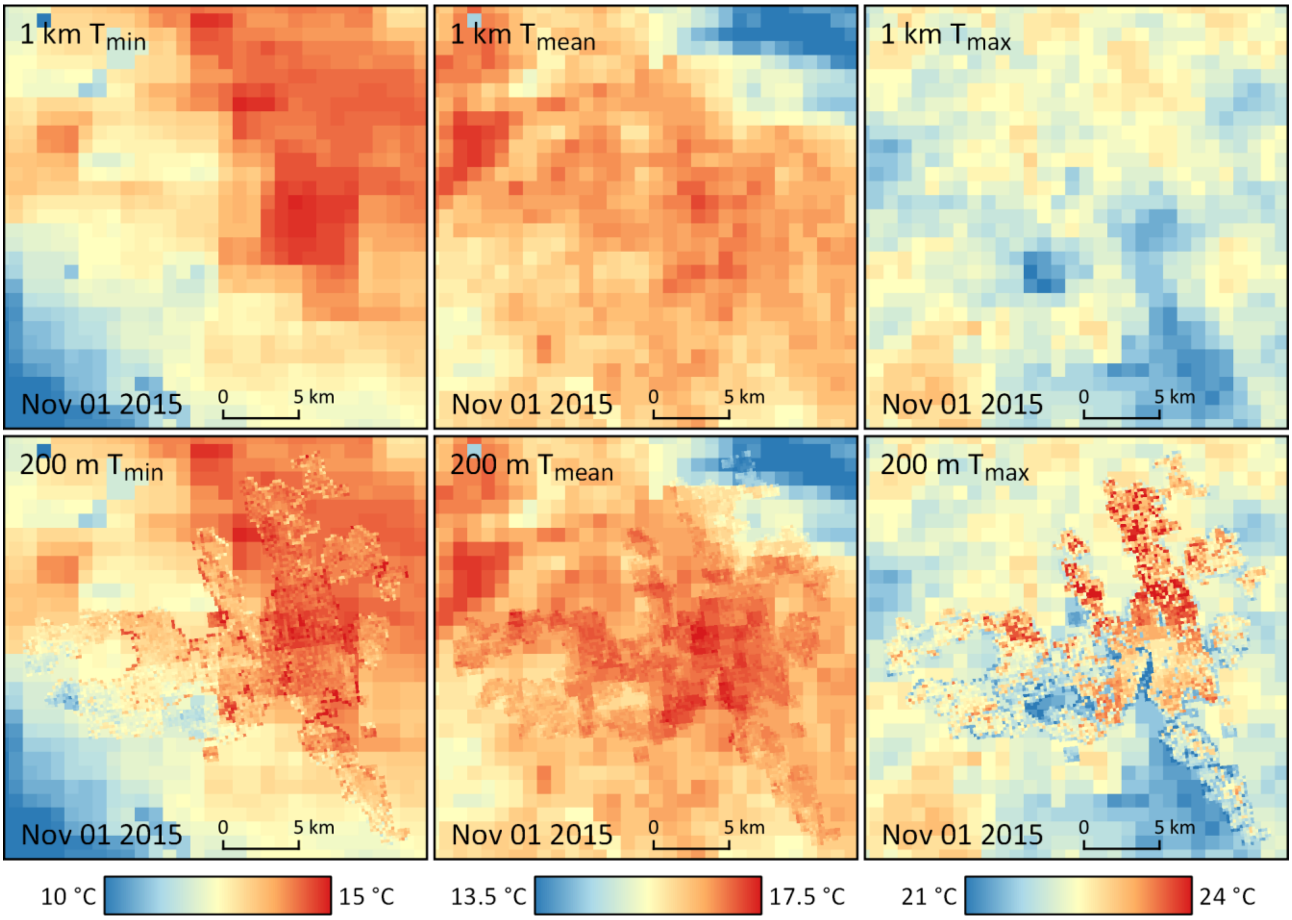

Fig. S5. Predicted 1 km T_a from the stage 2 model alone (top row) and with predicted 200 m T_{min} from the stage 4 model overlaid (bottom row) on Nov 01, 2015 over the city of Toulouse.

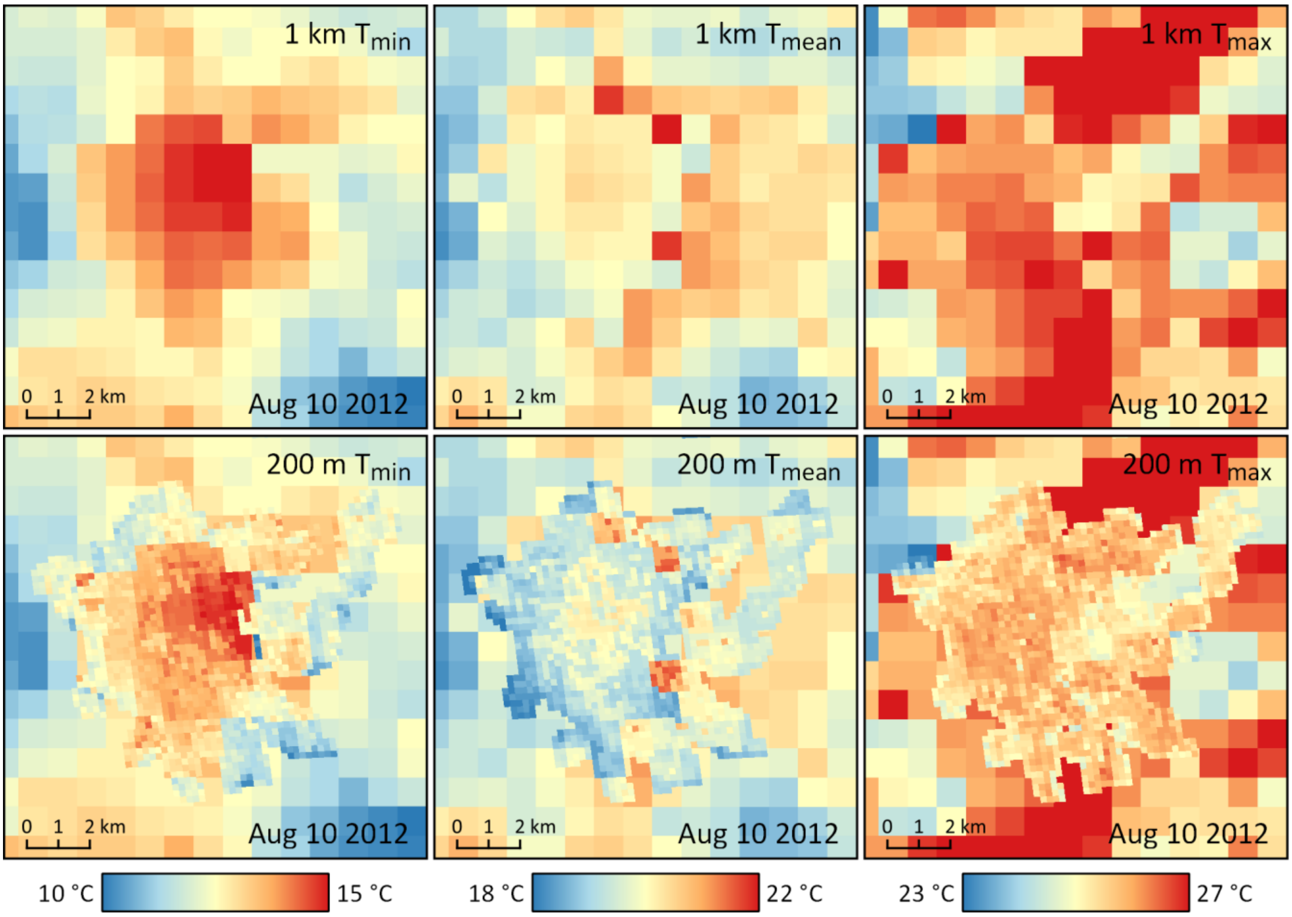

Fig. S6. Predicted 1 km T_a from the stage 2 model alone (top row) and with predicted 200 m T_{min} from the stage 4 model overlaid (bottom row) on Aug 10, 2012 over the city of Nancy.