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

Ian Hough

2019-02-15

Climate change, air pollution, and perinatal health

Ian Hough

Dr. Johanna Lepeule

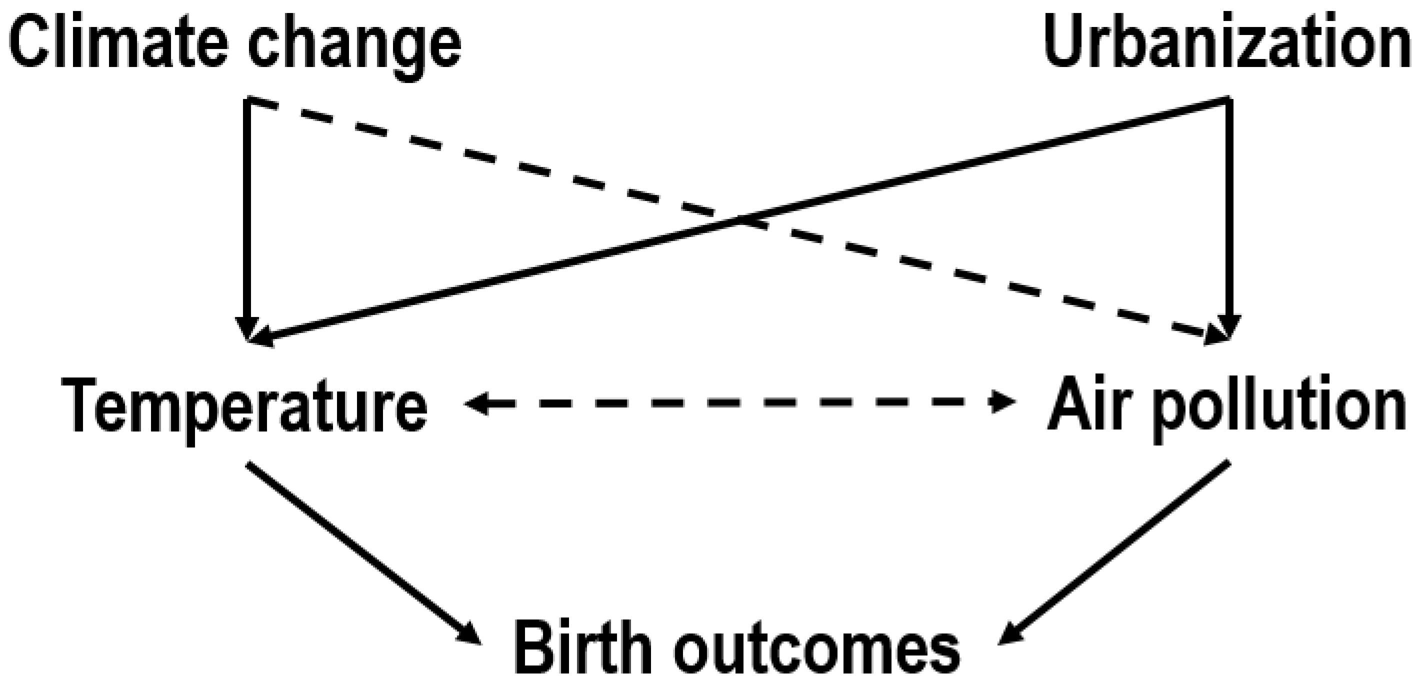
Institute for Advanced Biosciences

University Grenoble Alpes

Dr. Itai Kloog

Department of Geography and Environmental Development

Ben Gurion University of the Negev


Climate change
Urbanization
Temperature
Air pollution
Birth outcomes

Adverse birth outcomes

Preterm birth (<37 weeks gestation)

- 11% of all births and increasing (Harrison, et al., 2016)
- Leading cause of child mortality (Liu, et al., 2016)
- Sequalae in childhood and adulthood (McCormick, et al., 2011)
    - Asthma, cerebral palsy, behavioural problems, etc.

Term low birth weight (<2500 g)

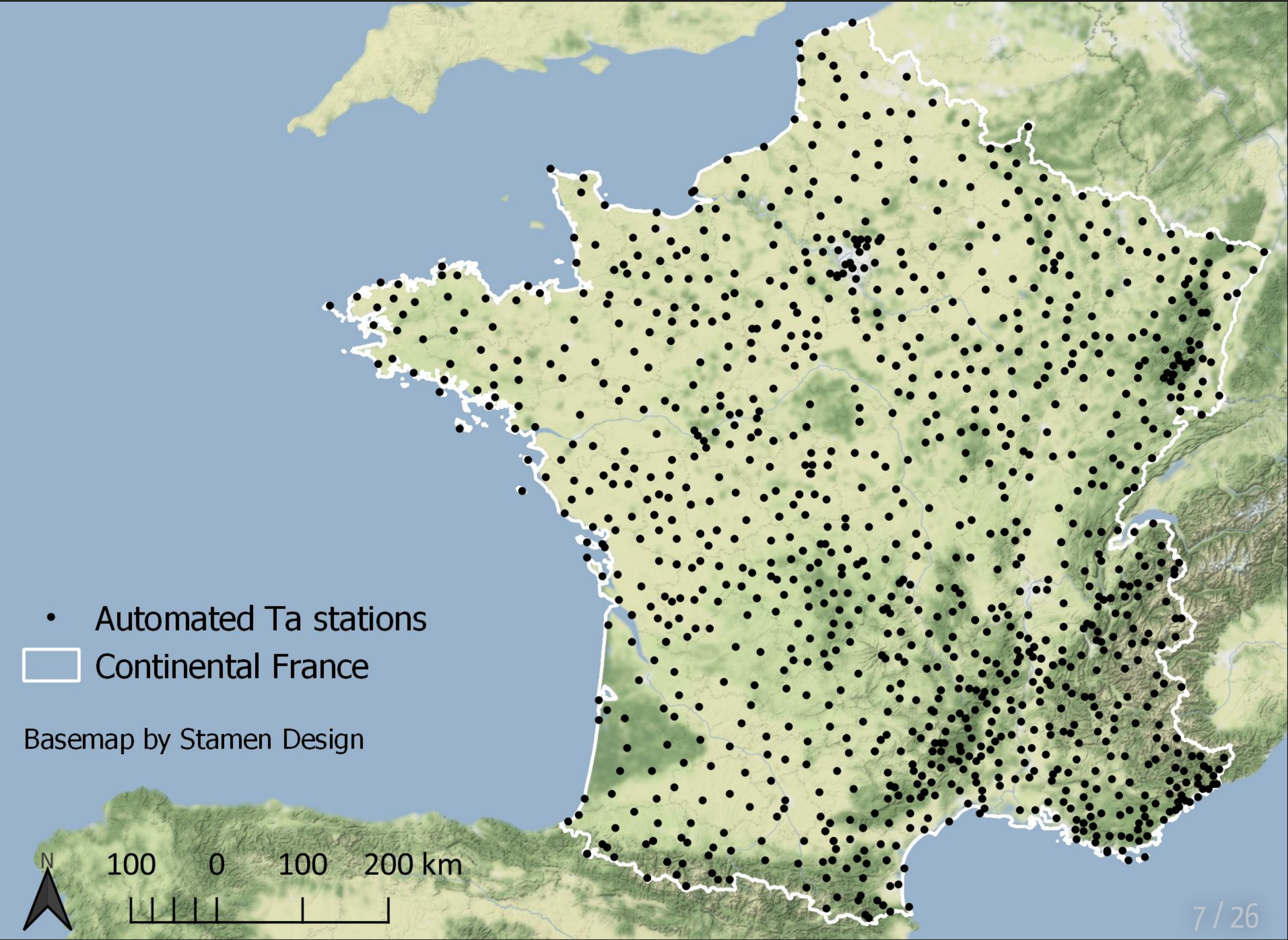
- Increased morbidity and mortality in childhood & adulthood (Barker, 2004; Belbasis, et al., 2016)

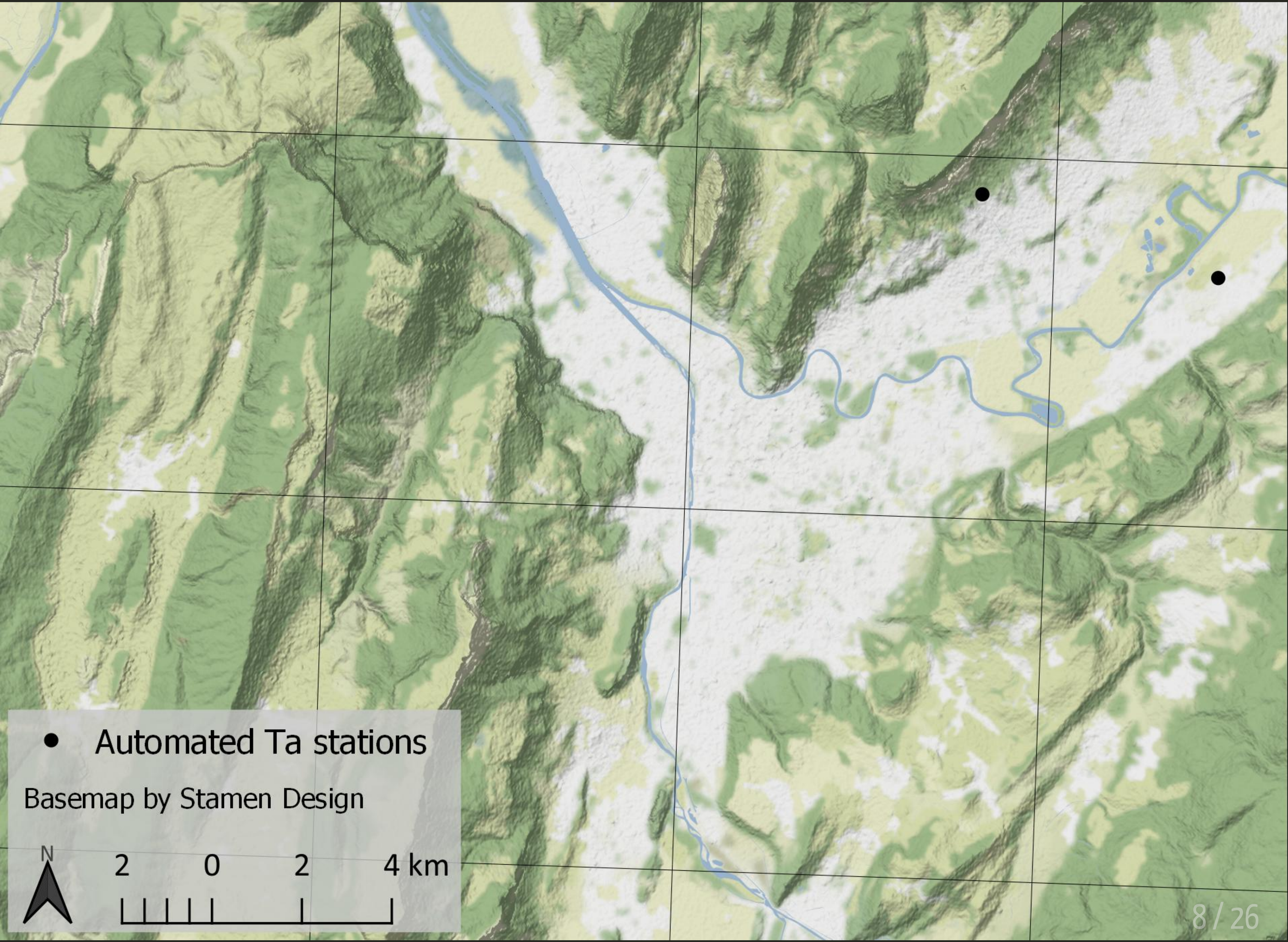
Ambient temperature (T_a) and health

- Heat, cold, or variable T_a can increase risk (Zhang, et al., 2017)
- Response may depend on local population & climate
- Hard to synthesize findings

	Preterm birth	Birth weight	Term low birth weight
Exposure	Cold (<10th %ile)	IQR Ta increase	Heat (>95th %ile)
Window	Weeks 1–7	Last 30 days	Trimester 3
Statistic	Relative risk	Decrease	Odds ratio
Effect	1.09 [1.04–1.15]	16.6 g [5.9–27.4]	1.31 [1.15–1.49]
Reference	Ha, et al. (2017)	Kloog, et al. (2015)	Ha, et al. (2017)

How do we estimate T_a exposure?


Automated Ta stations
Continental France
Basemap by Stamen Design
N
100 0 100 200 km


Automated Ta stations
Basemap by Stamen Design
N
2 0 2 4 km

Exposure error

- Sparse monitoring networks
- Coarse gridded meteorological data

$\longrightarrow$ May bias effect estimates towards null

Our T_a model

- Daily minimum, maximum, and mean T_a 2000 - 2016
- 1 x 1 km^2 for continental France[1]
- 200 x 200 m^2 for large urban areas

[1] Extension of (Kloog, et al., 2017) (daily 1 km mean T_a 2000 - 2011)

Model components

1. Spatiotemporal and spatial predictors
    - Land Surface Temperature (LST), elevation, etc.
2. Linear mixed model
    - T_a ~ LST with daily varying slope
3. Gapfilling
    - T_{pred} ~ T_a at nearby stations
4. Local interpolation of residuals
    - High spatial resolution predictors + machine learning ensemble

Satellite data

MODIS (1 km)

- Land Surface Temperature (LST)
    - Terra: 10:30 / 22:30 (day / night)
    - Aqua: 13:30 / 01:30 (day / night)
- NDVI
    - Monthly composite

Landsat 5 / 7 / 8 (30 m)

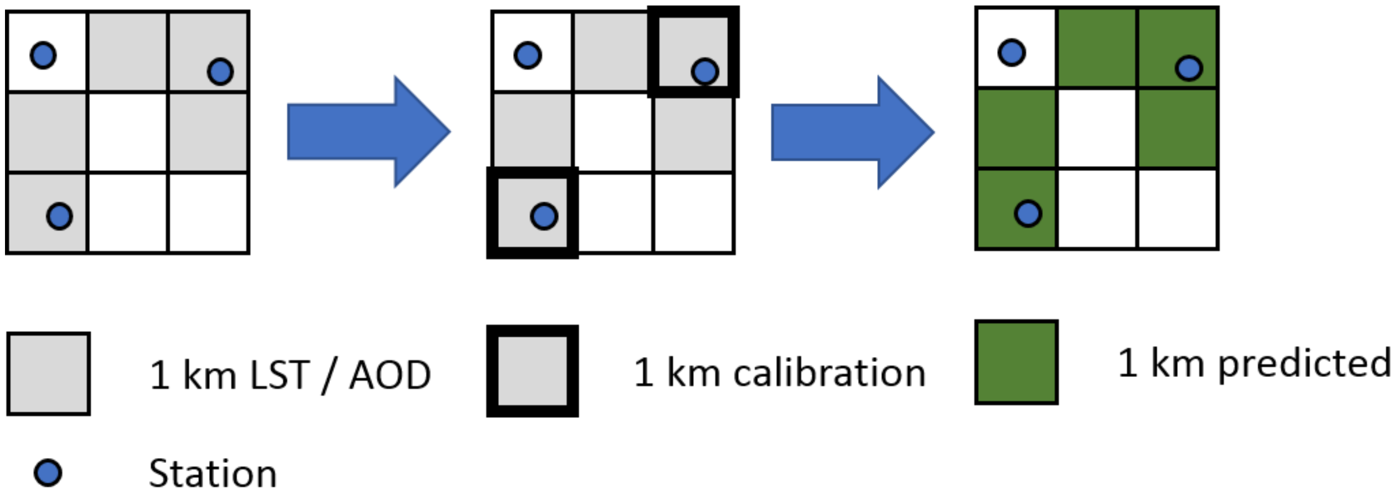
- Top-of-atmosphere brightness temperature (T_B)
- NDVI
- ↑ composited by month across 2000 - 2016

Spatial predictors

- Elevation
- Land cover
- Population
- Climatic regions

↑ Aggregated to 1 km and 200 m grids

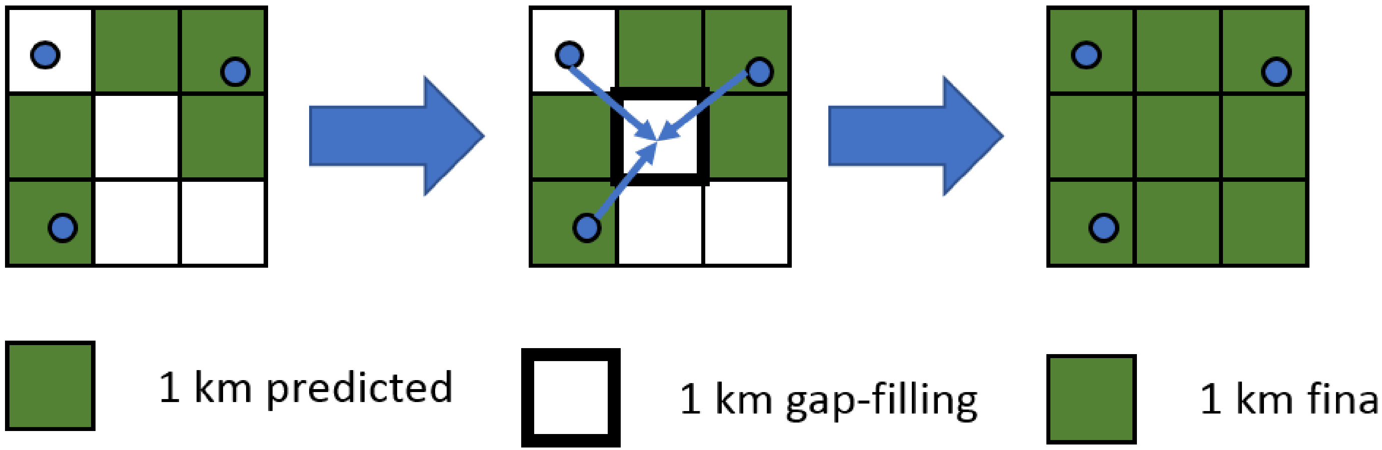
Stage 1: linear mixed model (1 km)



$$T_a = (\alpha + \mu_{jr}) + (\beta_1 + \nu_{jr}) \cdot LST + \beta_2 \cdot Emissivity + \beta_3 \cdot NDVI + \beta_4 \cdot Elevation + \beta_5 \cdot Population + \beta_6 \cdot LandCover + e$$

j = day r = climatic region e = error

Stage 2: Gapfilling

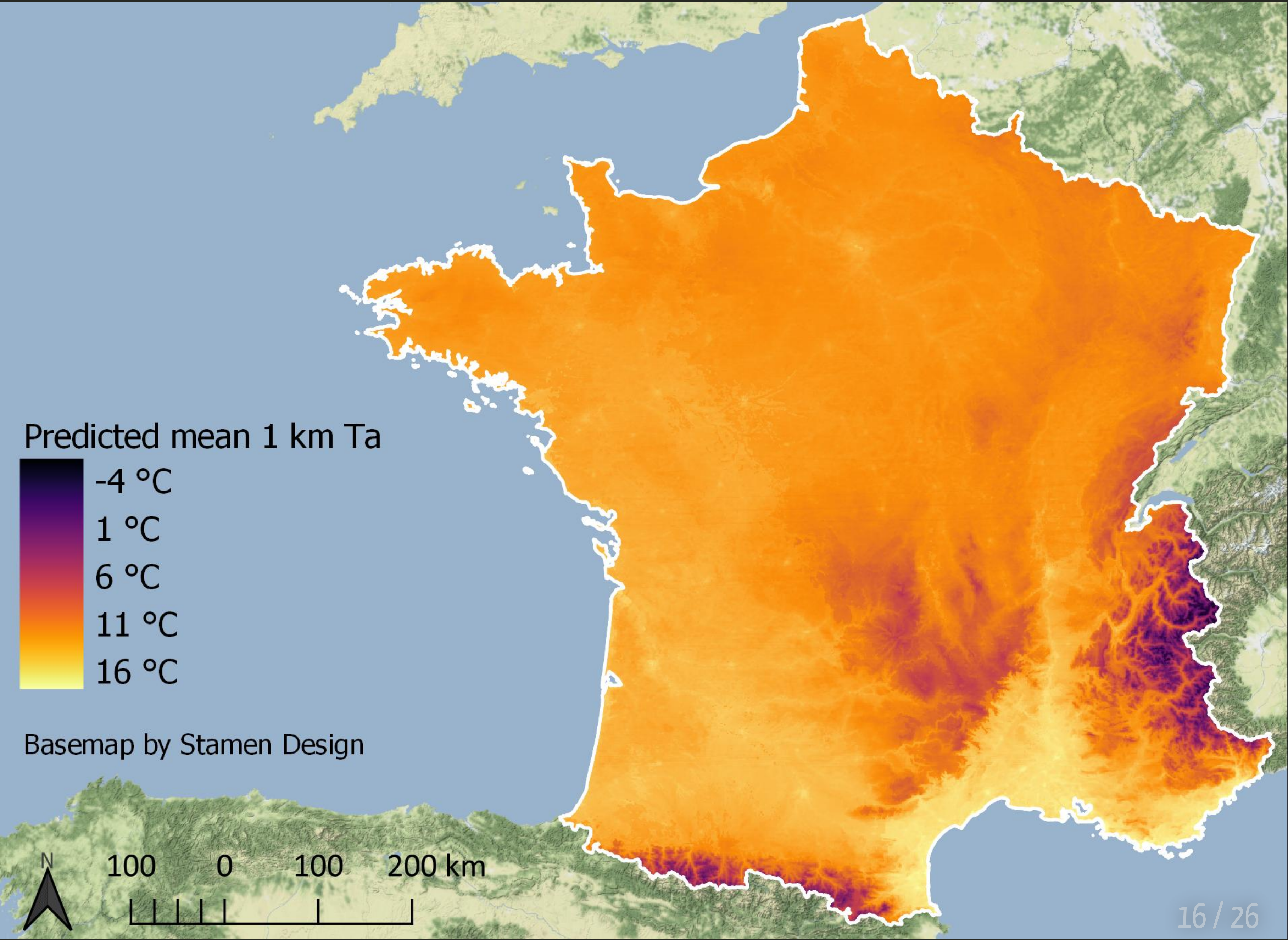


$$T_{pred} = (\alpha + \mu_{ip}) + (\beta_1 + \nu_{ip}) \cdot T_{IDW} + e$$

i = grid cell

p = two-month period

T_{IDW} = inverse distance weighted T_a


Predicted mean 1 km Ta
-4 °C
1 °C
6 °C
11 °C
16 °C
Basemap by Stamen Design
N
100
0
100
200 km

1 km model performance

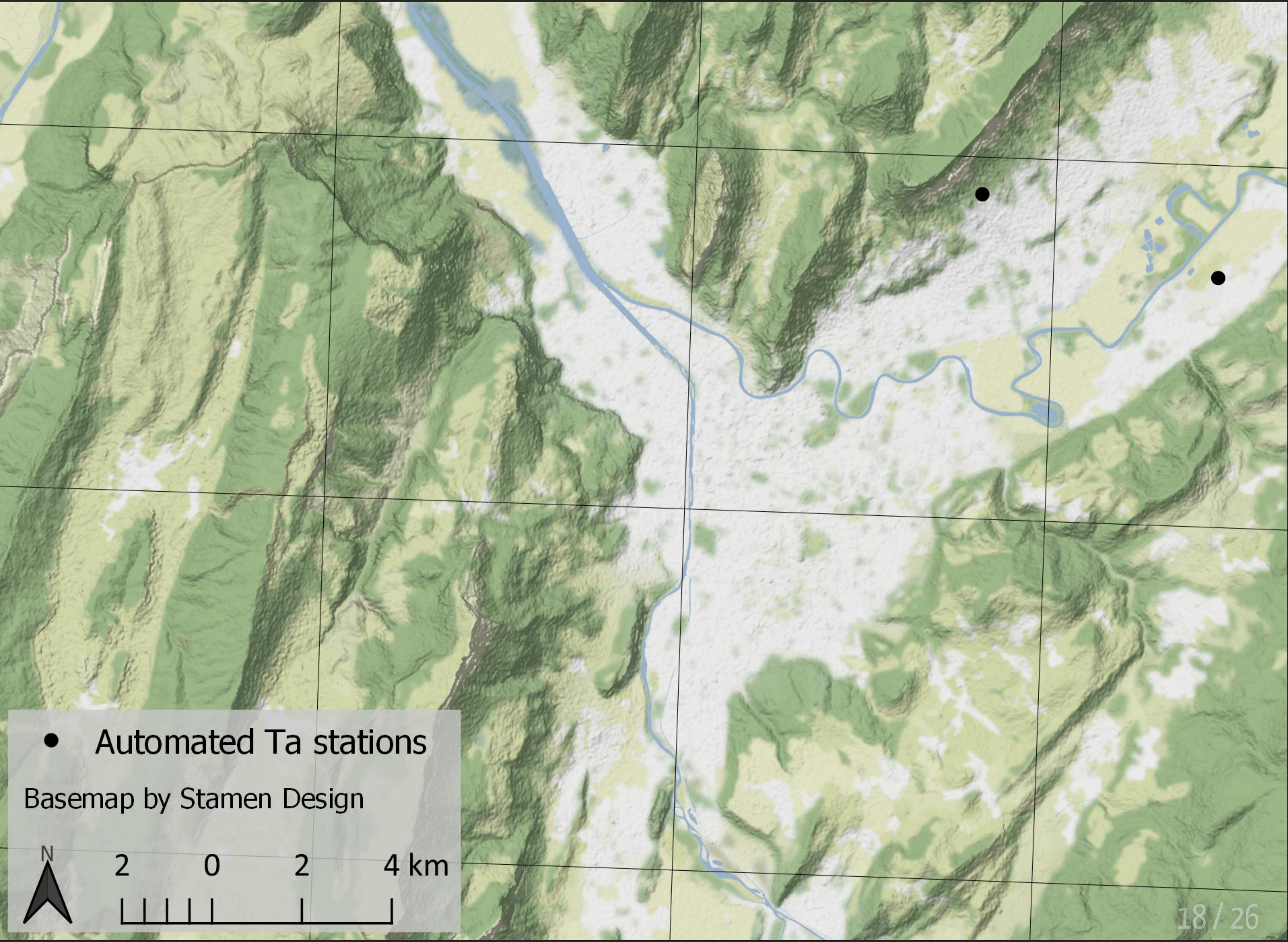
Cross-validated 1 km predictions (calibration stage)

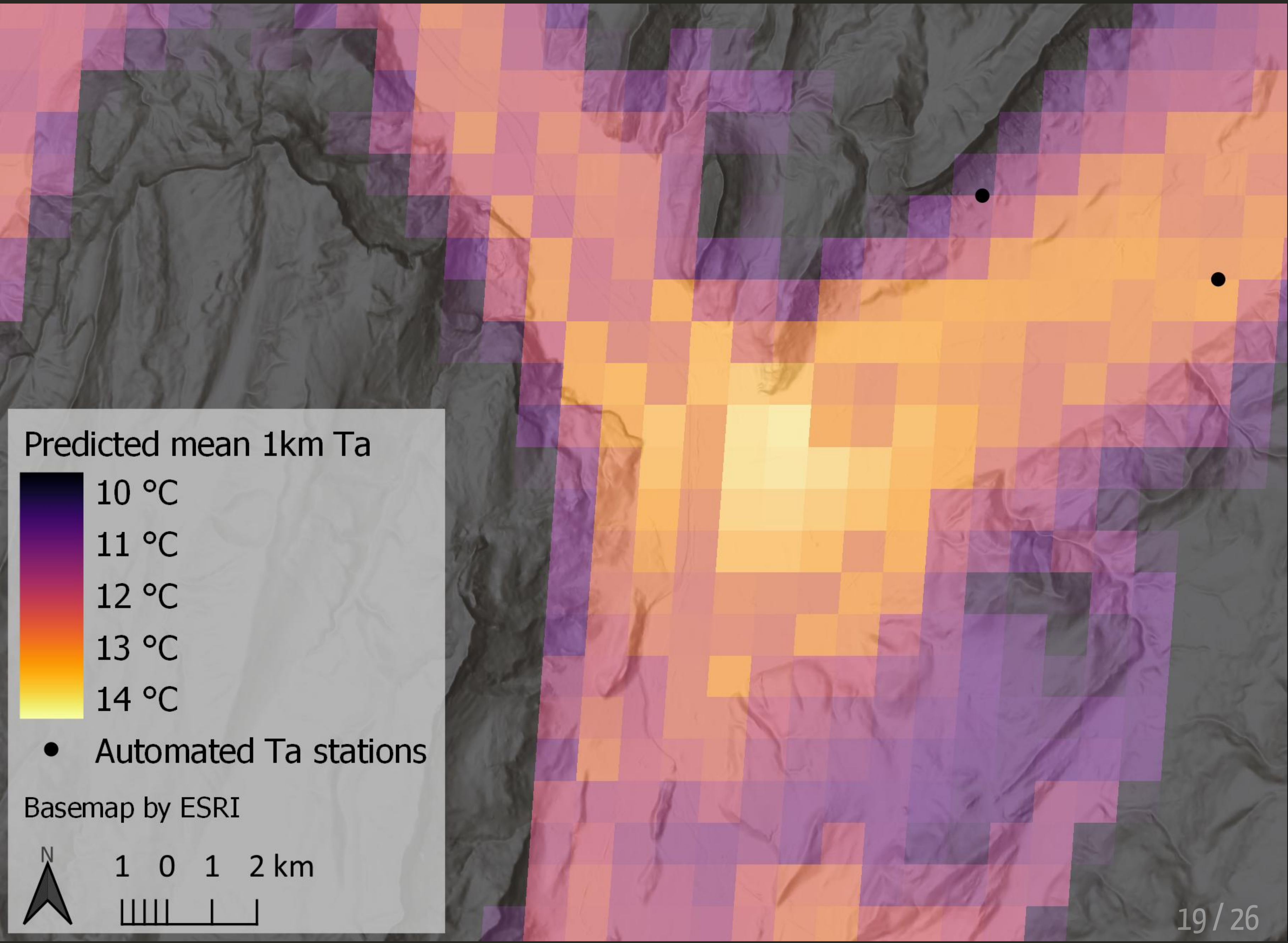
2000-2016	R2	RMSE	MAE	Spatial R2	Spatial RMSE	Temporal R2	Temporal RMSE
T_a min	0.92	1.9	1.4	0.89	1.1	0.94	1.6
T_a mean	0.97	1.3	0.9	0.95	0.8	0.97	1.2
T_a max	0.95	1.8	1.4	0.88	1.2	0.96	1.5

Previous model (Kloog, et al., 2017)

2000-2011	R2	RMSE	MAE	Spatial R2	Spatial RMSE	Temporal R2	Temporal RMSE
T_a mean	0.95	1.5	*	0.91	0.65	0.96	*

* = not reported


Automated Ta stations
Basemap by Stamen Design
N
2 0 2 4 km



Predicted mean 1km Ta
10 °C
11 °C
12 °C
13 °C
14 °C
Automated Ta stations
Basemap by ESRI
N
1 0 1 2 km

Stage 3: Residual interpolation (200 m)

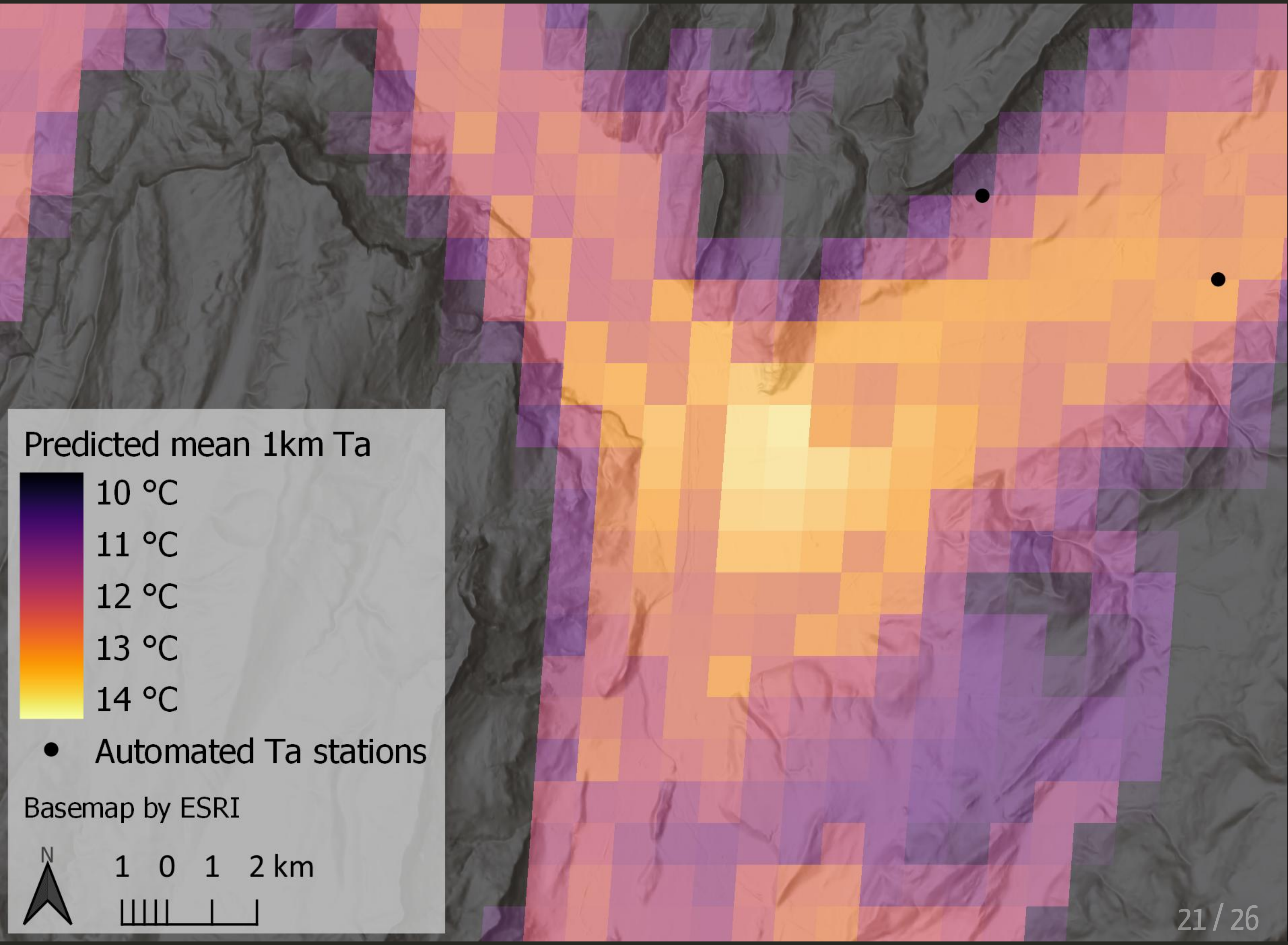
Contiguous urban areas with > 50,000 inhabitants

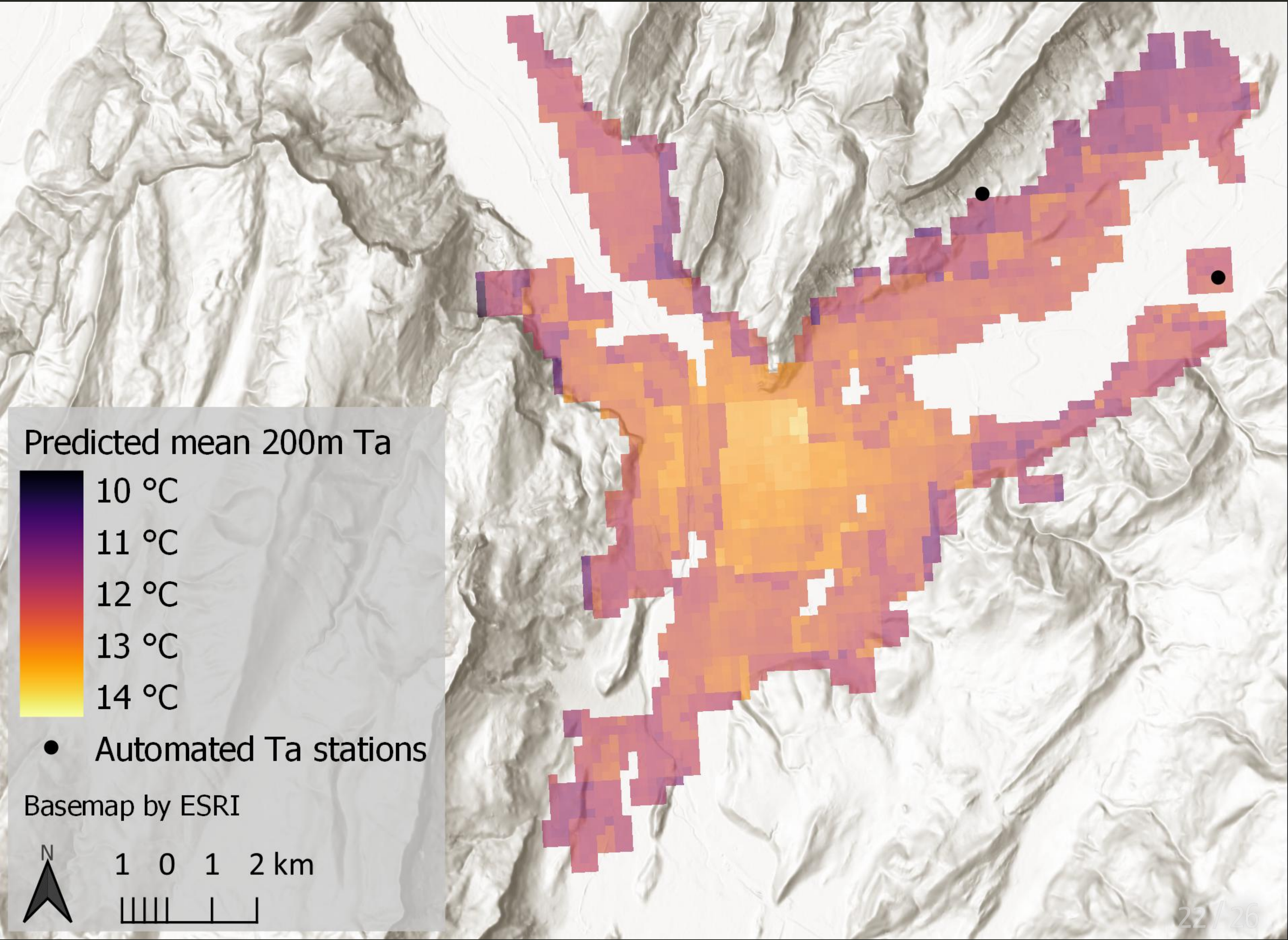
Random forest and XGBoost models

$$R \sim T_{pred},\ T_B,\ NDVI,\ Elevation,\ Population,\ LandCover,\ lat,\ lon,\ day$$

GAM ensemble

- Weights vary by location and predicted residual


Predicted mean 1km Ta
10 °C
11 °C
12 °C
13 °C
14 °C
Automated Ta stations
Basemap by ESRI
N
1 0 1 2 km


Predicted mean 200m Ta
10 °C
11 °C
12 °C
13 °C
14 °C
Automated Ta stations
Basemap by ESRI
N
1 0 1 2 km

200 m model performance

Cross-validated 200 m ensemble predictions (residual scale)

2000-2016	R2	RMSE	MAE	Spatial R2	Spatial RMSE	Temporal R2	Temporal RMSE
R_{min}	0.79	0.6	0.4	1.0	0.05	0.66	0.6
R_{mean}	0.89	0.4	0.3	1.0	0.04	0.87	0.4
R_{max}	0.85	0.5	0.3	1.0	0.03	0.73	0.5

Next steps

Fine particulate matter models (PM_{10} & $PM_{2.5}$)

- Similar to T_a model
- MODIS aerosol optical depth (AOD)

Birth outcomes study

- EDEN, PELAGIE, SEPAGES
- Birth weight and preterm birth
- T_a, PM, and interaction

Thanks!

Ian Hough

ian.hough@univ-grenoble-alpes.fr

References

Barker, D. J. P. (2004). "The Developmental Origins of Adult Disease". In: *Journal of the American College of Nutrition* 23.2004, pp. 588S-595S. DOI: 10.1080/07315724.2004.10719428.

Belbasis, L, et al. (2016). "Birth weight in relation to health and disease in later life: An umbrella review of systematic reviews and meta-analyses". In: *BMC Medicine* 14. DOI: 10.1186/s12916-016-0692-5.

Ha, S, et al. (2017). "Ambient temperature and early delivery of Singleton Pregnancies". In: *Environmental Health Perspectives* 125.3, pp. 453-459. DOI: 10.1289/EHP97.

Ha, S, et al. (2017). "Ambient temperature and air quality in relation to small for gestational age and term low birthweight". In: *Environmental Research* 155, pp. 394-400. DOI: 10.1016/j.envres.2017.02.021.

Harrison, M. S, et al. (2016). "Global burden of prematurity". In: *Seminars in Fetal and Neonatal Medicine* 21.2, pp. 74-79. DOI: 10.1016/j.siny.2015.12.007.

Kloog, I, et al. (2014). "A new hybrid spatio-temporal model for estimating daily multi-year PM2.5 concentrations across northeastern USA using high resolution aerosol optical depth data". 95, pp. 581-590. DOI: 10.1016/j.atmosenv.2014.07.014.

Kloog, I, et al. (2015). "Using Satellite-Based Spatiotemporal Resolved Air Temperature Exposure to Study the Association between Ambient Air Temperature and Birth Outcomes in Massachusetts". In: *Environmental Health Perspectives* 123.10, pp. 1053-1058. DOI: 10.1289/ehp.1308075.

Kloog, I, et al. (2017). "Modelling spatio-temporally resolved air temperature across the complex geo-climate area of France using satellite-derived land surface temperature data". In: *International Journal of Climatology* 37.1, pp. 296-304. DOI: 10.1002/joc.4705.

Liu, L, et al. (2016). "Global, regional, and national causes of under-5 mortality in 2000-15: an updated systematic analysis with implications for the Sustainable Development Goals". In: *The Lancet* 388, pp. 3027-3035. DOI: 10.1016/S0140-6736(16)31593-8.

McCormick, M. C, et al. (2011). "Prematurity: An Overview and Public Health Implications". In: *Annual Review of Public Health* 32, pp. 367-379. DOI: 10.1146/annurev-publhealth-090810-182459.

Rosenfeld, A, et al. (2017). "Estimating daily minimum, maximum, and mean near surface air temperature using hybrid satellite models across Israel". In: *Environmental Research* 159, pp. 297-312. DOI: 10.1016/j.envres.2017.08.017.

Shi, L, et al. (2016). "Estimating daily air temperature across the Southeastern United States using high-resolution satellite data: A statistical modeling study". In: *Environmental Research* 146, pp. 51-58. DOI: 10.1016/j.envres.2015.12.006.

Zhang, Y, et al. (2017). "Temperature exposure during pregnancy and birth outcomes: An updated systematic review of epidemiological evidence". In: *Environmental Pollution* 225, pp. 700-712. DOI: 10.1016/j.envpol.2017.02.066.