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

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Climate change, air pollution, and perinatal health

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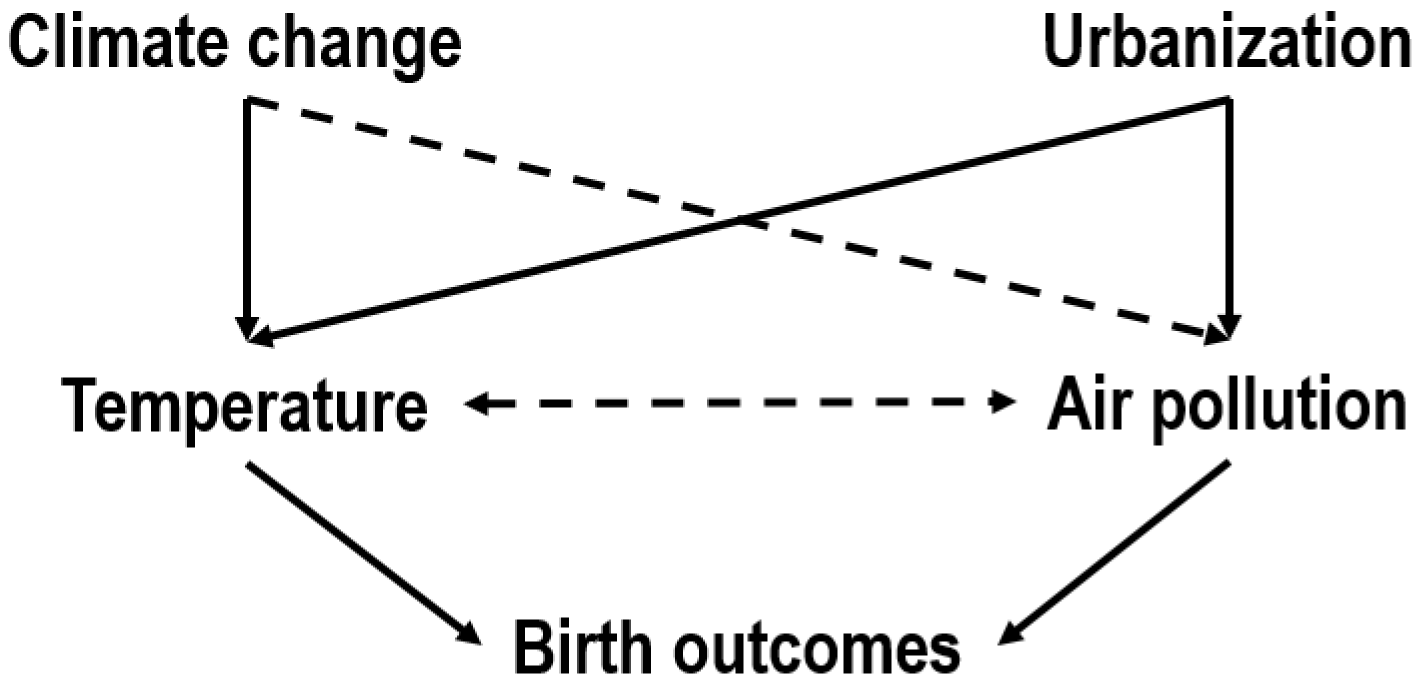

Climate change
Urbanization
Temperature
Air pollution
Birth outcomes

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)

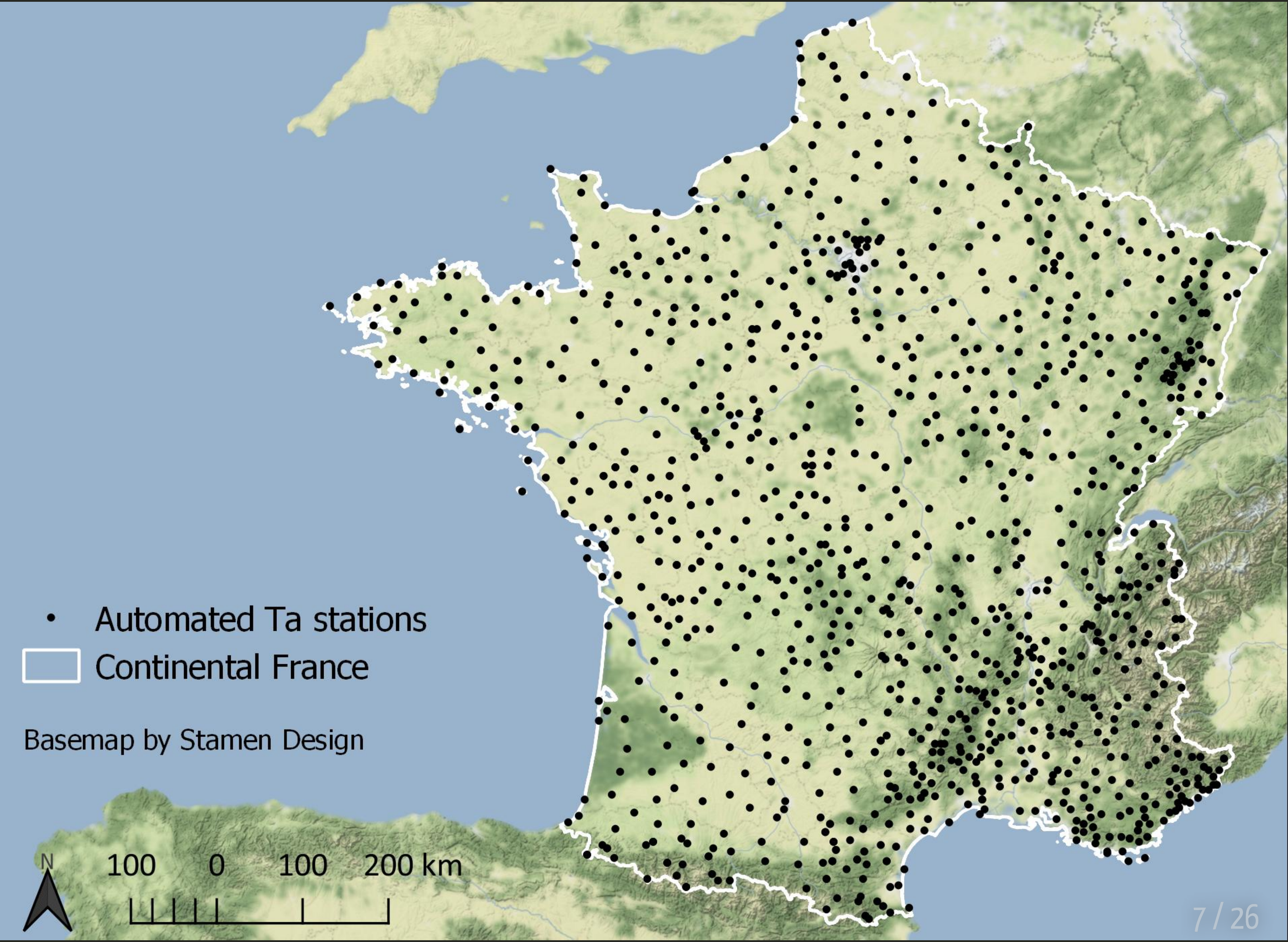
- Increased morbidity and mortality in childhood & adulthood (Barker, 2004; Belbasis, et al., 2016)

Ambient temperature (T_a) and health

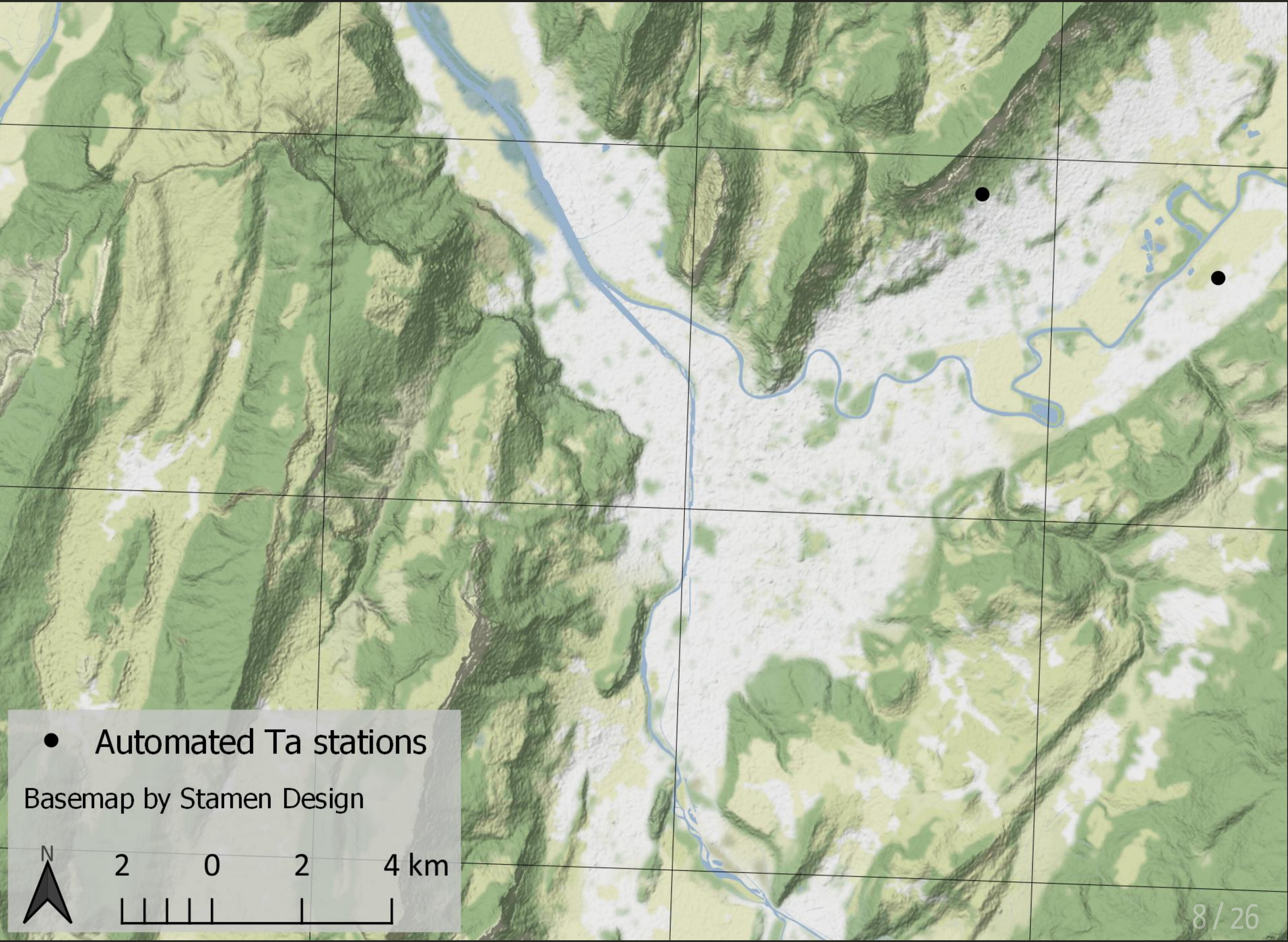
- Heat, cold, or variable T_a can increase risk (Zhang, et al., 2017)
- Response may depend on local population & climate
- Hard to synthesize findings

	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
- 200 x 200 m^2 for large urban areas

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)

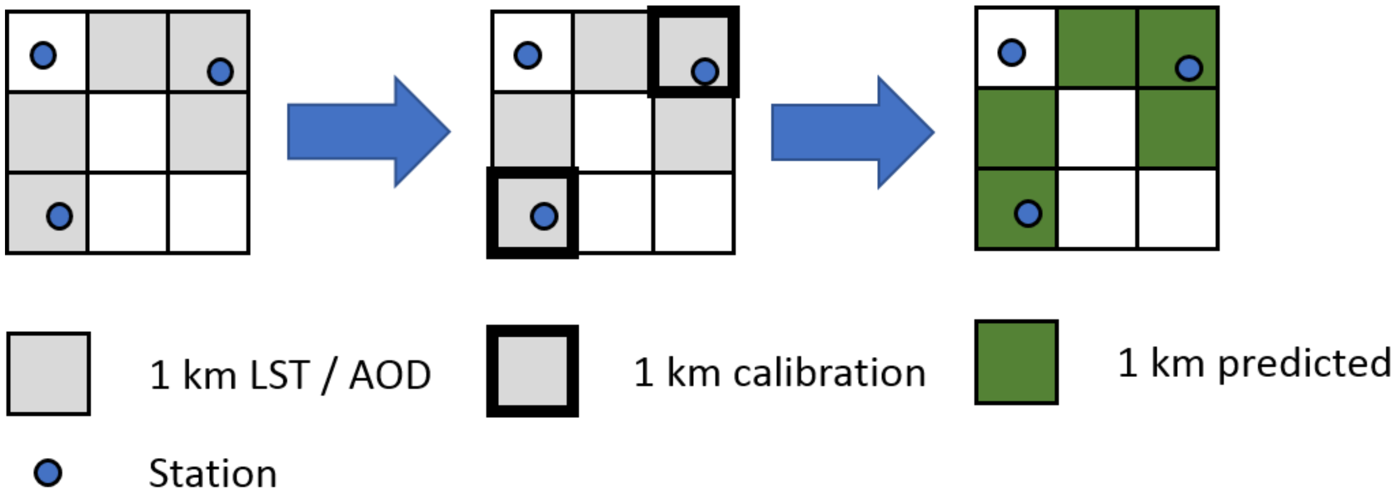
- Top-of-atmosphere brightness temperature (T_B)
- NDVI
- ↑ composited by month across 2000 - 2016

Spatial predictors

- Elevation
- Land cover
- Population
- Climatic regions

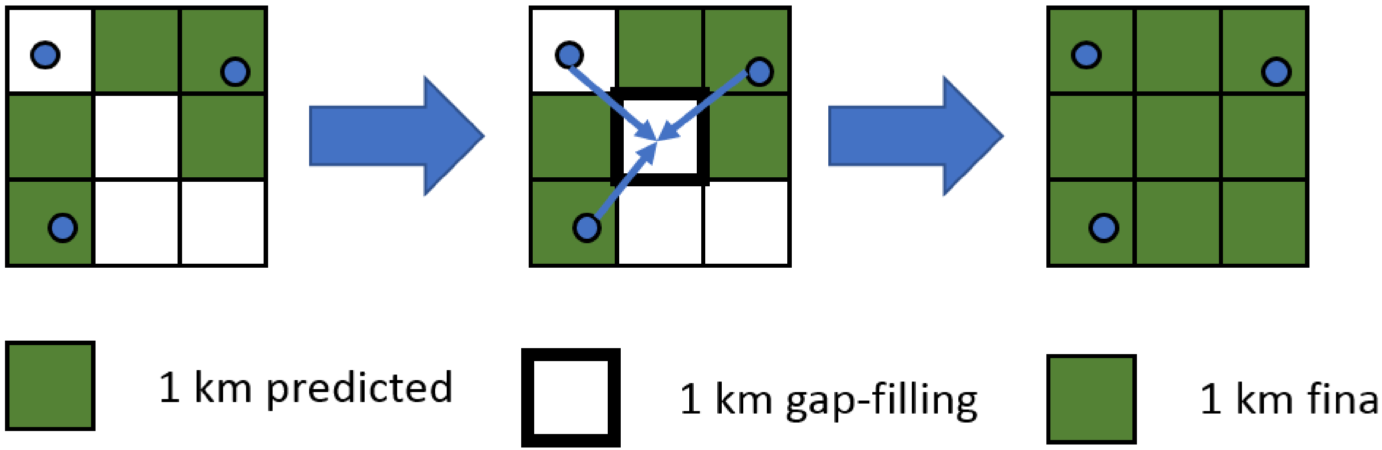
↑ Aggregated to 1 km and 200 m grids

Stage 1: linear mixed model (1 km)



j = day r = climatic region e = error

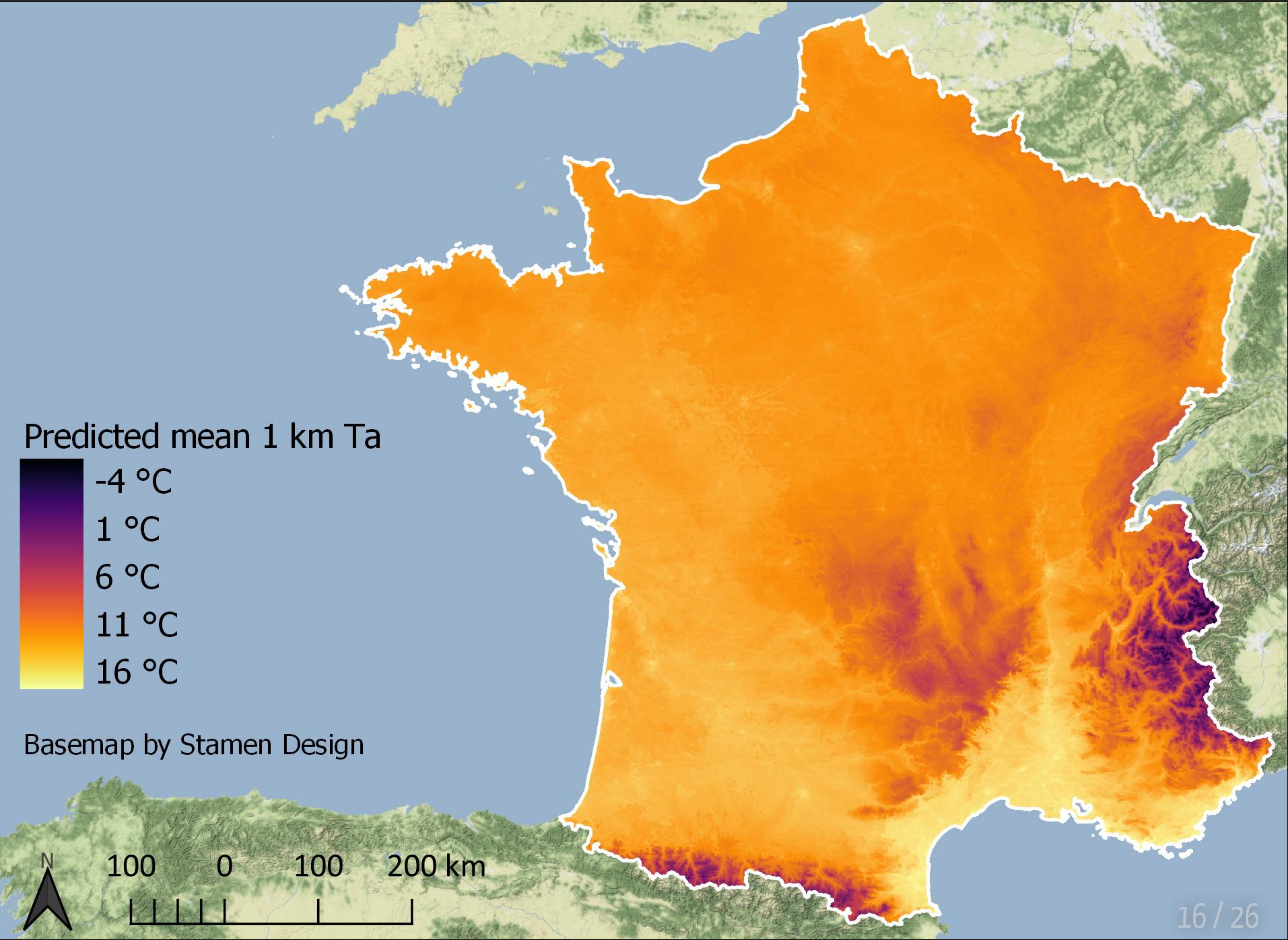
Stage 2: Gapfilling



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

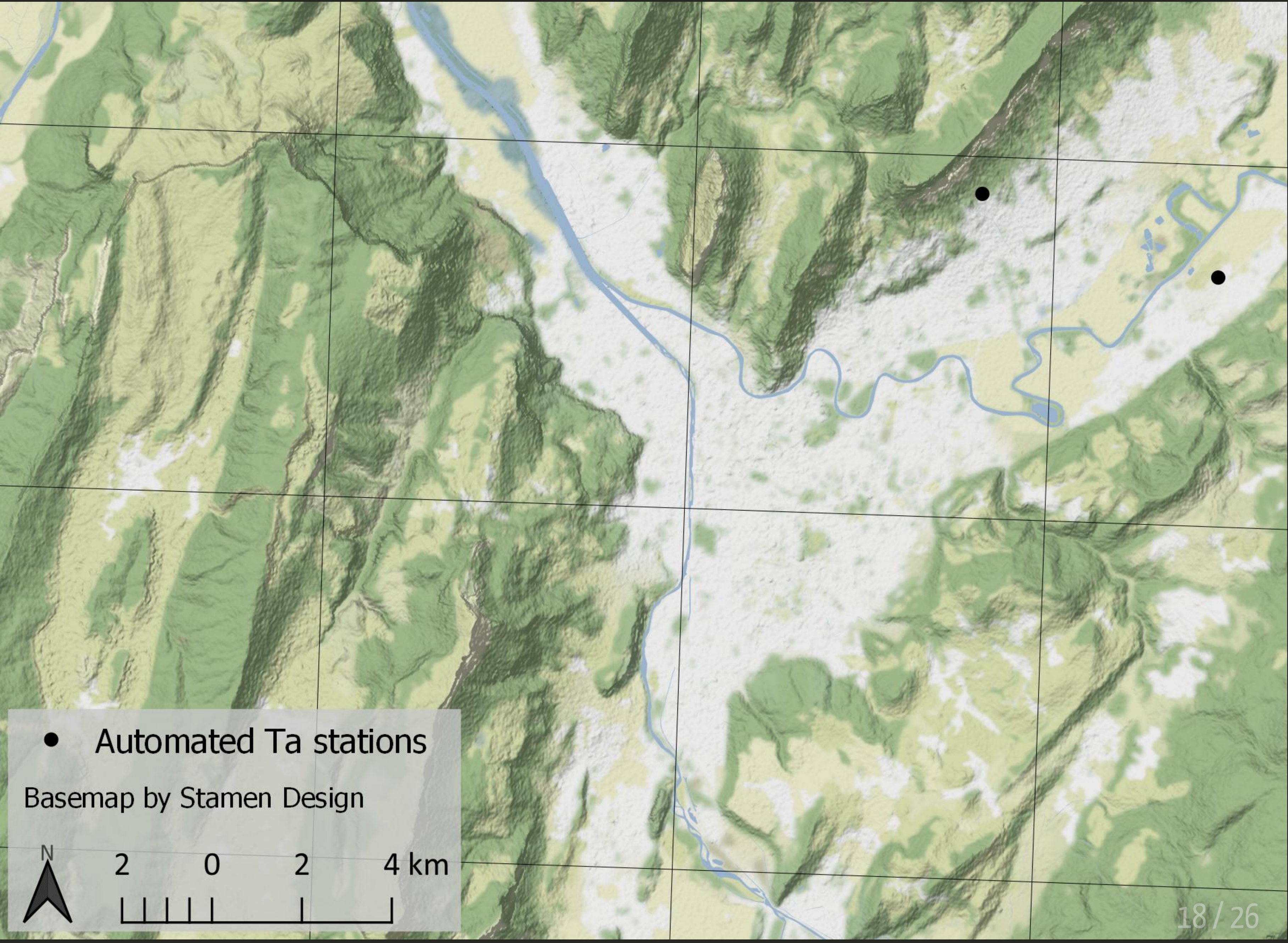
Cross-validated 1 km predictions (calibration stage)

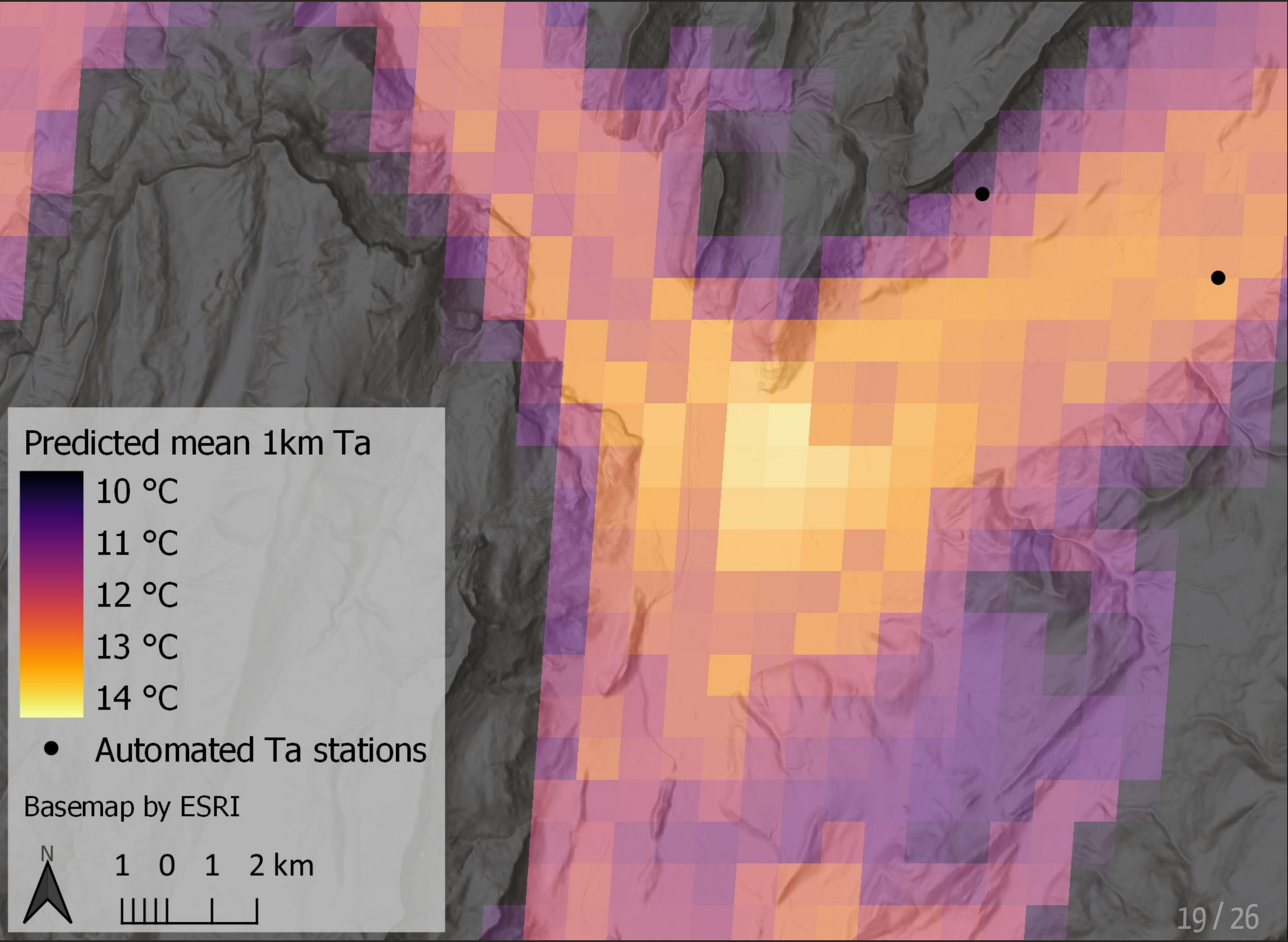
2000-2016	R2	RMSE	MAE	Spatial R2	Spatial RMSE	Temporal R2	Temporal RMSE
T_a min	0.92	1.9	1.4	0.89	1.1	0.94	1.6
T_a mean	0.97	1.3	0.9	0.95	0.8	0.97	1.2
T_a max	0.95	1.8	1.4	0.88	1.2	0.96	1.5

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

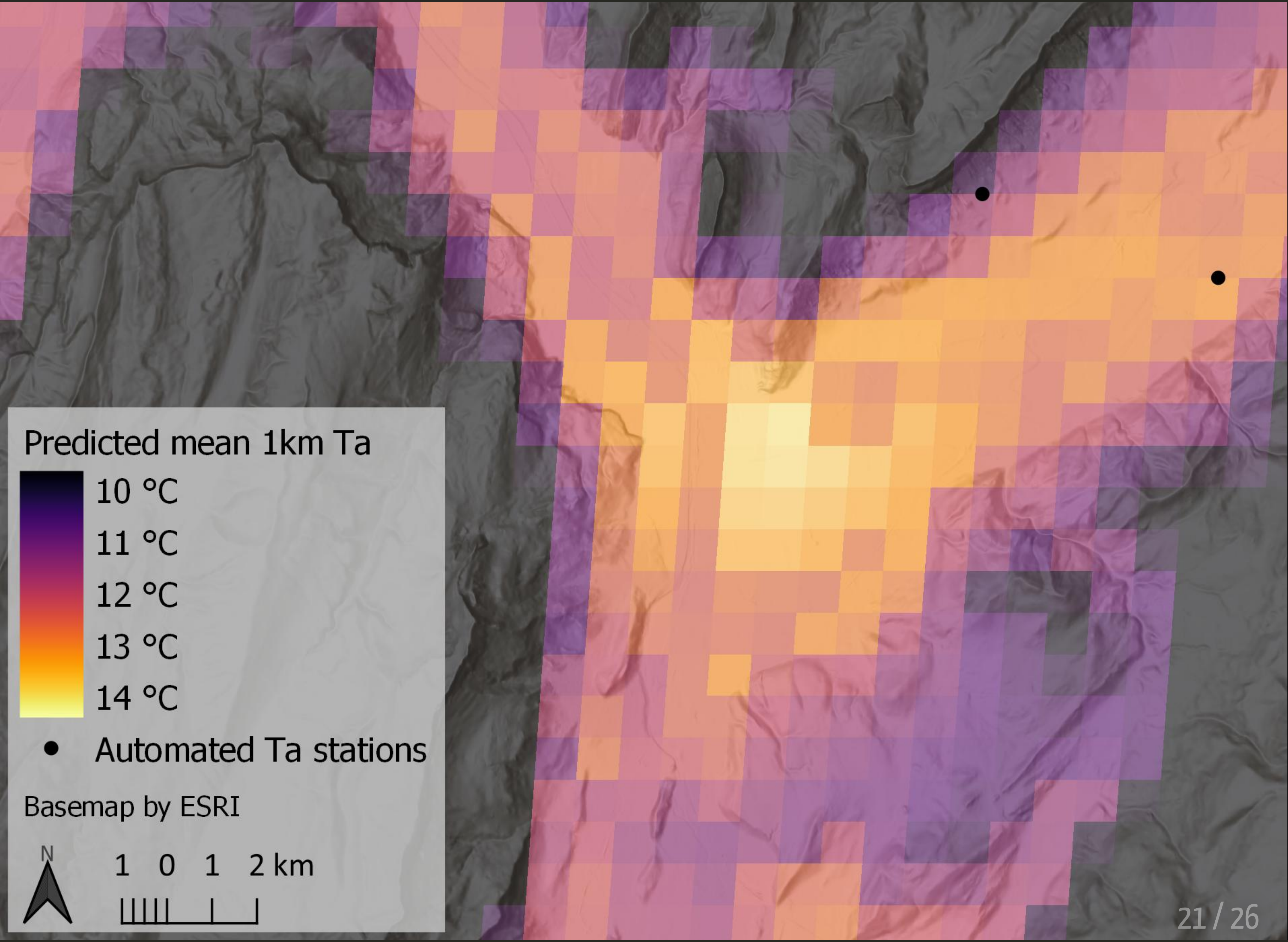
Stage 3: Residual interpolation (200 m)

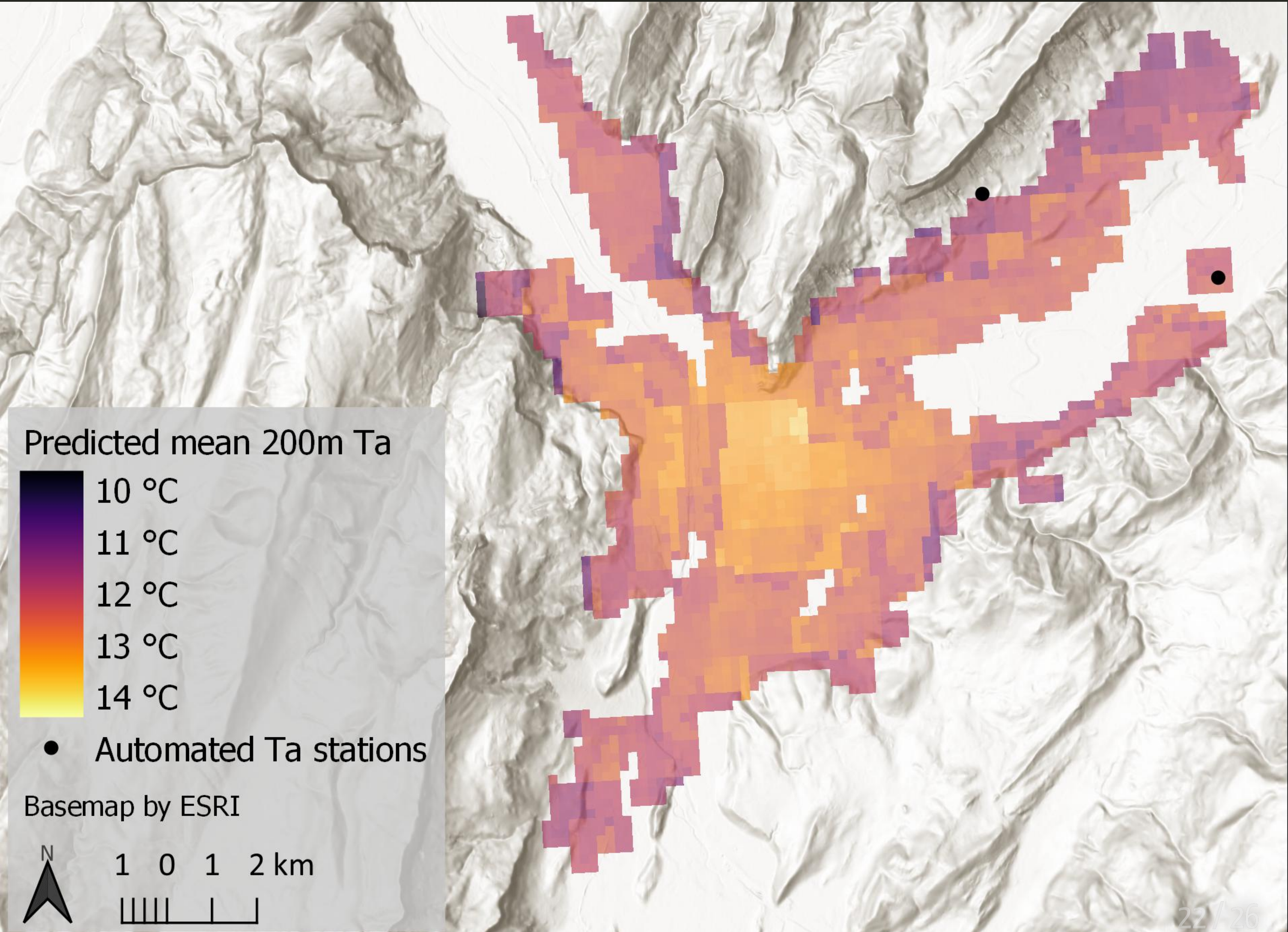
Contiguous urban areas with > 50,000 inhabitants

Random forest and XGBoost models

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!

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