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Using LiDAR and remote microclimate loggers to downscale near-surface air temperatures for site-level studies

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A spatial mismatch exists between regional climate models and conditions experienced by individual organisms. We demonstrate an approach to downscaling air temperatures for site-level studies using airborne LiDAR data and remote microclimate loggers. In 2012–2013, we established a temperature logger network in the forested region of central Missouri, USA, and obtained sub-hourly meteorological measurements from a centrally located weather station. We then used linear mixed models within an information theoretic approach to evaluate hourly and seasonal effects of insolation, vegetation structure, elevation, and meteorological measurements on near-surface air temperatures. The best-supported models predicted fine-scale temperatures with high accuracy during both the winter and growing seasons. We recommend that researchers consider the scales relevant to specific applications when using our approach to develop site-specific spatio-temporal models.

1. Introduction

The threat of anthropogenic climate change to biodiversity has prompted repeated calls for spatial models that downscale climate conditions to scales experienced by organisms (Ackerly et al. 2010; Dobrowski 2011; McMahon et al. 2011; Suggitt et al. 2011). Models developed from regional weather station networks, e.g. using statistical interpolation methods, are not equipped to account for fine-scale microclimate variation in complex landscapes (Daly 2006; Dimri and Mohanty 2007; Trivedi et al. 2008; Graae et al. 2012). However, development of low-cost microclimate loggers and availability of high-resolution spatial data have permitted researchers to develop landscape-specific spatio-temporal models. For example, temperature logger networks have recently been used to create relatively fine-scale temperature models for specific applications, including predicting species distributions under projected climate scenarios or identifying refugia (e.g. Ashcroft, Chisholm, and French 2009; Fridley 2009; Holden et al. 2011; Shoo et al. 2011). Such models typically attempt to predict average high or low temperatures for a given time period; models predicting temperatures for specific times are rare (Chung and Yun 2004).

Whereas previous models have downscaled climate conditions to regional and landscape scales, climate warming is likely to affect microclimates experienced by individual organisms during their daily activities. For example, fine-scale spatio-temporal variation in air temperature and relative humidity can affect the physiology, activity patterns,

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resource selection and demography of numerous taxa (Huey 1991; Porter et al. 2000; Jamieson et al. 2012; George, Thompson, and Faaborg 2015). Biologists often rely on regional weather stations or physical models placed in habitats of interest to infer conditions experienced by organisms (e.g. Cox et al. 2013; Bakken and Angilletta 2014). Despite their potential in predicting climate effects on biodiversity, fine-scale spatio-temporal models have not been widely adopted for site-level studies (Potter, Woods, and Pincebourde 2013).

Here, we used sub-hourly meteorological measurements and high-resolution spatial data to develop a dynamic spatio-temporal model of near-surface air temperatures. Our goal was to demonstrate how temperature logger networks can be used with remotely sensed data to create accurate site-level models for fine-scale ecological applications.

2. Methods

The Thomas S. Baskett Wildlife Research and Education Center encompasses 917 ha in central Missouri (38°44′ N, 92°12′ W; Figure 1) and is classified as Oak Woodland/Forest Hills within the Outer Ozark Border ecological subsection (Nigh and Schroeder 2002). The region consists of dissected limestone hills with elevation ranging from 166 m in creeks and drainages to 261 m along ridges. Predominant cover types include mixed deciduous forest interspersed with dense successional habitats and abandoned fields. From

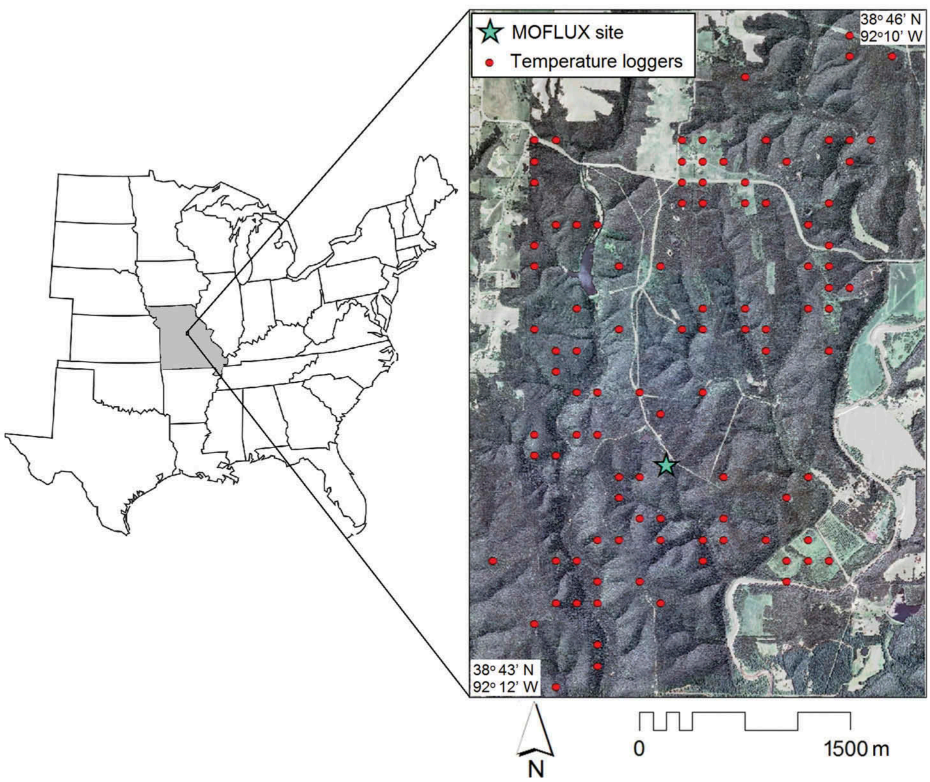

Figure 1. Study area map showing the location of the MOFLUX site and remote temperature loggers at the Thomas S. Baskett Wildlife Research and Education Center in Missouri, USA.

1981 to 2010, the mean annual temperature was 12.56°C and the mean monthly temperature ranged from −1.28° in January to 25.17° in July; mean annual precipitation was 108.25 cm (Missouri Climate Center 2014).

We collected weather measurements from the Missouri Ozark AmeriFlux site (MOFLUX; http://ameriflux.ornl.gov/), which was centrally located within the study area and included a 32 m tower equipped with meteorological and ecological instrumentation. Weather data collected from the MOFLUX site included air temperature, relative humidity, and direct and diffuse solar radiation (Table 1). All measurements were taken at 30 min intervals through the duration of the study.

We used airborne LiDAR data to derive spatial layers within a geographic information system. We developed high-resolution (<10 m) elevation, canopy height, and canopy cover models for the study area from data collected in March 2009 (Table 1). The elevation model was used to derive a dynamic solar radiation raster (S) using the equation

$$S = H \times S_{\text{dir}} + S_{\text{dif}} \tag{1}$$

where H represents a temporally specific hillshade raster, S_{dir} represents measured direct solar radiation, and S_{dif} represents measured diffuse solar radiation. The radiation model thus downscaled measured solar radiation to the complex terrain according to the angle of the sun and light conditions at a given time. Programme FUSION and R packages insol and raster were used for spatial analyses (Corripio 2014; Hijamas 2014; R Core Team 2014). Original LiDAR files and detailed metadata have been permanently archived and can be accessed via the Missouri Spatial Data Information Service (http://www.msdis.missouri.edu/).

We obtained air temperature measurements from an initial network of 100 temperature loggers (iButton® model DS1021G, Maxim Integrated, San Jose, CA, USA) placed throughout the study area. To ensure adequate representation of spatial covariates, we established a random point grid across the study area such that temperature loggers were at least 150 m apart (Figure 1). Each temperature logger was placed inside a solar shield

Table 1. Predictor variables included in candidate mixed models of the effects of spatial and meteorological measurements on near-surface air temperatures.

			Winter		Growing season	
Variable	Description	Source	Mean value	Range	Mean value	Range
Temp	Air temperature (°C)	MOFLUX	2.01	−18.23–26.09	21.61	2.04–37.22
RH	Relative humidity (%)	MOFLUX	66.45	17.83–100	71.34	21.85–100
Solar	Solar radiation (W m^{-2})	dynamic model	103.03	8.26–893.67	187.84	2.00–1100.88
Height	Canopy height (m)	LiDAR	14.13	0–25.20	14.13	0–25.20
Cover	Canopy cover (%)	LiDAR	53.63	0–97.71	53.63	0–97.71
Elev	Elevation (m)	LiDAR	224.05	175.72–249.07	224.05	175.72–249.07

and mounted 1 m high on the north side of a tree or a shaded wooden stake when trees were absent. Solar shields were constructed from 15 cm sections of 7.62 cm diameter PVC pipe. Temperature loggers were coated with Plasti Dip® (Plasti Dip International, Blaine, MN, USA) and suspended inside solar shields to promote adequate airflow. All temperature loggers took measurements every 3.5 hours from 1 June 2012 to 21 January 2014.

We used linear mixed models within an information theoretic approach (Burnham and Anderson 2002) to develop separate predictive temperature models for the winter (November–March) and growing season (May–September). Temperature logger measurements were treated as the response variable and different combinations of the corresponding spatial (LiDAR derived) and temporal (MOFLUX derived) covariates were treated as predictor variables. Mantel tests did not detect spatial autocorrelation among measurements taken during the same periods so we did not include a spatial autocorrelation term in models. We included day of year as a random effect and data logger within hour as a nested random effect in all models to account for non-independence of measurements taken by the same data loggers and at the same times and dates. We also included the air temperature measured at the MOFLUX site as a fixed effect in all candidate models because our goal was to predict spatial temperature variation that was not already explained by temperature measured at a single location. Candidate models were evaluated using a multistep approach to reduce the number of models fit. An initial comparison of the global model with day of year and hour as quadratic fixed effects, without day of year, without hour, and with neither day of year or hour indicated strong support for both temporal variables. Therefore, day of year and hour were included as quadratic terms in all subsequent models. Next, we evaluated all combinations of solar radiation, canopy height, canopy cover, and elevation as additive fixed effects. In addition, we evaluated all two-way interactions among spatial variables. We included a global model that contained all variables and a null model that contained only air temperature. Finally, we tested for two-way interactions between day of year and spatial variables and hour and spatial variables. Candidate models were developed a priori and ranked using Akaike's Information Criterion and model weights. We tested for overdispersion by calculating the ratio of the sum of squared Pearson residuals to the residual degrees of freedom and assessed the overall fit of each model to the data by calculating the marginal and conditional R^2 (Nakagawa and Schielzeth 2013). The marginal R^2 indicates the proportion of variance explained by the fixed effects alone, and the conditional R^2 indicates the proportion of variance explained by both the fixed and random effects. We used k-fold cross-validation to evaluate each model's predictive power (Boyce et al. 2002). We sequentially removed each temperature logger from the data set and fit the model to the remaining data. We then calculated Pearson correlations between the removed logger's data and the model predictions. Models were constructed in R version 3.0.1 on z-transformed data and with package lme4 (Bates et al. 2014; R Core Team 2014).

3. Results and discussion

We omitted 23 temperature logger locations from analyses because they were either damaged by rodents or lost. Of those remaining, we obtained 122,665 temperature measurements. Temperature logger measurements were highly correlated (Pearson correlation coefficient = 0.98) to MOFLUX temperature measurements, but temperature loggers ranged from 19.03° below to 14.58° above the MOFLUX temperatures in

Table 2. Estimated coefficients, standard errors (SEs) and 95% confidence limits (CLs) for the best supported winter and growing season models of the effects of spatial and meteorological measurements on near-surface air temperatures.

	Winter				Growing season			
Parameter	Coefficient	SE	Lower (95% CL)	Upper (95% CL)	Coefficient	SE	Lower (95% CL)	Upper (95% CL)
Intercept	2.66	0.30	2.08	3.23	20.97	0.07	20.83	21.11
Temp	6.65	0.02	6.62	6.69	5.69	0.02	5.66	5.72
RH	0.27	0.01	0.24	0.30	0.35	0.01	0.33	0.37
Solar	0.03	0.02	−0.01	0.07	0.59	0.02	0.56	0.62
Height	0.00	0.02	−0.03	0.04	−0.30	0.06	−0.41	−0.19
Cover	−0.03	0.02	−0.08	0.01	−0.14	0.05	−0.24	−0.03
Elev	−0.21	0.03	−0.26	−0.15	0.10	0.04	0.03	0.17
Hour	−0.06	0.16	−0.37	0.24	−0.37	0.05	−0.46	−0.28
Hour^2	0.25	0.18	−0.10	0.60	1.03	0.07	0.90	1.17
DOY	0.67	0.15	0.38	0.96	0.10	0.03	0.05	0.15
DOY^2	−0.75	0.16	−1.07	−0.43	−0.01	0.03	−0.06	0.05
Solar × height	–	–	–	–	−0.35	0.02	−0.38	−0.31
Solar × cover	−0.18	0.01	−0.20	−0.16	−0.02	0.02	−0.05	0.02
Solar × elev	−0.07	0.01	−0.09	−0.04	–	–	–	–
Elev × height	0.15	0.02	0.11	0.20	–	–	–	–
Cover × elev	−0.08	0.02	−0.12	−0.04	–	–	–	–
Height × elev	–	–	–	–	0.10	0.02	0.06	0.14
Solar × hour	0.22	0.04	0.15	0.29	−0.55	0.03	−0.61	−0.48
Solar × hour^2	1.28	0.05	1.18	1.38	1.89	0.07	1.75	2.03
Height × hour	–	–	–	–	−0.01	0.04	−0.08	0.07
Height × hour^2	–	–	–	–	0.23	0.04	0.15	0.31
Cover × hour	0.07	0.01	0.04	0.09	0.06	0.03	0.00	0.13
Cover × hour^2	0.08	0.02	0.05	0.11	0.21	0.04	0.13	0.29
Elev × hour	−0.01	0.01	−0.03	0.02	0.00	0.02	−0.05	0.05
Elev × hour^2	0.12	0.02	0.08	0.15	0.13	0.03	0.08	0.18
Solar × DOY	−0.55	0.02	−0.59	−0.51	0.10	0.01	0.09	0.11
Solar × DOY^2	1.03	0.02	0.99	1.07	0.18	0.01	0.17	0.19
Cover × DOY	–	–	–	–	0.08	0.00	0.07	0.09
Cover × DOY^2	–	–	–	–	0.01	0.01	0.00	0.02
Elev × DOY	−0.18	0.02	−0.21	−0.14	0.06	0.00	0.05	0.07
Elev × DOY^2	0.27	0.02	0.23	0.31	−0.01	0.01	−0.02	0.00

Note: DOY and hour represent day of year and hour of day, respectively.

winter and 16.45° below to 14.28° above the MOFLUX temperatures during the growing season. The ranges of temperature recorded across the study area varied from 0.5° to 19.5° (mean = 5.30°) during the winter and 0.5° to 17.0° (mean = 5.19°) during the growing season.

The best supported winter and growing season models included spatial and temporal variables as additive fixed effects and two-way interaction terms (Table 2). Variation in solar radiation is among the most important determinants of near-surface temperatures (Geiger, Aron, and Todhunter 2009) and was included in our best supported models. Canopy cover × hour and canopy cover × day of year interaction terms were also included in the best models, reflecting daily and seasonal changes in how forest cover affects temperatures. Forests act synergistically with other physiographic factors to stabilize near-surface temperatures by buffering the ground against

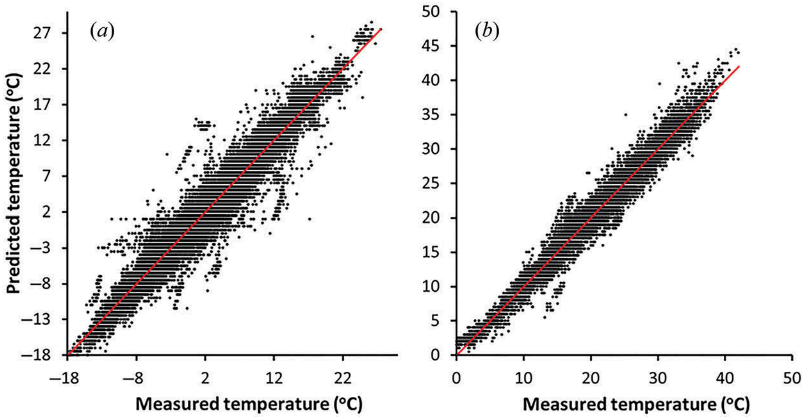

Figure 2. Temperatures predicted by the best supported winter (*a*) and growing season (*b*) models plotted against temperature logger measurements.

solar radiation during the day and retaining heat at night. The relative importance of this buffering effect changes seasonally with the annual cycle of deciduous trees.

Surprisingly, our best supported models included elevation, despite the fact that elevation varied by <75 m in our sampling grid. The inclusion of elevation in the best supported models likely reflects that elevation was correlated to other climate forcing factors that we did not measure. For example, soil moisture influences near-surface temperatures (Fridley 2009; Geiger, Aron, and Todhunter 2009), and lower elevations in our study area were located in drainages or closer to streams. In contrast, higher elevations were located on dry ridges.

The models carried forward at each model selection step explained more than 95% of the model weight in each candidate set. The final winter model yielded marginal and conditional R^2 values of 0.92 and 0.95, respectively, and a *k*-fold correlation coefficient of 0.96. The final growing season model yielded marginal and conditional R^2 values of 0.96 and 0.98, respectively, and a *k*-fold correlation coefficient of 0.98. Model predictions plotted against measured values indicated very high predictive power across the range of temperatures (Figure 2); outliers were clustered on the same dates, suggesting that specific weather events affected model performance. Model predictions generally showed higher temperature variation in fields than forests and at higher elevations than lower elevations (Figure 3).

4. Conclusions

We used a low-cost temperature logger network to develop a dynamic high-resolution spatio-temporal temperature model to be used in site-level ecological studies. By incorporating airborne LiDAR data and sub-hourly meteorological measurements, we demonstrated that air temperatures can be predicted with high accuracy at scales experienced by individual organisms. LiDAR technology is well suited for microclimate modelling because it permits fine-scale characterization of terrain and vegetation structure across broad areas (Vierling et al. 2008; van Leeuwen and Nieuwenhuis 2010). Microclimate conditions are determined by numerous factors, including many that we did not measure (Geiger, Aron, and Todhunter 2009). Depending on the specific application, models could be further refined by accounting for additional variables. For example, we did not directly

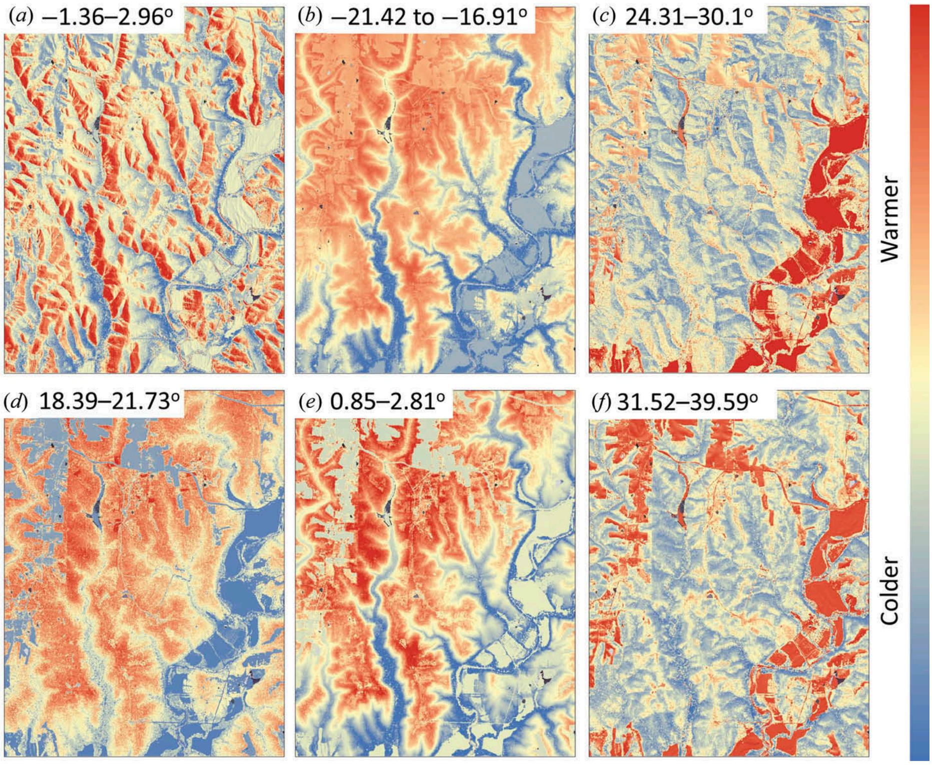

Figure 3. Predicted near-surface air temperatures made by the best supported winter and growing season models at the Thomas S. Baskett Wildlife Research and Education Center in Missouri, USA. Panels show downscaled temperatures and temperature ranges for (*a*) 16 February 2013, 17:00, (*b*) 24 December 2013, 06:30, (*c*) 17 March 2013, 15:00, (*d*) 10 August 2013, 20:00, (*e*) 3 May 2013, 05:30, and (*f*) 31 August 2013, 13:00. The depicted time periods coincided with the seasonal mean, low, and high air temperatures measured at the Missouri AmeriFlux site.

account for cumulative effects of solar radiation over time. Our models might be improved by including the sum of solar radiation at each location for a time period prior to when the temperature was measured. Likewise, it would be straightforward to deploy additional loggers that measure relative humidity or soil temperatures that vary spatially across the study area. Researchers should consider local microclimate forcing factors and research questions of interest when developing site-specific models. Nevertheless, we demonstrated an approach for developing high-resolution spatio-temporal microclimate models for fine-scale ecological applications.

Disclosure statement

No potential conflict of interest was reported by the authors.

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