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METHODS
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A Satellite-Based Model for Estimating Latent Heat Flux From Urban Vegetation

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The impacts of extreme heat events are amplified in cities due to unique urban thermal properties. Urban greenspace mitigates high temperatures through evapotranspiration and shading; however, quantification of vegetative cooling potential in cities is often limited to simple remote sensing greenness indices or sparse, in situ measurements. Here, we develop a spatially explicit, high-resolution model of urban latent heat flux from vegetation. The model iterates through three core equations that consider urban climatological and physiological characteristics, producing estimates of latent heat flux at 30-m spatial resolution and hourly temporal resolution. We find strong agreement between field observations and model estimates of latent heat flux across a range of ecosystem types, including cities. This model introduces a valuable tool to quantify the spatial heterogeneity of vegetation cooling benefits across the complex landscape of cities at an adequate resolution to inform policies addressing the effects of extreme heat events.

Keywords: latent heat flux, evapotranspiration, urban heat island, greenspace, vegetation model

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INTRODUCTION

Urban areas make up only a small fraction of global land area (<3%; Liu et al., 2014), but have a disproportionately large influence on human quality of life and well-being. Cities are home to the majority of the world's population (Grimm et al., 2008) and continue to grow in both spatial extent (Seto et al., 2012) and population (United Nations Department of Economic and Social Affairs Population Division, 2018). Urbanization often leads to environmental degradation, prompting cities to implement policies to ameliorate the environmental impacts. Such policies, however, are currently limited by a dearth of actionable urban ecological data and theory to implement demonstrated best practices (Zhou et al., 2019).

Urbanization disrupts the background surface energy balance via higher amounts of impervious surface area (ISA), increased thermal admittance of surface materials, lower albedo due to the presence of buildings and urban canyons, and fluxes of anthropogenic heat from buildings and automobiles (Oke et al., 2017). In many regions, the modified thermal characteristics of the urban landscape result in excessive heat, thermal discomfort of residents, and an urban heat island (UHI) effect, where temperatures within the city tend to exceed those of local rural environments (Taha, 1997). Historically, the primary driver of extreme urban daytime temperatures has been thought

to result from decreases in daytime latent heat flux (λE) due to higher fractions of ISA, less vegetation, less moisture availability, and therefore less evapotranspiration (Carlson and Boland, 1978; Taha, 1997). Novel attribution methods evaluating the component contributions of net radiation, aerodynamic resistance, the Bowen ratio (or ratio of sensible heat flux to λE), and heat storage provide evidence supporting the theory that the daytime UHI intensity is mostly controlled by variations in the capacity of urban and rural environments to evaporate water (Li et al., 2019). The UHI is often cited as grounds for improving urban heat resilience but is not necessarily a phenomenon that requires mitigation due to the dependence of UHI magnitude on the background rural conditions (Martilli et al., 2020). For example, some cities that do not experience a large daytime UHI (e.g., Phoenix, AZ, United States; Chow et al., 2012) still experience extreme summer temperatures. Instead, urban heat mitigation should focus on absolute temperature reduction. Nonetheless, the role of evapotranspiration in moderating extreme heat in cities points to municipal greening initiatives as promising pathways for urban heat mitigation.

Cities are warming at a faster rate than their rural counterparts (Fitzpatrick and Dunn, 2019) with increases in the magnitude and frequency of extreme weather events. Excessively high temperatures can increase electricity demand (McPherson et al., 1994; Ruijven et al., 2019), induce vegetation stress (Wahid et al., 2007; Reinmann and Hutyra, 2017), and represent a critical risk factor for human mortality (Basu, 2009; Gasparrini et al., 2015). Many city governments have undertaken efforts to increase canopy cover (Roman, 2014) to offset local climate changes driven by urbanization. Common surface materials found in the urban environment are impervious and do not retain much moisture for evaporation. Vegetation, however, can be used as a tool to cool the urban environment via evapotranspiration. When plants open their stomata to take up carbon dioxide (CO_2), they simultaneously release water vapor in a process that utilizes energy for the conversion of liquid water to a vapor state, cooling the plant and the air around it. Remote sensing observations reveal an inverse relationship between surface temperature and the Normalized Difference Vegetation Index (Tiangco et al., 2008) and field experiments have shown that rooftop gardens can reduce the surface temperature of buildings and the air around them (Wong et al., 2003). Ziter et al. (2019) found the proportions of canopy cover and ISA to be interactive drivers of urban temperature variation. While previous research has established the potential for vegetative cooling in urban environments, less attention has been given to quantifying evapotranspiration rates and the corresponding λE variations across entire cities.

Direct measurements of λE at discrete locations are commonly made using eddy covariance flux towers. However, this technique assumes uniform vegetation canopies on flat terrain (Munger and Loescher, 2004). The heterogenous landscape associated with cities often violates some assumptions embedded in eddy covariance methodologies, making urban measurements difficult. Consequently, direct measurements of λE in urban areas are often made using tree-level measurements of evapotranspiration. While this can be done by taking leaf-level measurements of transpiration rates that are then scaled to the entire canopy, studies more commonly use measurements of sap flux rates in trees (Pataki et al., 2011; Winbourne et al., 2020). Sap flux measurements provide an integrative measure of water use and transpiration yielding important information about the energy balance of individual trees. Modeling approaches are necessary, however, to capture the spatial variability in λE across larger areas of interest.

The Penman-Monteith model (Monteith, 1965) is a commonly used approach to estimate λE based primarily on meteorological conditions and the capacity of the land surface to transfer water into the lower atmosphere. Recent Penman-Monteith applications have started to focus on urban areas (Liu et al., 2017; Zipper et al., 2017; Zhang et al., 2018; Wang et al., 2020), incorporating the unique climatological properties of cities by including the UHI (Zipper et al., 2017) and spectral mixture analysis to consider the unique physical structure of urban areas (Wang et al., 2020). Results show higher atmospheric demand for water in areas with higher amounts of ISA and alleviation of the UHI in regions with high evapotranspiration intensity (Zipper et al., 2017; Wang et al., 2020). Other models exist to partition surface energy fluxes in cities, however, the International Urban Energy Balance Comparison Project (Grimmond et al., 2010) found that the most commonly used models had the poorest performance in modeling the λE component of the surface energy balance and highlighted the importance of accurate representation of vegetation in correctly modeling the partitioning of turbulent fluxes. The focus on quantifying evapotranspiration in urban areas is advancing our knowledge of the surface energy balance within cities; however, urban vegetation exhibits unique physiological dynamics that to our knowledge have not yet been captured in previous studies (Winbourne et al., 2020).

Urban vegetation tends to grow at accelerated rates compared to rural vegetation (Briber et al., 2015; Smith et al., 2019), likely due to a combination of increased light availability due to open grown conditions, higher nitrogen (Rao et al., 2014; Decina et al., 2017) and phosphorus (Hobbie et al., 2017; Decina et al., 2018) deposition rates, higher surface CO_2 concentrations (Brondfield et al., 2012), lengthened growing seasons (Melaas et al., 2016) and in some cases, higher water availability (McCarthy and Pataki, 2010; Bijoor et al., 2011). Faster plant growth has important effects on stomatal conductance, the process governing the exchange of water vapor between the biosphere and the atmosphere, due to the strong coupling between the processes of photosynthesis and transpiration. Studies of the relationship between stomatal conductance and temperature in controlled experiments come to inconsistent conclusions (Weston and Bauerle, 2007; Teskey et al., 2014; von Caemmerer and Evans, 2015; Urban et al., 2017). While similar urban studies are rare, Winbourne et al. (2020) found a stronger positive relationship between stomatal conductance and temperature in urban versus rural settings with observations of persistent stomatal conductance in an urban maple tree at temperatures in excess of 30°C and vapor pressure deficits (VPD) greater than 2.5 kPa. Furthermore, Esperon-Rodriguez et al. (2020) found evidence of urban tree adaptation to climate via plasticity in drought tolerance traits, with urban trees of

the same species exhibiting more drought tolerance than rural trees. This suggests that urban trees may have the ability to acclimate to the extreme growing conditions found in the urban environment, underscoring the role of urban vegetation in providing temperature relief during extreme heat events.

Here, we introduce the Vegetation Photosynthesis and Respiration Model Latent Heat module (VPRM-LH) – a spatially explicit, remote sensing-driven model to produce hourly estimates of urban λE at 30 m spatial resolution. In contrast to frequently used vegetation indices characterizing the extent of urban greenspace, VPRM-LH explicitly includes information about the function of urban greenspace and its variation across space and time. VPRM-LH outputs are particularly relevant to the implementation of nature-based climate solutions in cities due to a specific focus on vegetation contributions to λE. We find strong agreement between field observations and model estimates of λE across a range of ecosystems and urbanization intensities, highlighting VPRM-LH as an effective tool in quantifying the spatial heterogeneity of vegetation cooling benefits within cities.

METHODS

As an overview, VPRM-LH iterates through three core equations that consider urban structural, climatological, and physiological characteristics. Surface conductance of water vapor is estimated as a function of photosynthesis and VPD using the Urban Vegetation Photosynthesis and Respiration Model (VPRM) (Mahadevan et al., 2008; Hardiman et al., 2017) and Medlyn stomatal conductance model (Medlyn et al., 2011). The Penman-Monteith model is used to produce estimates of λE, with meteorological inputs downscaled to 30 m resolution based on empirical relationships between ISA and temperature/VPD (Wang et al., 2017). We present the necessary model equations and data specifications to apply the VPRM-LH framework (summarized in **Supplementary Table 1**). Model equations were executed in R version 3.6 (R Core Team, 2020).

Model Description

Vegetation Photosynthesis and Respiration Model

We use the VPRM hourly carbon exchange as a means to estimate net photosynthesis and eventually stomatal conductance. Photosynthesis is defined as the gross biosphere-atmosphere ecosystem exchange (GEE; μmol CO_2 m^{-2} s^{-1}) of CO_2 and is estimated as a function of incoming photosynthetically active radiation (PAR) using a modified version of the Urban VPRM, introduced in Hardiman et al. (2017). The first of three core equations in VPRM-LH is:

$$GEE = \wedge \cdot T_{scale} \cdot P_{scale} \cdot W_{scale} \cdot EVI \cdot \frac{1}{1 + \frac{PAR}{PAR_0}} \cdot PAR \quad (1)$$

where T_{scale}, P_{scale}, and W_{scale} are dimensionless scaling terms ranging from zero to one describing the influence of air temperature, phenology, and moisture on photosynthesis. Λ and PAR_0 are ecosystem-specific parameters describing the light-use efficiency of vegetation and half-saturation value of *GEE* as a function of *PAR*. *EVI* is the enhanced vegetation index.

For rural applications, T_{scale} is calculated following the equations within the original VPRM parameterization (Mahadevan et al., 2008) as:

$$T_{scale} = \frac{(T - T_{min})(T - T_{max})}{(T - T_{min})(T - T_{max}) - (T - T_{opt})^2} \quad (2)$$

where T is the air temperature, T_{min} is the minimum temperature for photosynthesis, T_{max} is the maximum temperature for photosynthesis, and T_{opt} is the ecosystem-specific optimal temperature for photosynthesis. For urban applications, however, the T_{scale} equation is used for temperatures less than 20°C, but is set to one for all temperatures greater than 20°C to account for acclimation of urban vegetation to warmer temperatures. Our field observations of sap flux indicate that stomatal activity does not shut down in urban trees at temperatures up to 35.5°C, the highest observed temperature in the measurement period (**Supplementary Figure 1**). In this model, we set the maximum temperature for photosynthesis in both urban and rural pixels to 40°C. P_{scale} captures the impact of leaf age on vegetation activity and is calculated as:

$$P_{scale} = \frac{EVI - EVI_{min}}{EVI_{max} - EVI_{min}} \quad (3)$$

where EVI_{min} and EVI_{max} are the minimum and maximum EVI observed during the growing season.

W_{scale} is a function of the Land Surface Water Index (LSWI), which has been shown to be effective in monitoring vegetation water content (Maki et al., 2004; Gu et al., 2008), and is calculated as:

$$W_{scale} = \frac{1 + LSWI}{1 + LSWI_{max}} \quad (4)$$

where $LSWI_{max}$ is the maximum LSWI observed during the growing season.

Ecosystem respiration, required to estimate net photosynthesis (A_n; μmol CO_2 m^{-2} s^{-1}) at the leaf level, is calculated as:

$$R_{eco} = T \cdot \alpha + \beta \quad (5)$$

where T is the air temperature (°C), α is the sensitivity of R_{eco} to T, and β is the minimum value that R_{eco} can take on (μmol CO_2 m^{-2} s^{-1}). Leaf respiration typically accounts for 8–12% of ecosystem respiration (Tang et al., 2008) and is approximated to be 10% of R_{eco}. Therefore, net photosynthesis of the canopy is estimated as:

$$A_n = GEE - 0.1 \cdot R_{eco} \quad (6)$$

VPRM driver data come from publicly available remote sensing and modeling products. *EVI* and *LSWI* are calculated at 30 m resolution using Landsat 7 and Landsat 8 Tier 1 Surface Reflectance products retrieved from Google Earth Engine (Gorelick et al., 2017; Dwyer et al., 2018). Using data from two Landsat sensors allows for *EVI* to be obtained every 8 days. Daily *EVI* values are interpolated between collection dates using a spline function (**Supplementary Figure 2**). *PAR* data come from

the Geostationary Operational Environmental Satellite (GOES; EUMETSAT OSI SAF, 2021b) 16 which provides high spatial (0.05° × 0.05°) and temporal (hourly) resolution datasets of incoming shortwave radiation (SW; W m^{-2}) to North America. In our study, *PAR* (μmol m^{-2} s^{-1}) is approximated to be SW/0.505 (Mahadevan et al., 2008). Hourly temperature data come from the Rapid Refresh analysis product (RAP; Benjamin et al., 2016) at a native resolution of 13 km × 13 km. Temperature data are adjusted as a linear function of ISA (MassGIS, 2019) and hour of year using the coefficients derived in Wang et al. (2017) and methods described in Hardiman et al. (2017).

Medlyn Stomatal Conductance Model

Given estimates of photosynthesis, surface conductance at 30 m resolution is estimated using the Medlyn et al. (2011) as:

$$g_s = g_0 + 1.6 \cdot \left(1 + \frac{g_1}{\delta}\right) \cdot \frac{A_n}{\frac{c_s}{P_{atm}}} \quad (7)$$

where g_s is the surface conductance (μmol H_2O m^{-2} s^{-1}), g_0 is the minimum surface conductance (100 μmol H_2O m^{-2} s^{-1}), g_1 is a unitless plant functional type dependent parameter that captures the sensitivity of surface conductance to photosynthesis rate (de Kauwe et al., 2015), δ is the VPD (kPa), A_n is net photosynthesis (μmol CO_2 m^{-2} s^{-1}), c_s is the partial pressure of CO_2 (40.53 Pa), and P_{atm} is the atmospheric pressure (101325 Pa). P_{atm} and c_s are held constant due to little sensitivity of model outputs to variations in the values. δ is calculated from RAP temperature and relative humidity, where values are adjusted to account for urban heat and dry islands as a linear function of ISA and hour of year using the coefficients derived in Wang et al. (2017).

Penman-Monteith Model

Given estimates of surface conductance, λE (W m^{-2}) is calculated using the Penman-Monteith model as:

$$\lambda E = \frac{\Delta(R_n - G) + \rho_a c_p(\delta) g_a}{\Delta + \gamma\left(1 + \frac{g_a}{g_s}\right)} \quad (8)$$

where λ is the latent heat of vaporization of H_2O (2260 J g^{-1}), E is the mass H_2O evaporation rate (g s^{-1} m^{-2}), Δ describes the rate of change of saturation specific humidity with air temperature (Pa K^{-1}), R_n is the net radiation balance of the surface (W m^{-2}), G is the ground heat flux (W m^{-2}), ρ_a is the dry air density (1.275 kg m^{-3}), c_p is the specific heat capacity of air (1005 J kg^{-1} K^{-1}), δ is the VPD (Pa), g_a is the atmospheric conductance (m s^{-1}), g_s is the surface conductance (m s^{-1}), and γ is the psychrometric constant (66 Pa K^{-1}).

Δ is calculated following the methods outlined in Allen et al. (1998) as:

$$\Delta = \frac{4098[0.6108 \exp\left(\frac{17.27T}{T+237.3}\right)]}{(T + 237.3)^2} \quad (9)$$

where T is the ISA-adjusted air temperature. R_n is calculated as:

$$R_n = (1 - \alpha) K\downarrow + L\downarrow - (\varepsilon\sigma T_s^4 + (1 - \varepsilon) L\downarrow) \quad (10)$$

where α is the albedo (Trlica et al., 2017), K↓ is incoming shortwave radiation (W m^{-2}; GOES-16), $L\downarrow$ is incoming longwave radiation (W m^{-2}; EUMETSAT OSI SAF, 2021a), ε is the surface emissivity (Estimated to be 0.95 in urban areas; Oke et al., 2017), σ is the Stefan-Boltzmann constant (5.67×10^{-8} W m^{-2} K^{-4}), and T_s is the surface temperature (K; RAP). G is approximated as 10% of R_n. ρ_a and c_p are held constant as the model outputs show little sensitivity to variations in their values (**Supplementary Figure 3**). Previous work found λE estimates to be relatively insensitive to variation in g_a within the range of 0.010–0.033 m s^{-1} (Zhang and Dawes, 1995), consistent with values measured in city canopies (Chen et al., 2011; Ballinas and Barradas, 2016). We use the constant values of 0.033 and 0.010 m s^{-1} for forests/cities and croplands, respectively, as applied in Zhang et al. (2008).

Model Validation

Rural Validation

Vegetation photosynthesis and respiration model latent heat was validated across a range of rural ecosystem types. Three dominant North American land covers – deciduous broadleaf forest (DBF), evergreen needleleaf forest (ENF), and croplands (CRP) – were chosen as validation sites. Eddy covariance flux tower λE measurements were compared to model estimates in a 90 m × 9 0m grid (10 pixels) centered on the flux tower for the most recent full year of available data (2017 for ENF, 2018 for DBF and CRP).

The Harvard Forest (AmeriFlux ID: US-Ha1) in MA, United States was the validation site for DBF and is dominated by red oak (*Quercus rubra*) and red maple (*Acer rubrum*; Munger, 2021). The Howland Forest in Maine, United States (AmeriFlux ID: US-Ho1) was the validation site for ENF and is dominated by red spruce (*Picea rubens*) and eastern hemlock (*Tsuga canadensis*; Hollinger, 2021). The Nebraska Agricultural Research and Development Center (AmeriFlux ID: US-Ne1) in NE, United States was the validation site for CRP and is an irrigated maize field (Suyker, 2021).

Urban Heatwave Modeling and Validation

λE was modeled across Boston, MA, United States during mean and heatwave conditions during the summer of 2018. Mean conditions were modeled during a 6-day period from July 10–July 15, 2018 where the mean air temperature across the modeling domain was 23.1°C, approximately equal to the mean 2018 6-day rolling average temperature during June, July, and August (JJA; 23.0°C). Heatwave conditions were modeled during a 6-day heat event from August 2–August 7, 2018 where the mean air temperature across the modeling domain was 28.7°C (**Supplementary Figure 4**).

Validation of urban ecosystem models can be difficult due to limited field observations. Here, outputs were validated by modeling λE in five pixels ranging from 47 to 99% ISA containing trees outfitted with sap flux sensors between July 18 and September 26, 2019. Details on sap flux sensor methodology are described in Jones et al. (2020). Validation trees were in healthy condition and included two sugar maples (*Acer saccharum*), two Norway maples (*Acer platanoides*), and one red maple

(*Acer rubrum*). λE (W m^{-2}) was estimated from sap flux measurements by estimating the rate of transpiration (g H_2O s^{-1} m^{-2}) via multiplying sap flux density (g H_2O cm^{-2} s^{-1}) by the active sapwood area (the fraction of the basal area cross-section that is active xylem; cm^2) and dividing by the crown area of the tree (m^2). λE (W m^{-2}) was then computed as the transpiration rate multiplied by the latent heat of vaporization of H_2O (2260 J g^{-1}). The active sapwood area of the tree was estimated from species-specific allometric equations (Wullschleger et al., 2001; Gebauer et al., 2008). Statistical analyses were conducted in R version 3.6 (R Core Team, 2020).

RESULTS

Rural λE

We ran VPRM-LH for a full year in three rural ecosystems and compared outputs with eddy covariance flux measurements of λE. We find strong agreement between modeled and measured λE across a range of time scales, especially during the summer months (defined as JJA; **Figure 1**). Disagreement during the dormant season is likely due to a higher proportion of λE from evaporation not related to stomatal activity (e.g., evaporation from soils), rather than direct fluxes via transpiration. Modeled and measured λE show typical seasonal patterns with high rates during the warmer growing season and low rates during the cooler dormant season (**Figures 1A–C**). Modeled versus measured λE are of the same order of magnitude at hourly and daily time scales. Mean diurnal patterns in λE, including afternoon peaks and nighttime lows, are successfully captured by VPRM-LH (**Figures 1D–F**). JJA comparisons of hourly λE show a high correlation (R^2 values 0.83, 0.75, and 0.89 for DBF, ENF, and CRP, respectively; **Figures 1G–I**). The accuracy of VPRM-LH is comparable to the accuracy of VPRM estimates of net ecosystem exchange of CO_2 (NEE) as the R^2 values associated with hourly estimates of NEE for the same ecosystem types as reported in Mahadevan et al. (2008) are 0.83, 0.65, and 0.83 for DBF, ENF, and CRP, respectively.

Urban λE

λE across Boston varied substantially, with higher λE in the more vegetated portions of the city and lower λE in the more impervious portions of the city (**Figure 2A**). λE generally increased with temperature, except for cloudy days where λE was limited by available incoming solar radiation (**Supplementary Figure 4**). During the 6-day heatwave event, λE averaged 85.6 W m^{-2} and was approximately 17% higher than during the 6 days representing mean summer conditions (73.1 W m^{-2}). Daily maximum λE ranged from 135.4 W m^{-2} on a cloudy day to 334.5 W m^{-2} during the warmest day in the study period. For reference, the maximum estimated λE during JJA at the DBF site, located approximately 100 km west of Boston, was 486.4 W m^{-2}.

The model modifications intended to capture urban λE dynamics were evaluated by comparing model estimates of λE in a subset of five pixels in Boston, MA, United States to coincident λE estimates derived from sap flux measurements within the pixels. Hourly field and model estimates of daytime λE show a similarly strong agreement with the rural model application (R^2 = 0.80) across a range of urbanization intensities and tree species (**Figure 2B**).

In general, λE was lower in pixels with higher ISA (**Figures 2B**, **3A**), however, for a given EVI greenness the λE increased with ISA due to urban heat and dry island impacts on local meteorological conditions (**Figure 3A**). For example, for all pixels where EVI = 0.70 (n = 912), the average 14:00 EDT λE ranged from 219.1 to 249.7 W m^{-2} (**Figure 3A**). Furthermore, EVI remains relatively stable on the scale of weeks during the growing season, but λE has a diurnal cycle with peak fluxes occurring during the afternoon, is close to zero at night, and responds rapidly to changes in meteorological conditions. The temporal resolution of VPRM-LH captures this diurnal pattern and shows that enhancements of λE due to urbanization during the daytime, when exposure to high temperatures is greatest, is higher than nighttime (**Figure 3B**). The average range of λE for all pixels with an EVI = 0.70 was less than 1 W m^{-2} during the night and was greater than 30 W m^{-2} between 12:00 and 15:00 EDT.

The spatial patterns of λE and EVI are similar (**Figures 2A**, **3C**), however, using λE as a metric of vegetation cooling benefits captures interactive impacts of greenspace distributions, radiation, and temperature drivers (ISA; **Figure 3D**).

DISCUSSION

Cities are highly vulnerable to projected increases in mean air temperatures and the frequency of extreme heat events (Habeeb et al., 2015) and as a result are eager to obtain actionable ecological data informing their climate mitigation strategies (Zhou et al., 2019). Extreme temperatures already represent an important threat to public health, with vulnerable populations (in terms of age, race, and income) particularly susceptible to heat-related illness and death (Wellenius et al., 2017). Here, we introduce a simple tool to quantify vegetation cooling activity in cities with the potential to identify areas that will benefit most from tree planting or urban greening.

Model Implementation and Limitations

Vegetation photosynthesis and respiration model latent heat uses several readily accessible data sources such as the Landsat, GOES, and RAP archives. Urban applications require the use of an additional spatially explicit ISA product and information about the region-specific relationship between air temperature and ISA, however, this could be determined using local weather station archives or low-cost sensor networks, such as those used in Wang et al. (2017). VPRM-LH estimates λE with good accuracy across ecosystems and time scales; the model driver data is independent of the field observations used for validation. The assumptions embedded in estimation of ground heat flux, dry air density, specific heat capacity, and leaf respiration rates do not appear to introduce critical errors into λE estimates. A sensitivity analysis of the incremental change in λE resultant from incremental changes in model parameters points to the atmospheric conductance term (treated as a constant) as a main source of unaccounted for variance/uncertainty in the model

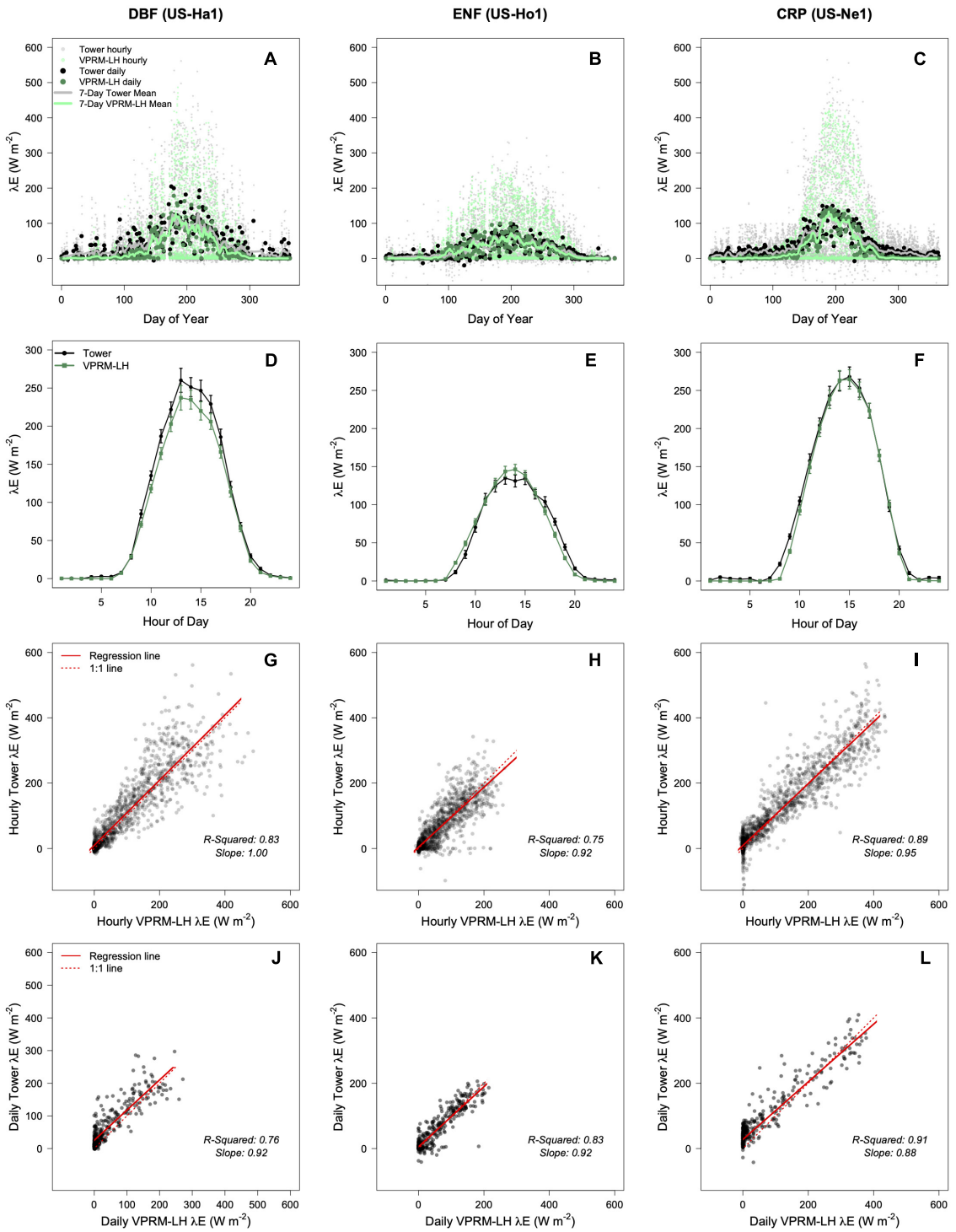

FIGURE 1 | Comparison of modeled vs. measured λE at DBF, ENF, and CRP flux tower sites. **(A–C)** Annual trends in hourly, daily, and weekly λE. **(D–F)** Average diurnal λE patterns during JJA. Error bars represent standard error for each hour during JJA. **(G–I)** Scatter plots of modeled vs. measure λE for each hour during JJA. **(J–L)** Scatter plots of modeled vs. measured daytime average λE over the entire year.

(**Supplementary Figure 3**). Implementation of additional data sources capturing the variability in atmospheric conductance could further improve model accuracy.

The model validation and application presented here was conducted in either mesic or irrigated ecosystems where water availability does not typically constrain transpiration. Model

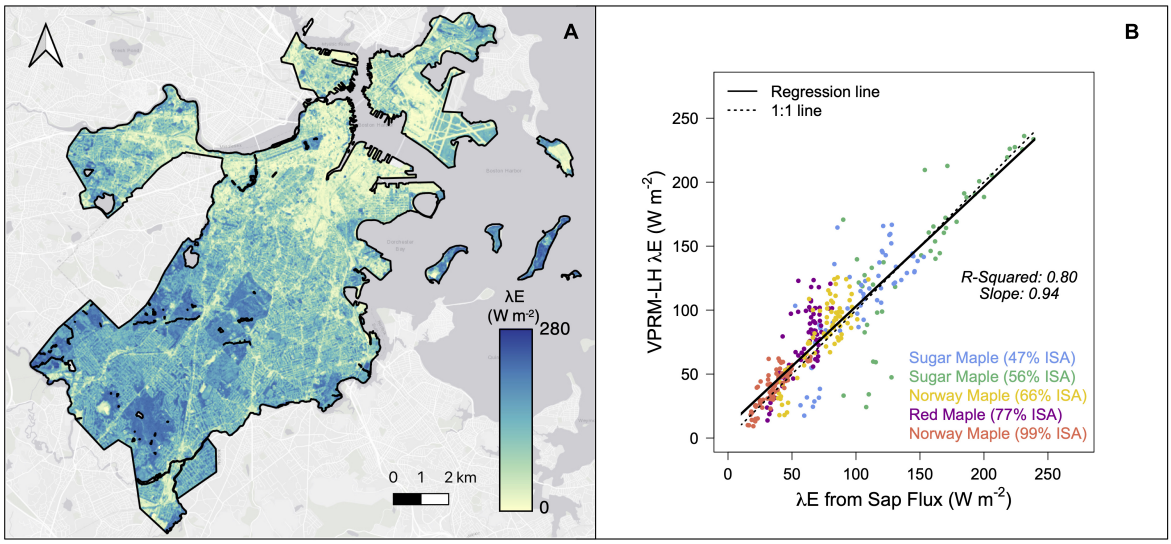

FIGURE 2 | (A) Average 14:00 EDT λE at 30 m resolution across Boston, MA, United States under heatwave conditions. **(B)** Daytime (9:30–14:30) hourly estimated λE vs. λE derived from sap flux measurements between July and September 2019.

application would benefit from further validation in more water-limited regions. VPRM-LH currently considers moisture limitations on transpiration in the W_{scale} term (eq. 3), which leverages LSWI to restrict vegetation activity during dry periods. The availability of water for vegetation, whether from irrigation or precipitation, is a critical consideration in determining the location for urban vegetation expansion. Additionally, VPRM-LH only distinguishes vegetation at the plant functional type level and does not consider species-specific differences in transpiration strategies (e.g., isohydric vs. anisohydric). While the omission of species-specific parameters may limit model accuracy under certain climate conditions, VPRM-LH does not require high-resolution tree species maps, which are likely not available for many cities.

The interpretation of model outputs in mesic climates, particularly on hot, humid days, should consider more than just the magnitude of λE. Regions with a relatively high λE will have more turbulent energy fluxes partitioned into latent rather than sensible heat, which results in a cooling effect on temperature. This interpretation, however, neglects to consider the impact of the increase in atmospheric moisture (resultant from increased transpiration) on perceived temperature. Higher atmospheric humidity reduces the ability of the human body to shed excess heat via the evaporation of sweat, lowering the rate that the body can cool and increasing the perceived temperature, where the perceived temperature is commonly quantified by the heat index. In New York City, NY, United States (approximately 300 km southwest of Boston), a significant increase in mortality risk was observed on days where the maximum heat index exceeded 35° C (Metzger et al., 2010). Heat indices in excess of 35°C were not observed when modeling mean summer conditions in Boston. However, during the 6-day heatwave event, the average daily maximum temperature ranged from 27.7 to 35.7°C, with 5.7% of pixels exceeding 35°C. The average daily maximum heat index during the same time period ranged from 29.0 to 43.9°C with 78.4% of pixels exceeding the 35°C threshold, highlighting the impact of atmospheric moisture concentration on perceived temperature.

The provision of shade, which represents another important determinant of perceived temperature, counteracts humidity effects. For example, Rahman et al. (2018) found that the daytime air temperature under urban tree canopies in a temperate climate was always lower than the air temperature in open areas. Furthermore, while λE was the predominant cooling mechanism of the air on days up to 30°C, shading effects were more prominent on extremely hot days in excess of 30°C (Rahman et al., 2018). Model output interpretation should consider the implications of atmospheric moisture inputs and the type of vegetation present, where trees will provide shade benefits that are not provided by shrubs and grasses.

Implications for Cities

Urban greening, widely espoused as a climate mitigation strategy, has been implemented around the world (Mell et al., 2013; Pincetl et al., 2013; Tan et al., 2013) despite debates around the exact services and tradeoffs with disservices provided by urban canopies. Urban vegetation does store (Raciti et al., 2014) and take up more atmospheric carbon (Sargent et al., 2018) than most ecosystem models currently account for Churkina (2008), but due to accelerated turnover (Smith et al., 2019) and respiration (Decina et al., 2016) rates, tree planting is likely not a viable avenue for meaningful carbon sequestration. Additionally, urban trees are capable of removing atmospheric pollutants and particulates (Weber et al., 2014) but are also sources of volatile organic compounds (Churkina et al., 2015) and allergens (Beck et al., 2013). The urban canopy, however, undoubtedly contributes to local cooling via shading and transpiration (Bowler et al., 2010), with temperature reductions from vegetation

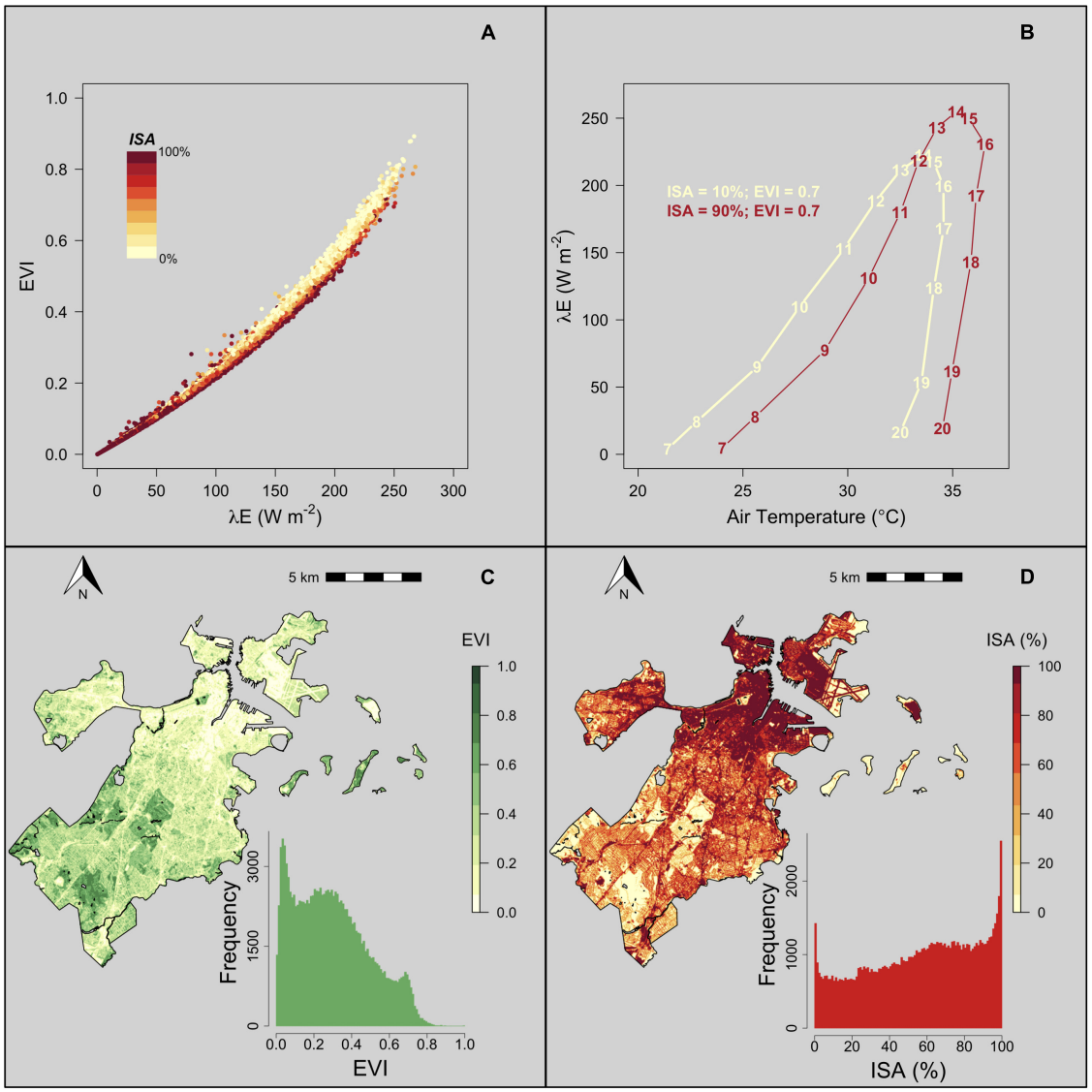

FIGURE 3 | (A) EVI vs. average 14:00 λE color coded by ISA. **(B)** Diurnal hysteresis comparison of λE as a function of air temperature in two pixels with EVI = 0.70 and ISA = 10 and 90%. Numbers represent the hour of day (EDT). **(C)** Map and distribution of EVI in Boston on August 2, 2018. **(D)** Map and distribution of ISA in Boston.

observed to be up to 8°C (Rahman et al., 2017). The potential for vegetative cooling in cities is well established, but implementation of greening plans for effective urban cooling has been heretofore limited due to the inability to quantify variation in cooling potential across the complex landscape of cities.

Vegetation photosynthesis and respiration model latent heat offers a simple, satellite-based methodology for estimating urban λE contributions from vegetation at fine spatial and temporal resolution. The model incorporates a novel combination of urban-specific parameters capturing climatological, physical, and physiological intricacies of the urban environment and its components. Model outputs are consistent with ground measurements of λE and can be scaled to explore the cooling potential of vegetation across cities at hourly, diurnal, seasonal, and annual scales. In contrast to vegetation indices that are commonly used to quantify the benefits of urban greenspace, λE captures vegetation activity in addition to abundance and offers nuanced information about the ecosystem services provided by urban vegetation. VPRM-LH will be a valuable tool in the implementation of policies combatting heat related consequences of urbanization, especially as cities take the forefront in addressing climate-related matters. VPRM-LH offers an easy implementation and the ability to combine outputs with sociodemographic datasets at sufficient resolution for political action. The result is a unique opportunity to identify vulnerable neighborhoods and optimize municipal decisions that repartition the surface energy balance to address historic inequities in canopy distribution and UHI (Hoffman et al., 2020).

DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: Smith (2021). "Data for 'A satellite-based model for estimating latent heat flux from urban vegetation,"' https://doi.org/10.7910/DVN/TQLSIU, Harvard Dataverse.

AUTHOR CONTRIBUTIONS

IAS, DL, and LRH conceptualized the research, developed the framework, and analyzed the data. JBW, TSJ, and FLB collected the validation data. IAS, JBW, KFT, TSJ, FLB, DL, and LRH wrote the original draft, and reviewed and edited the manuscript. All authors contributed to the article and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fevo.2021.695995/full#supplementary-material

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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