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Assessing a decision-support tool to estimate the cooling potential and economic savings from urban vegetation in Singapore

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ABSTRACT

To mitigate the growing threat of urban heat, cities are implementing greening strategies such as tree planting or the development of parks. Effectively integrating these solutions into planning requires quantitative information on the cooling effect of urban vegetation. Here we examined the performance of an open-source decision-support tool, the Integrated Valuation of Ecosystem Services and Tradeoffs Urban Cooling model, to estimate the cooling effect and economic benefits from urban vegetation in a tropical city context, using Singapore as an exemplar case study. Using observed temperature data, we calibrated the model to estimate the spatial distribution of annual average day- and night-time temperature at 10 m spatial resolution and validated the results using leave-one-out cross validation. The calibrated models performed well to estimate annual average daily mean and maximum (day), and minimum (night) temperatures (R^2 of 0.78, 0.65, and 0.52, respectively). We estimated that urban cooling in Singapore provides economic savings of $47.14 million SGD annually from reduced energy consumption in public residential buildings, based on the relationship between energy consumption and mean temperature. Our results give confidence in the model as a decision-support tool to estimate urban heat island effects and evaluate heat mitigation strategies in tropical cities.

1. Introduction

Mitigating urban heat is a growing priority in cities. Urban areas are frequently warmer than non-urban surrounds, known as the urban heat island (UHI) effect (Chakraborty & Lee, 2019; Manoli et al., 2019). Urban heat islands are caused by changes to the energy balance in cities, primarily due to altered surface morphology and the replacement of vegetation with artificial, impervious surfaces (Oke, 1982; Rizwan et al., 2008). Increased urban temperatures have health and economic impacts, increasing morbidity and mortality, reducing workplace productivity and increasing energy and water demand (Nazarian et al., 2022). Given the increasing frequency and severity of extreme heat due to global climate change (IPCC, 2023) and ongoing urbanisation (United Nations, 2019), reducing UHIs is a key strategy to manage the growing risks posed by extreme heat. Yet many cities still lack the spatially explicit data and modelling tools required to implement effective heat mitigation, especially in data poor, and densely populated cities across the tropics (Hamel et al., 2021).

Strategies to mitigate UHIs range from building- and neighborhood-level, to city-wide measures (Jamei et al., 2020; Wong et al., 2021; Aydin et al., 2024). Increasing the albedo of building and road surfaces, for example, helps to reflect heat, whilst the orientation of streets and buildings can be designed to maximise ventilation and shading (Goh & Chang, 1999; Jamei et al., 2020). Meanwhile, policies aiming to reduce car usage by promoting public transport can reduce anthropogenic heat emissions, which can be a considerable contributor to UHIs (Degirmenci et al., 2021). One of the most effective strategies to mitigate UHIs, however, is urban greening (Wong et al., 2021). Vegetation lowers temperature by means of shading, evapotranspiration, and increased albedo. Tree canopies intercept solar radiation, blocking shortwave and longwave radiation from reaching the ground (Gunawardena et al., 2017). Vegetated surfaces also tend to have a higher albedo than artificial surfaces (compared to asphalt, for example), decreasing the proportion of incoming radiation that is absorbed, whilst transpiration

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converts solar radiation into latent heat (Wong et al., 2021). The mechanisms through, and the extent to which urban greenery reduces temperature is, however, dependent on prevailing climatic conditions and local biophysical context (Gunawardena et al., 2017; Wong et al., 2021). Urban greenery also provides other ecosystem services including reducing air pollution (Selmi et al., 2016) and stormwater runoff (Donovan et al., 2016; Soulis et al., 2017), as well as providing recreational opportunities which benefit residents physical and mental health (Jim & Chen, 2006).

Yet the planning and implementation of urban green spaces to maximise urban heat mitigation is still prohibited by a lack of spatially explicit data and decision-support tools (Hamel et al., 2021; Oukawa et al., 2025). Remote-sensed surface temperature provides spatially explicit information and is a good indicator of UHI intensity (Ramsay et al., 2022; Zhang et al., 2024). However, surface temperature is not always well correlated with air temperature and is therefore less relevant when considering the impacts of urban heat on human health (Venter et al., 2021). Moreover, the availability of remote-sensed data is limited by cloud cover, especially for tropical cities (Zhou et al., 2018). Numerical modelling approaches are often computationally expensive and have high data requirements either as inputs (Meili et al., 2020; Mughal et al., 2020), or to train models (Venter et al., 2020). Simpler models, such as those estimating statistical relationships between land cover and temperature (e.g., Masoudi & Tan, 2019; Zhang & Yuan, 2023), are not typically transferable between cities (Pena Acosta et al., 2023) and do not explicitly represent the biophysical processes of cooling from vegetation (Bartesaghi Koc et al., 2018).

Further, these approaches lack the flexibility (e.g., in scale and in data requirements) required by urban planners and policy makers, nor do they quantify outputs in terms of economic or health indicators relevant to policy making and planning (Hamel et al., 2021). The Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST®) models aim to fill these gaps by providing open-source models with minimal data requirements to quantify the benefits provided by natural ecosystems (Natural Capital Project, 2024). The InVEST Urban Cooling model quantifies the heat mitigation benefits from urban vegetation and estimates the subsequent economic savings of reduced energy consumption (Bosch et al., 2021a; Hamel et al., 2021). The model has been applied to assess the cooling capacity of vegetation in England (Zawadzka et al., 2021) and Milan, Italy (Ronchi et al., 2020), and to compare future greening scenarios in Nagpur City, India (Kadaverugu et al., 2021); Wuhan, China (Hu et al., 2023) and Lausanne, Switzerland (Bosch et al., 2021b). The model parameters have been calibrated for Lausanne (Bosch et al., 2021a); Paris, France,the Twin Cities, United States (Hamel et al., 2024) and Busan, Korea (Chung et al., 2024). To our knowledge, the model parameters have not been calibrated, nor the performance validated, for a tropical city. In addition, past studies have not examined the salience and applicability of the economic valuation component of the model.

Here we address the need for a simple decision-support tool to support urban heat mitigation in tropical cities and fill key knowledge gaps in the calibration and economic valuation components of the InVEST Urban Cooling model. We do so by assessing the performance of the Urban Cooling model to estimate the spatial distribution of urban air temperatures and evaluate the cooling potential of urban greenery and its economic implications, using Singapore as an exemplar case study. We calibrate and validate the model using observed temperature data and quantify the estimated economic benefits of urban cooling from reduced energy consumption. In doing so, we aim to address key knowledge gaps in the application of the model to tropical cities and provide confidence in the application of the model as an urban planning and decision-support tool. We provide calibrated model parameters that can be applied to other tropical cities.

2. Methods

2.1. Study area

Singapore (Fig. 1) is an island city-state located on the southern tip of the Malaysian Peninsula with an equatorial wet climate (Roth & Chow, 2012). Despite its small geographical extent (719.2 km^2), Singapore has one of highest population densities in the world, with a population of nearly 5.69 million people (as of 2020) equating to 7485 people per square kilometer (Department of Statistics Singapore, 2020). As a result, dense urbanisation has caused considerable UHI effects which have expanded with ongoing urban development (Roth & Chow, 2012). However, Singapore employs innovative urban greening strategies, presenting it as an interesting case study of compact and green cities (Tan et al., 2013; Friess, 2016; McDonald et al., 2023).

2.2. Overview of the InVEST Urban Cooling model

The InVEST Urban Cooling model (V3.1.4.0; Natural Capital Project, 2024) estimates daytime urban cooling for each pixel in a land cover raster as a linear function of shade, evapotranspiration and albedo, specified for each land cover class, which represent differences in vegetation structure and canopy cover. It additionally accounts for the cooling effects of large green spaces ($>$ 2 ha) and spatial air mixing. To simulate nighttime conditions, urban cooling is computed as a function of building intensity (the ratio of building floor area to footprint area) to represent longwave radiation released by buildings in the form of sensible heat.

Based on the above cooling mechanisms, urban air temperatures are estimated between a rural reference temperature and the maximum UHI observed over the city, which are input based on the temporal period of interest. The model outputs retain the same spatial resolution as the input land cover data. The model is detailed in Bosch et al. (2021a) and in the user guide (Natural Capital Project, 2024).

The weighting of the cooling effects of shade, evapotranspiration and albedo; the distance over which large green spaces have a cooling effect and the radius over which air mixing is computed can be defined based on local context (Hamel et al., 2024). Previous work has focused on the development of a calibration tool to derive these parameters based on local data (Bosch et al., 2021a). Here we use this tool to systematically calibrate these parameters for a tropical climate, using Singapore as a case study.

2.3. Land cover and biophysical data

The primary data inputs for this study include land cover data with biophysical information for each land cover class and observed temperature data to calibrate and validate the estimated temperature outputs. Land cover data for Singapore were sourced from a previously published work (Gaw et al., 2019), which classified land cover based on high-resolution satellite imagery at 0.3 by 0.3 m spatial resolution. We resampled the land cover raster to 10 m resolution and reclassified the built-up land cover class to low- ($<$ 10 m), mid- (10–25 m) and high-rise ($>$ 25 m), to account for differences in building density and morphology, following the local climate zone classification scheme (Stewart & Oke, 2012; Fig. 1). A spatial resolution of 10 m was chosen to capture variation in urban land cover, including roads, urban greenery and buildings, whilst maintaining computational efficiency.

We assigned all vegetation classes with canopy cover a shade proportion of one (Table S1). To account for shade provided by buildings we computed the inverse of the mean sky view factor given for each built-up class in the local climate zone classification scheme (Stewart & Oke, 2012). Albedo was calculated as the mean of 83 cloud masked Landsat 8 surface reflectance images collected between 2015 and 2018, to match the temporal period of the land cover data (Tahooni et al., 2023; Tasumi et al., 2008), and the mean was calculated for each land cover class

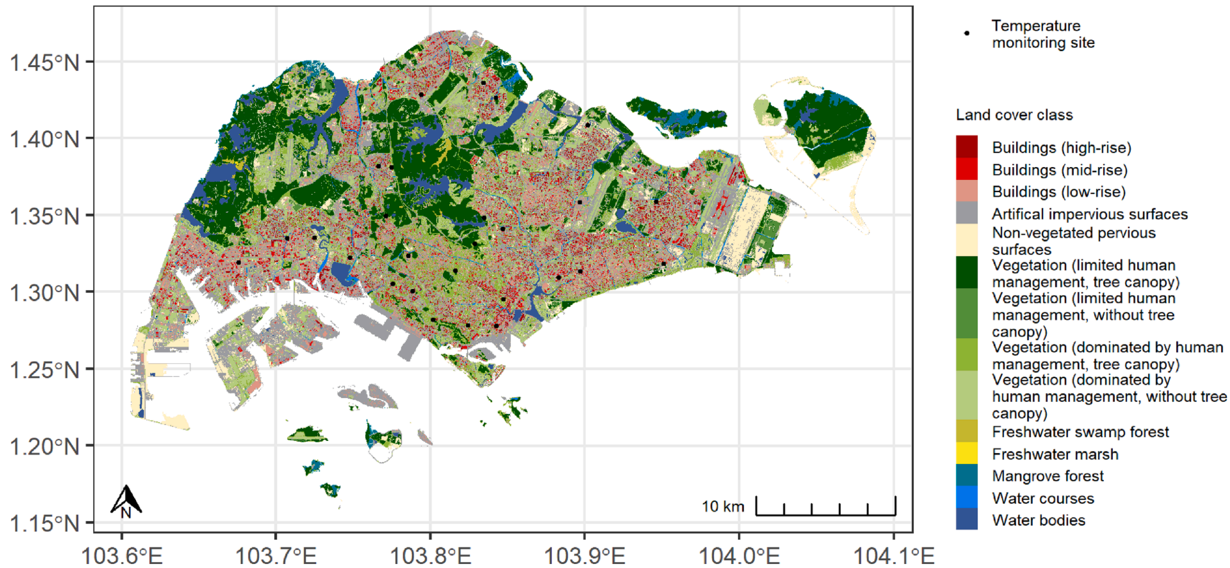

Fig. 1. Land cover (adapted from Gaw et al., 2019) and temperature monitoring sites in Singapore.

(Table S1). The evapotranspiration coefficient for each class was assigned following previous literature (Allen et al., 1998). Reference evapotranspiration was obtained from the Global Aridity Index and Potential Evapotranspiration Climate Database v2 (Trabucco & Zomer, 2019), which provides global raster climate data at the spatial resolution of 1 km based on data between 1970 and 2000 following a Penman-Monteith Reference Evapotranspiration Equation.

2.4. Model calibration and validation

To calibrate the model parameters (shade, albedo and evapotranspiration weights, cooling distance of large green spaces and air mixing distance) for a tropical city context we used an automated algorithm based on simulated annealing optimisation, described in previous work (Bosch et al., 2021a; Hamel et al., 2024). Simulated annealing optimisation is an efficient method to calibrate multiple parameters whilst avoiding convergence at local optima and being robust to stochasticity (Kirkpatrick et al., 1983). The calibration algorithm begins with an initial simulation using the default InVEST parameters (Table 2) and converges on a solution which maximises R^2 between estimated and observed air temperature (Bosch et al., 2021a)

We calibrated the model using a dataset of hourly microclimate temperature measurements collected at 27 locations across Singapore (Fig. 1) using 88 Thermocron iButtons (DS1921G-F5#) from January 2017 to January 2018 (Richards et al., 2020). These data were collected to capture variation in the cooling potential of vegetation across Singapore (Richards et al., 2020) and are thus particularly suitable to calibrate the Urban Cooling model parameters which represent the biophysical processes of cooling from vegetation.

We averaged hourly temperature measurements within each of the 27 clusters (1–4 sensors per cluster), and calculated the daily mean, 5th and 95th percentile temperature for each cluster. We used the 5th percentile to represent minimum and the 95th to represent maximum temperature as microclimate sensors can be prone to error, for example, from incident solar radiation (Maclean et al., 2021).

To test the model's ability to simulate the spatial distribution of temperature averaged over one year, we computed the annual average daily mean and maximum (to represent daytime conditions), and minimum (to represent nighttime) temperature for each cluster in 2017. Singapore is a densely urbanised city, precluding direct comparisons of rural and urban temperature observations (Chow & Roth, 2006). Therefore, we set the rural reference temperature to the cluster with the lowest annual average temperature, and the maximum UHI to the difference between this and the cluster with the highest annual average temperature. The initial model simulation used the default InVEST parameters (Table 2) and the number of iterations for calibration was set to 100 (Hamel et al., 2024). The calibration algorithm was run between four and six times for each simulation to test the stability of the calibrated parameters (Table S2). The final calibration parameters were selected based on the highest post-calibration R^2.

To validate the air temperature estimates we performed leave-one-out cross validation (LOOCV) by calibrating the model 27 times, leaving out one observed temperature datapoint each time. We then calculated the LOOCV R^2 based on how well the model predicted the left-out data point in each calibration. Finally, we computed the R^2, mean absolute error (MAE) and root mean square error (RMSE) between observed and estimated temperature of the final calibrated model (calibrated using all 27 observed temperature locations) and the model pre-calibration. The LOOCV method is useful in cases such as this where there are limited data for model testing which therefore cannot not be split into independent calibration and validation datasets.

2.5. Economic valuation

We estimated the economic benefits of urban cooling based on energy savings associated with lower temperatures, primarily due to reduced air conditioning consumption (Santamouris et al., 2015). We estimated economic savings for public residential buildings built by the Housing & Development Board of Singapore, for which shapefiles of building footprints were publicly available. Building footprints were obtained from Singapore's open data collective (data.gov.sg) and filtered to include only residential buildings and those built prior to 2018.

First, we estimated the relationship between monthly energy consumption for public residential buildings (Energy Market Authority of Singapore, 2023) and monthly average mean, minimum and maximum temperatures between 2016 and 2018 (derived as the average across 20 Meteorological Service Singapore stations; MSS, 2024) using univariate linear regression models. Second, we divided the coefficient of the best fitting model (mean temperature, in this case; Fig. S1) by the total footprint area of public residential buildings to obtain a parameter for the increase in monthly energy consumption, per degree Celsius increase in temperature, per square meter of building footprint (2.56 kWh/ $^{\circ}C/m^2$). We also calculated this parameter for the 5 and 95 % confidence intervals (CIs) of the relationship between energy consumption and temperature (5 % CI = 1.53 kWh/ °C/m^2; 95 % CI = 3.60 kWh/ °C/m^2)

The Urban Cooling model uses this parameter to estimate the economic savings associated with cooling from vegetation, at the building level, in comparison to a scenario of no vegetation (i.e. maximum urban heat island; T_{airmax}) (Natural Capital Project, 2024). Therefore, economic savings are calculated as follows, where T_{air} is the mean estimated temperature of the building footprint:

$$Economic\ savings\ = 2.56\ * (T_{airmax} - T_{air}) * footprint * cost$$

We estimated monthly energy savings for each building using the calibrated Urban Cooling model for mean temperature and multiplied these by 12 to obtain annual savings (we followed the same procedure using the 5 and 95 % CI parameters to quantify the uncertainty of this estimate). We calculated economic savings based on the average cost of electricity in 2017 of 20.7 cents/kWh (Energy Market Authority of Singapore, 2023), and summed savings across all buildings.

3. Results

3.1. Model performance

The InVEST Urban Cooling model estimated annual average temperature over Singapore with good accuracy when compared with observed temperature data. The model for mean temperature had the strongest performance (LOOCV R^2 = 0.78), although there was no change in R^2 and only a minor decrease in error statistics after calibration (Table 1). In contrast, the models for maximum and minimum temperature performed slightly worse (LOOCV R^2 0.65 and 0.52 post-calibration, respectively), but improved after calibration (Table 1). Both mean and maximum temperature models had MAE < 0.3 °C and RMSE < 0.4 °C, indicating good accuracy for day-time simulations (Table 1). The model for minimum temperature captured the variation in temperature well (R^2 = 0.52), but underestimated the magnitude of temperature, with much higher MAE of 0.844 °C and RMSE of nearly 1 °C (Table 1; Fig. 2).

The calibrated parameters for the distance over which large green spaces have a cooling effect and the distance over which air mixing occurs were most different from the default (Table 2). The distance over which large green spaces have a cooling effect was considerably larger in the minimum temperature model (419 m), and considerably smaller in the maximum temperature model (44 m). The calibrated air mixing distance was smaller than the default parameter (500 m) for all three models, with the most significant change for maximum temperature (38 m). The weights of shade, albedo and evapotranspiration for the daytime models (mean and maximum temperature) were not substantially changed by the calibration, although the weighting of shade was decreased in the maximum temperature model (Table 2). The calibrated parameters for each model remained relatively stable between independent calibration runs, although there was more variation in the calibrated parameters for minimum and maximum temperatures (Table S2).

3.2. Energy savings and economic value of vegetation

Monthly energy consumption in public residential buildings in Singapore had the strongest relationship with monthly mean temperature (β = 28,500,696, $p < 0.001$, R^2 = 0.40; Fig. S1). Based on this relationship, urban cooling (Fig. 3) across all public residential buildings (total footprint area 11,126,692 m^2) reduced annual energy consumption by 228 GWh, equating to annual economic savings of $47.14 million SGD (95 % CIs: $28.17 million; $66.23 million).

4. Discussion

4.1. Model performance

Here we show that the InVEST Urban Cooling model performed well at estimating annual average temperatures in Singapore, providing confidence in the model as a decision-support tool. The model estimated annual average mean temperature with the highest accuracy (R^2 = 0.78), followed by maximum (R^2 = 0.65) and minimum (R^2 = 0.52). The high R^2 for all models supports their use for estimating spatial variation in temperature (i.e. capturing urban heat island effects), in agreement with previous applications of the model in temperate cities (Bosch et al., 2021a; Hamel et al., 2024). The accuracy of our models when compared with observed air temperature (MAE 0.29–0.84 °C post-calibration) was broadly in line with previous work in Singapore which achieved MAE between 0.30 and 0.92 °C using a more complex Multilayer Urban Canopy Model, albeit at a finer scale temporal resolution (Mughal et al., 2019). Low error statistics (< 0.3 °C MAE post-calibration) for mean and maximum temperature support the use of the model for estimating the magnitude of daytime temperature (when heat stress is of most concern), but not nighttime for which the model considerably underestimated temperature (0.84 °C MAE).

In all cases, the calibrated model parameters were different than those estimated in previous work for other cities, highlighting the importance of local calibration (Table 2). An advantage of the InVEST Urban Cooling model is that the biophysical processes of cooling are explicitly represented by the model parameters, meaning they can be interpreted and verified within the local context (Bosch et al., 2021a). Following our systematic calibration, the air mixing distance parameter, for example, was estimated to be higher during the day than the night, in line with previous research in Singapore (Mughal et al., 2019). Previous research in Singapore has also measured the cooling effect of green spaces beyond their boundaries, showing cooling extending by up to 500 m, albeit with much stronger cooling effects closer to the green space (Yu & Hien, 2006). This parameter was considerably higher in our calibrated model for nighttime temperatures (419 m; Table 2), which contributed to lower estimated temperatures compared to *in situ* measurements. The biophysical interpretation of model parameters suggests that the optimal values determined for Singapore may be suitable for other tropical cities (Table 2), and future work could test this hypothesis in the region.

4.2. Economic valuation of vegetation

We estimated that urban cooling in Singapore provides annual economic savings of $47.14 million SGD through reduced energy usage in public residential buildings. To our knowledge, this study is the first to demonstrate the applicability of this component of the InVEST Urban Cooling model. The economic valuation provides a relatively simple

Table 1
Model performance for annual average mean (day), maximum (day) and minimum (night) temperatures based on observed vs estimated temperature, before and after calibration. LOOCV: leave-one-out cross validation, MAE: Mean Absolute Error, RMSE: Root Mean Square Error.

	R^2			MAE (°C)		RMSE (°C)	
	Pre- calibration	Post-calibration	LOOCV validation	Pre-calibration	Post- calibration	Pre-calibration	Post-calibration
Mean	0.80	0.80	0.78	0.294	0.287	0.359	0.345
Maximum	0.63	0.74	0.65	0.370	0.298	0.466	0.380
Minimum	0.52	0.63	0.52	0.862	0.844	0.977	0.990

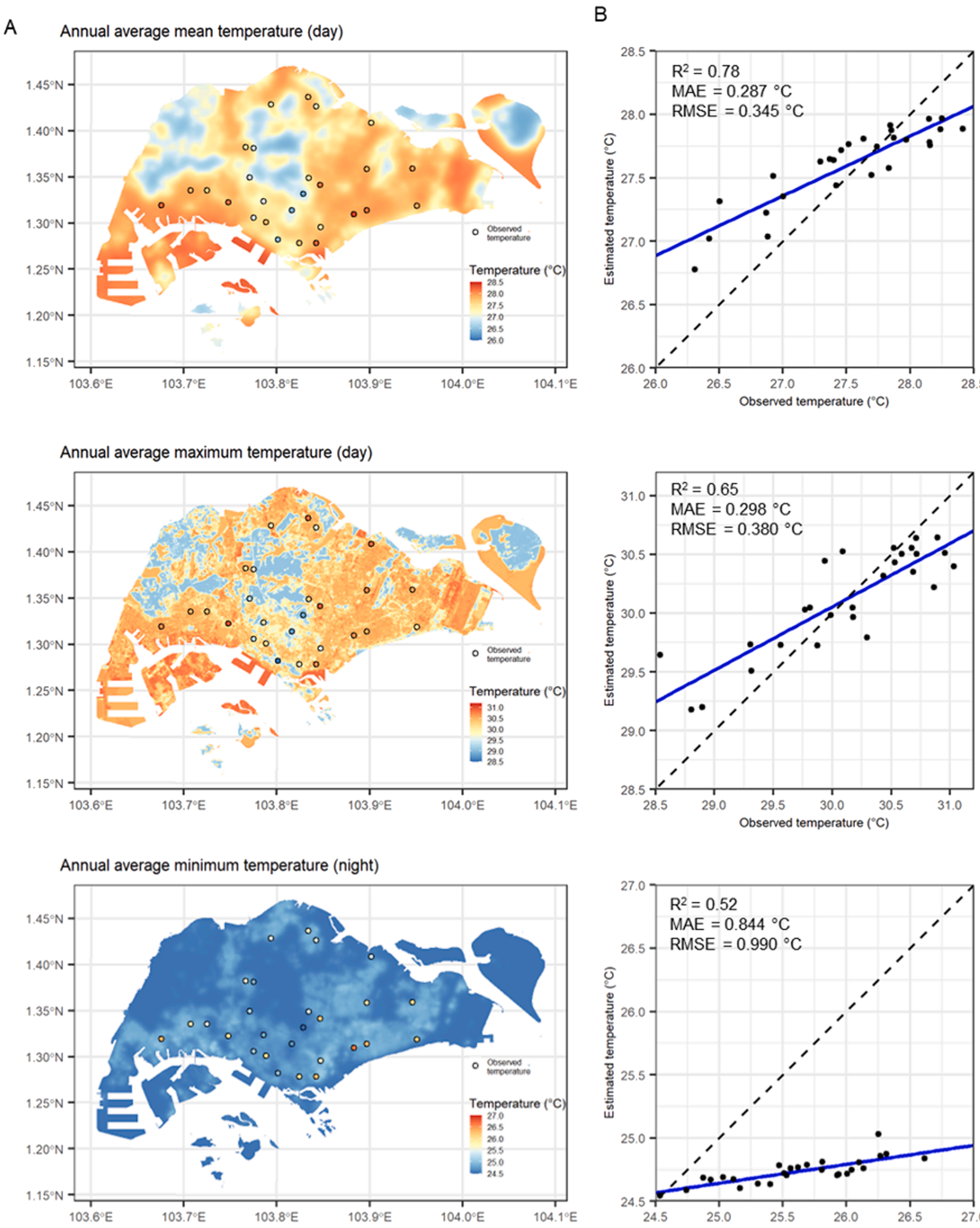

Fig. 2. Performance of the InVEST Urban Cooling model in Singapore. (A) Annual average estimated (maps) and observed (points) temperature over Singapore. (B) Estimated vs observed temperature with linear regression line (blue) and 1:1 regression line (dashed).

method to estimate the economic value of vegetation, a key step in producing policy-relevant information.

The simplified approach to economic valuation does, however, have some limitations (reflected in the reasonably wide CIs for this estimate). First, we estimated the relationship between temperature and energy consumption using a simple linear regression. We estimated an increase in monthly energy usage of 28.5 GWh per 1 °C increase in mean temperature, equating to a change of 7.9 % (based on monthly average

Table 2
Default and calibrated InVEST Urban Cooling model parameters for Singapore and other cities.

Study location	Temporal period	Weight Shade	Weight Albedo	Weight Evapotran-spiration	Cooling distance (m)	Air mixing (m)
Default	NA	0.6	0.2	0.2	100	500
Singapore	Mean (day)	0.57	0.22	0.21	99	389
	Max (day)	0.48	0.25	0.27	44	38
	Min (night)	NA	NA	NA	419	189
Lausanne, Switzerland (Bosch et al., 2021a)	Day	0.59	0.24	0.17	89.21	236.02
Twin Cities, USA (Hamel et al., 2024)	Day	0.62	0.21	0.17	109	771
	Night	NA	NA	NA	66	630

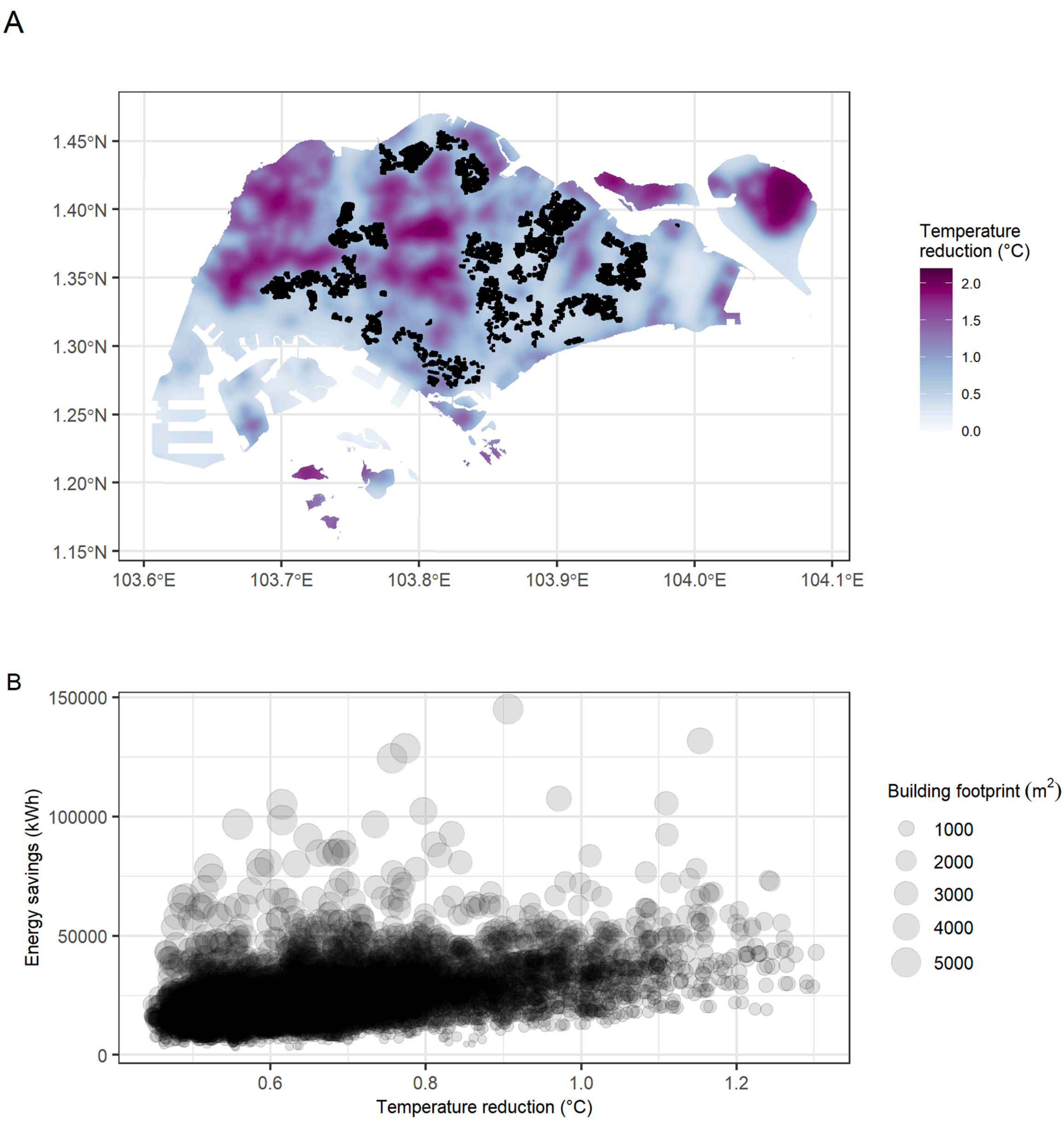

Fig. 3. Economic valuation of energy savings from urban vegetation in Singapore. (A) Estimated reduction in annual mean temperature provided by vegetation in Singapore (compared to maximum urban heat island) showing footprints of public residential buildings. (B) Annual energy savings (kWh) for each building as a function of temperature reduction and footprint area.

public residential energy consumption of 360.8 GWh between 2015 and 2017; Energy Market Authority of Singapore, 2023). Despite our simple approach, this estimate is nearly identical to previous work which estimated a 7.8 % change in residential energy usage per 1 °C change in temperature in Singapore, using more complex time-series modelling (Ang et al., 2017).

Second, the model estimates economic savings relative to a baseline of no vegetation (or maximum UHI) and does not account for building or household-level variation. It assumes that the estimated temperature at the footprint of a building applies to all floors, not accounting for vertical variation in temperature, which can be considerable and impact energy consumption (Gui et al., 2021; Li et al., 2022). We also limited our analysis to one building type, public residential buildings (economic savings would be higher across all buildings in Singapore), and did not account for variation in the socioeconomic characteristics of households (e.g. income) or the number of residents in a household or building. The InVEST model can, however, use different parameters for the relationship between energy consumption and temperature for different building types, if appropriate data are available (Natural Capital Project, 2024).

Third, as the InVEST Urban Cooling model estimates air temperature based only on the cooling capacity from vegetation, it neglects the contribution of anthropogenic heat emissions from air-conditioning usage which may exacerbate urban heat, especially in high density residential buildings which are common in Singapore (Boehme et al., 2015). Given these limitations, the economic valuation component of the Urban Cooling model represents a good first approximation of the energy savings from urban cooling. More complex simulations should be used to include anthropogenic heat emissions, specific building morphologies and finer temporal resolutions (see for example Litardo et al., 2020).

4.3. Limitations and future directions

The InVEST Urban Cooling model has some limitations related to the simplified representation of the mechanisms of cooling from urban vegetation and spatial air mixing (Bosch et al., 2021a; Hamel et al., 2024). Whilst these simplifications facilitate the broad scale applicability of the model, users should consider the potential impacts on model outputs. Where detailed biophysical data and technical capability are available, users can consider more complex urban heat modelling approaches for fine scale spatial and temporal resolution simulations (Tiwari et al., 2021). Such approaches are particularly useful for specific case studies such as green roofs and walls which are not easily modelled using the Urban Cooling model.

Estimated temperatures are constrained between the input reference temperature and maximum UHI before spatial air mixing is computed. Estimated temperatures after air mixing are, therefore, lower than the maximum UHI, which contributed to our estimated temperatures being lower than observed temperatures (Fig. 2). Further, the maximum UHI should represent the maximum UHI spatially (i.e. the highest temperature above the rural reference in a city). We estimated the maximum UHI as the difference between the minimum and maximum observed temperature (spatially), from observations primarily in vegetated areas (Richards et al., 2020), meaning that we likely underestimated the maximum UHI. This limitation could be alleviated by forcing the maximum UHI parameter based on ancillary literature values, although capturing the true maximum UHI is difficult given sparse meteorological networks in cities, especially in the tropics (Ramsay et al., 2024). Deploying temperature sensors networks with the intention of capturing maximum urban heat islands in dense built-up areas would allow this parameter to be accurately estimated and could be a direction for future research.

Further, the model assumes a uniform cooling distance for all large green spaces. Observational studies show that the extent and magnitude of cooling varies with the size and shape of green spaces, variation in surrounding land cover, and the effects of other climatic conditions such as wind speed and direction (Lin et al., 2015; Wong et al., 2021). The model could be improved by applying a decay function to the cooling effect of large green spaces and allowing the distance of cooling to vary with characteristics of large green spaces.

There are also limitations pertaining to our calibration of the model for tropical cities. Firstly, we calibrated the model using a previously-published dataset of microclimate observations in vegetated areas (Richards et al., 2020). Future work could calibrate the model using different observed temperature datasets (e.g. weather stations vs microclimate sensors) and compare performance outcomes. More detailed analyses are required to test the ability of the InVEST Urban Cooling model to simulate temperature over finer temporal ranges in Singapore, such as daily or monthly averages, or over diurnal cycles. Urban heat islands can have complex seasonal and diurnal dynamics (Chakraborty et al., 2016; Chow & Roth, 2006), which would likely result in different calibration outcomes. Singapore, however, has little annual variation in temperature with a monthly temperature range of less than 2 °C (Roth & Chow, 2012), and the cooling effect of vegetation is relatively homogenous year-round (Meili et al., 2021), supporting our use of annual average daily temperature in this study. Future work could also test the ability of the Urban Cooling model to simulate climate change scenarios (e.g., by manipulating the reference air temperature and maximum urban heat island to reflect expected temperature changes).

4.4. Implications for decision-making

Here we demonstrated that the InVEST Urban Cooling model accurately estimated the spatial distribution of annual average temperatures in Singapore. Such information can be used by decision makers (e.g., urban planners, city councils) to identify high-risk neighborhoods (Nazarian et al., 2022) and prioritise the locations of new green spaces. The calibrated models can also be used to simulate and evaluate greening scenarios (e.g. tree planting or development of new parks) and estimate the cooling benefits of new greenery, relative to the current state (see for example, Bosch et al., 2021b; Hu et al., 2023). In Singapore, for example, the model would be highly beneficial to prioritise the location of new parks to maximise their cooling benefit, given land constraints, or to simulate the configuration of new developments (see for example, Tan et al., 2021). Moreover, the InVEST software suite includes other ecosystem service models, including carbon sequestration and stormwater retention, which can be employed in conjunction with the Urban Cooling model to conduct multi-ecosystem service analyses (Tan et al., 2021; Natural Capital Project, 2024).

The drivers of UHIs are largely determined by the climatic context of a city (Manoli et al., 2019; Yu et al., 2018). Therefore we expect that the mechanisms of urban cooling from vegetation would be similar among tropical cities and that the model parameters derived here would be suitable for model applications in other tropical cities. We do, however, recommend that the model parameters be calibrated locally when suitable observed temperature data are available. Local calibration can capture variation within a city, such as the species composition of urban vegetation, which can influence the cooling capacity of urban green spaces (Tan et al., 2020). Future research could independently validate the Urban Cooling model in a tropical city with different urban morphologies and vegetation characteristics.

One of the main advantages of the InVEST models are the minimal data requirements. The primary input for the Urban Cooling model is land cover data, which are now globally available at 10 m spatial resolution, or easily derived from remote-sensing data (e.g., Brown et al., 2022; Zanaga et al., 2021). This means that the model can be readily applied in cities with limited *in situ* data, which include many low-income cities across the tropics. The model could also be applied in particularly data poor contexts such as urban informal settlements, which are especially vulnerable to urban heat, and a growing demographic in tropical cities (Ramsay et al., 2024).

5. Conclusion

Here we demonstrated the applicability of the InVEST Urban Cooling model to estimate the cooling provided by vegetation and derive associated economic savings in a tropical city context. Through a systematic calibration and validation process we show that the model accurately estimates the spatial distribution of annual average air temperatures with mean error less than 0.3 °C for mean and maximum temperature.

We provide calibrated model parameters suitable for a tropical climate to facilitate the application of the Urban Cooling model to other tropical cities. Our results give confidence in the use of the model as a decision-support tool. The model can be applied in other tropical cities, especially those with a dearth of *in situ* data, to support decision making, including heat vulnerability mapping and the implementation of nature-based solutions.

Declaration of interests

The authors declare no competing interests.

Data availability statement

This study used open access or previously published data. The land cover map of Singapore is available from Gaw et al. (2019), observed temperature data are available from Richards et al. (2020), building footprints are available from Singapore's open data collective (data.gov.sg) and energy consumption data are available from the Energy Market Authority of Singapore (2023). The InVEST Urban Cooling model is open source and available through Natural Capital Project (2024; naturalcapitalproject.stanford.edu/software/invest).

CRediT authorship contribution statement

Emma E. Ramsay: Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis. **Yuan Wang:** Writing – review & editing, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation. **Mahyar Masoudi:** Writing – review & editing, Writing – original draft, Supervision, Resources. **Min Wei Chai:** Writing – review & editing, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Tiangang Yin:** Writing – review & editing, Resources. **Perrine Hamel:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.scs.2025.106337.

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