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ORIGINAL PAPER

A performance comparison of mobile transect methods for heat and humidity prediction in complex urban environments

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Abstract

Wet Bulb Globe Temperature is a heat stress metric that accounts for air temperature, humidity, solar radiation, and wind speed. While methods of WBGT calculation from standard meteorological variables have been developed, these are often only used at coarse spatial scales or at specific points and overlook the underlying land use and land cover that is vitally important to microclimate development. This is particularly important in cities where the urban heat island has significant and spatially disparate impacts on local climate; some areas warm more than others. To address this gap, easily accessible and standard instrumentation was utilized to gather meteorological and environmental factors relevant to WBGT with common mobile measurement methods: walking, cycling, and driving transects. Machine learning methods are used to model and estimate each component of WBGT at a 10-m resolution using underlying land use and land cover data as inputs. The viability, challenges, accuracy, applications, and benefits of this novel mobile WBGT mapping method are assessed. Results indicate that for a sound UHI mapping campaign, a variety of transects should be used in a dense route network as allowed by the total number of citizen science volunteers and the size of the total study area.

Highlights

- A wide range of WBGT flag conditions can be observed on a limited spatial scale on a hot day, influenced by the local land characteristics.
- Mobile transect methods that capture a wide variety of local land characteristics should produce a better model.
- Models perform best where the transects are located, making it important to consider human exposure and vulnerabilities when designing transect based heat mapping studies.

Keywords Wet Bulb Globe Temperature · Machine Learning · Mobile Mapping · Heat Stress · Urban Heat

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Introduction

Heat is a deadly and growing concern for communities across the globe (US EPA, 2021). Anthropogenic climate change is expected to contribute to higher temperatures and more frequent extreme heat events in the coming decades. Compounding climate change on a local scale is the urban heat island (UHI) effect. A UHI can be defined as the phenomenon where cities are markedly warmer than the surrounding rural areas (Yow 2007; Oke 2002). UHIs are the result of urbanization and changes made to the local land use and land cover, such as the replacement of forested areas with apartment complexes and asphalt. (Gartland 2012). As a city grows and becomes more dense, the warming effect of the city increases (Kotharkar and Surawar 2016; Li et al. 2020). By 2050, two-thirds of the world's population is projected to live in urban areas (United Nations 2018), which will further compound the UHI problem while also increasing the number of people exposed to extreme heat. This compounding and developing hazard presents a complex challenge to urban policymakers, leaders, and community members across the globe. This will be further exacerbated in areas where the local climate is already dangerously hot.

Wet Bulb Globe Temperature (WBGT) was developed in the 1950 s as a holistic heat stress metric. Originally used by the United States Marine Corps (USMC), WBGT measures the thermal load on soldiers at hot and humid training locations (Budd 2008). WBGT incorporates air temperature (Ta), humidity, wind speed (WS), and solar radiation (SR) (see Eq. 1). The weights in Eq. 1 were determined qualitatively by the USMC but align with measurements made of effective temperature, a heat stress metric used prior to the invention of WBGT (Budd 2008). This is a more complex calculation of thermal load compared to the Heat Index (HI) metric that utilizes only air temperature and humidity. This is accomplished by using a weighted average formula between the natural wet bulb temperature (NWB), black globe temperature (Tg), and Ta. The NWB temperature and Tg are non-standard meteorological variables, meaning that only select weather stations have the ability to measure WBGT. WBGT is often described as the best heat stress metric for hot and humid environments due to its ability to capture the wide variety of atmospheric variables (Budd 2008; Clark and Konrad 2020; Heo et al. 2019).

$$\mathrm{WBGT} = 0.7 \text{ x } \mathrm{NWB} + 0.2 \text{ x } \mathrm{Tg} + 0.1 \text{ x } \mathrm{Ta} \quad (1)$$

Equation 1: The equation for WBGT where NWB = Natural Wet Bulb Temperature, Tg = Black Globe Temperature, and Ta = Air Temperature.

Due to the diverse spatial distribution of different kinds of land characteristics and human activities within cities, the corresponding spatial distribution of WBGT and its various components within a city is not uniform. Areas of a city with low tree canopy and high amounts of impervious surface coverage are found to have higher air temperatures than areas of a city with high tree canopy coverage. Tree canopy coverage is conducive to lower air temperatures but higher humidity rates due to the increased rates of evapotranspiration and shade coverage. Studies that have examined temperature have found substantial social bias, with marginalized communities being warmer than more affluent neighborhoods (Hsu et al. 2021; Hoffman et al. 2020). However, WBGT is less examined and could lead to potentially different results due to the more complex weighted average between the different variables. Through understanding the driving factors of local WBGT, greater insights can be drawn to develop actions to create cooler microclimates in cities.

Urban heat mapping is a common way to evaluate levels of heat exposure throughout a city (Wang et al. 2023; Shandas et al. 2019). When temperature maps are paired with heat vulnerability (e.g., Hsu et al. 2021; Hoffman et al. 2020), this allows policymakers to make spatially informed decisions for heat risk mitigation. (Fuhrmann et al. 2024; Tomlinson et al. 2011; Buchin et al. 2016). There have been a variety of methods used to create "thermal fingerprints" of cities. These include mobile transects, in-situ stations, and remotely sensed data.

While remotely sensed data is one of the most easily accessible measures of land surface temperature and has excellent spatial coverage and temporal resolution through the use of LANDSAT data, it lacks the specificity of 2-m Ta (Hsu et al. 2021; Liebowitz et al. 2019; Sun et al. 2009; Tran et al. 2006). This causes potential issues with identifying urban hot spots and UHI impacts, as surface temperature often overestimates the UHI effect and is not a direct indicator of air temperature or WBGT, as WBGT incorporates variables that are not always directly related to surface or air temperature, such as wind speed. Studies using in-situ station networks have the highest temporal resolution of any method but the lowest spatial coverage due to the expense associated with a high-density network of in-situ weather stations that would provide continuous weather data (Oukawa et al. 2022). The use of mobile transects involves capturing air temperature measurements across a large spatial area within a narrow observation window (often less than 1-h). A notable example is the NOAA-funded urban heat island mapping campaigns called Heat Watch. The Heat Watch campaign has mapped heat in over 60 cities in the United States, South America, and Africa (Mapping Campaigns, n.d.). Others have also used mobile transects to evaluate the UHI effect (Robinson et al. 2024; Shandas et al. 2019; Clay et al. 2016), citing advantages such as improved

spatial coverage and the ability to measure air temperature directly, in contrast to remote sensing studies that assess surface temperature.

However, there are limitations to the mobile transect method. The Heat Watch Campaigns use a machine learning model trained on the observations during the transects and the underlying land characteristics to predict spatially continuous temperature across the study areas. Most of these studies only use one form of mobile transect (i.e., driving, walking, or biking) in their evaluation of the UHI. This could lead to bias within the model, which could produce inaccurate temperature predictions across the study area. For example, many of the Heat Watch studies only use vehicle transects, and while this allows the study to capture a large spatial domain, it limits the sampling of environments to the microclimates around roads. While Heat Watch does use satellite-based imagery and machine learning to assess the environment away from the roads they are collecting data on, a traditional Random Forest model will not be able to predict the value of an independent variable outside of the range of the observed data set. This could lead to a warm temperature bias in the model when predicting Ta further from a road because of the direct influence of the pavement and vehicle exhaust (Husni et al. 2022) on the temperatures recorded with the mobile transect. On the other hand, a walking or cycling transect can capture conditions away from the influence of driving infrastructure but might be limited by study area size when predicting conditions further from the transect route. This study aims to evaluate the benefits and drawbacks of each kind of mobile transect method by employing all three kinds of commonly used transect methods and cross-validating the results. It is hypothesized that each kind of transect will perform best in the spatial domain they are located in and worst in areas with environments that are not sampled by an individual transect. By combining all three transects to create a model, the most combinations of land characteristics are sampled.

Data and methods

Study area

This study takes place in Carrboro and Chapel Hill, North Carolina. The two towns have a combined population of around 80,000 and are situated in southeast Orange County in the Piedmont region of North Carolina. The area consists of rolling hills and diverse land characteristics. Elevations for the area range between 66 m (216 feet) and 212 m (695 feet) above sea level. There are several distinct areas that represent various climate zones (Anjos et al. 2020). These include the impervious downtown areas, urban forests, neighborhoods, the University of North Carolina–Chapel Hill (UNC) campus and hospital, and the surrounding rural buffer. The highly interdigitated urban/rural boundary can be seen in Figs. 1 and 2.

The areas identified in Fig. 2 are areas that have been identified as having features, including varying tree canopy and impervious surface coverage, that could have drastically different impacts on the local microclimates. Figure 3 provides imagery from some of the selected areas from Google Street View. It can be seen that these areas have widely varying land characteristics and sky view factors.

All of these areas were selected to be included in the mobile transect routes in the effort of collecting as much data as possible from a diverse set of locations. The aim of the transect is to capture as many different combinations of the local land characteristics as possible. This includes variable vegetative patterns, sky view factors, elevations, and impervious surfaces.

Table 1 shows the different NLCD classifications (shown in Fig. 1a) from the most recent 2021 dataset covered in the mobile transects. The transects aimed for a diverse combination of transects while still considering that this is an urban heat island study, so samples will be inherently biased towards more developed areas. This is because the study area has more developed land than undeveloped. The table highlights some of the advantages and disadvantages of each kind of transect. The bicycle transect stood out for its ability to traverse a somewhat balanced array of land cover classifications.

Mobile transects

In this study, three different mobile transects were run in parallel to evaluate variables that have a strong influence on WBGT UHI. The three methods that have been used to measure the air temperature UHI in the past are vehicle transects (Shandas et al. 2019; Kousis et al., 2021; Tran et al. 2006), bicycle transects (Robinson et al. 2024; Romero Rodriguez et al., 2020; Silva et al., 2024; Yan et al. 2020), and walking transects (Middel et al. 2021; Dzyuban et al. 2022). In each of these methods, a temperature sensor and GPS have been transported around a fixed set of transects that co-locate temperature readings with air temperature and humidity data gathered from data loggers carried along the transect route, both metrics that contribute to WBGT. Additionally, wind speed data is vertically downscaled from the NC Econet station using the methods given in Clark and Konrad (2024) and calculated across the study area.

Figure 3 displays the various mobile transect routes undertaken in this study. The black route corresponds to the driving transect, the red route corresponds to the bicycle transect, and the blue route corresponds to the walking

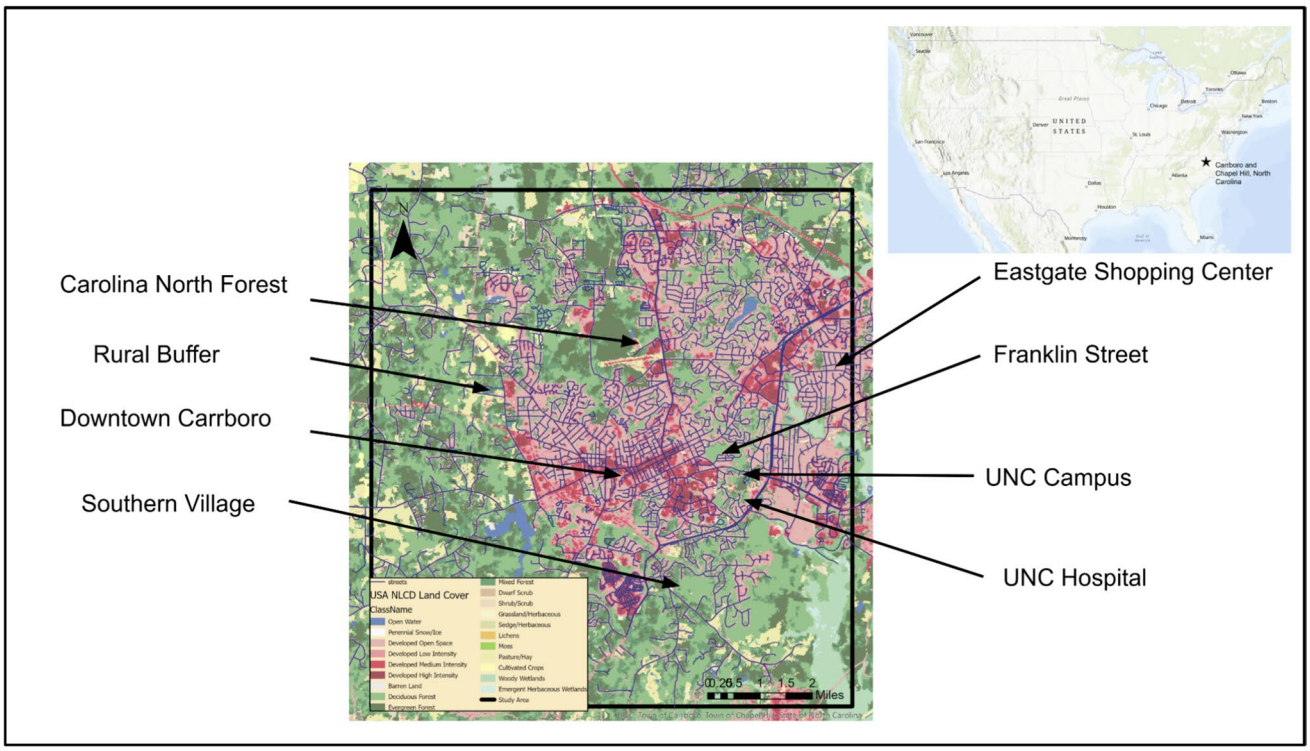


Fig. 1 A map of the study area, Carrboro and Chapel Hill, North Carolina, with key features that should influence the local climate highlighted. Upper Right: Carrboro and Chapel Hill, Located in Orange County, North Carolina in relation to the rest of the CONUS



Fig. 2 **A**—Eastgate Shopping Center; **B**—Franklin Street (downtown Chapel Hill); **C**—Carolina North Forest (CNF); **D**—UNC Hospital

transect. These mobile transects were carefully designed with local geography in mind. They attempt to capture areas that would exhibit hot, moderate, and cool conditions across the study area within approximately a 1-h period. The vehicle transect covers important areas such as the rural buffer, the Franklin Street corridor, Highway 54, and many surrounding neighborhoods. The bicycle transect covers important areas such as CNF and the Bolin Creek

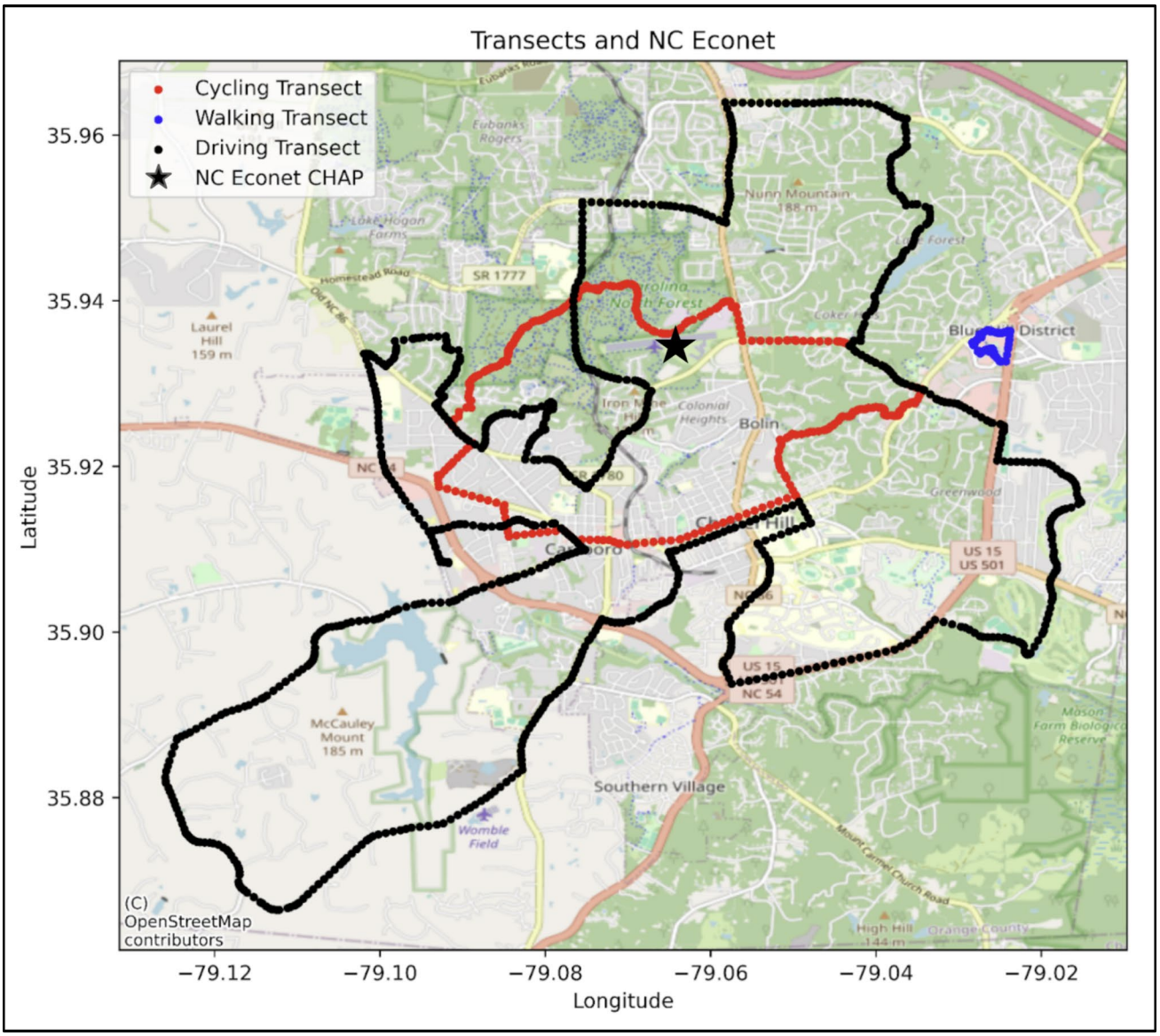


Fig. 3 Mobile transect routes as well as the reference NC Econet Weather Station at Horace Williams Airport

Table 1 A breakdown of samples taken from different NCLD classifications during the mobile transect routes on 28 August 2024

Transect	Developed Open Space (21)	Developed Low Intensity (22)	Developed Medium Intensity (23)	Developed High Intensity (24)	Deciduous Forest (41)	Evergreen Forest (42)	Mixed Forest (43)	Pasture/ Hay (81)
Walking	155	187	428	431	0	0	0	0
Cycling	818	712	542	221	330	560	123	0
Driving	2024	1864	830	274	50	46	38	32
Total Samples	2997	2763	1800	926	380	606	161	32

Greenway. The walking transect covers the Eastgate shopping center. This selection of routes carefully balances and samples as many different environments as possible from across the study area. It could be hypothesized that the Rural Buffer, Carolina North Forest and Bolin Creek Greenway may provide cooler environments due to ample tree canopy and the relatively lower development intensity. Inversely, the areas with more impervious surfaces and more intense development, including Franklin Street, Highway 54, and Eastgate shopping center, might be hypothesized to be

warmer than the average of the study area. Additional considerations were taken when designing the transects for the safety of the equipment operators, particularly the cyclist and walker, giving preference to areas with bicycle lanes, trails, greenways, and sidewalks where possible. Each transect will vary by the amount of area they can cover because of the differences in the speed of vehicles, bicycles, and walking. By incorporating each of the three transects, data are gathered at three levels of accessibility and spatial scale.

Prior to the fieldwork, a meeting was held briefing the co-authors on the routine for each transect. Before performing the route, each participant pre-ventilated their instrumentation, familiarized themselves with the route ahead of time, and all began their routes at 3 pm exactly. 3 pm was chosen as that is at the climatological peak of heat during the day in the Piedmont region of North Carolina. Since WBGT is a heat stress metric and incorporates variables that account for solar load (NWB and Tg), it is best mapped during the hottest part of the day and during hours that have a high amount of incoming solar radiation. This is opposed to some studies that map the surface UHI or canopy air temperature urban heat island that peaks during the nocturnal hours and are not specifically trying to map heat stress and the associated solar load (Eastin et al. 2018; Robinson et al. 2024; Yuan and Bauer 2007). WBGT could additionally be mapped at night, but this would mitigate any variations in heat stress provided by shading.

Each of the three mobile transects was performed with a Wahoo Element GPS (Wahoo Fitness, Atlanta, GA, USA) unit and a new, factory-calibrated HOBO U23 Pro v2 humidity and temperature data logger (Onset Computer Corporation, Bourne, MA, USA). The HOBO units were placed inside of radiation shields to mitigate any errantly high readings that would result from exposure to direct solar radiation. Each device was located between one and two meters off of the ground (limitations exist with the bicycle; for safety, the HOBO was mounted to the bars that are about 1 m above the ground). Each device was pre-ventilated prior to the transect for five minutes to allow the device to equilibrate to the ambient environment. On the vehicle and cycling transects, the units relied on natural ventilation from the forward speed, which forced air through the radiation shield. On the unit with the walker, a fan was used to mechanically force air through the radiation shield and prevent stagnation and errantly high readings. These units collected temperature and dew point data at one-second intervals. Attached to the vehicle unit was an Apogee pyranometer (Apogee Instruments, Logan, UT, USA). This unit faced directly upwards, collecting incoming solar radiation data from across the vehicle traverse. Once collected, this data was processed and cleaned along the same guidelines as Robinson et al. (2024) and Shandas et al. (2019). Data with 0 speed was removed from the dataset, and the temperature and humidity were linearly adjusted for drift in ambient temperature from the start time of each route as each route began and ended at the same point. All temperature drift from the beginning to the end of the routes could be attributed to changes in ambient conditions, as the land characteristics stayed constant throughout each route. No appreciable time lag was detected, as each temperature and humidity sensor had adequate ventilation, either from the forward motion of the bicycle or vehicle or from the fan on the walking transect. The solar radiation data was adjusted as well using the Ineichen model (Fig. 4).

Station data

The NC ECONet Station is a research-grade weather station operated by the North Carolina State Climate Office. It is located at the now-closed Horace Williams Airport, directly

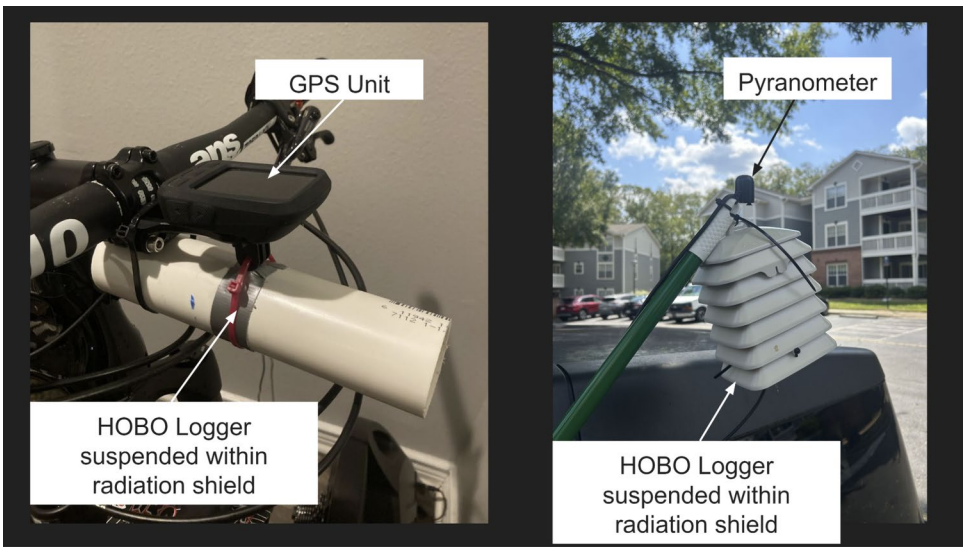


Fig. 4 The instrumentation setup for the bicycle (left image) and vehicle (right image) used to gather the temperature, humidity, and solar radiation data across the study area. The setup for the walking transect was the same as the vehicle transect, minus the pyranometer and with a fan attached to the suspension pole

adjacent to CNF. This station is used as a reference station for the study, offering data on the broadly present weather in the area, as well as an external source of validation for the UHI modeling.

Raster data

The data collected from the transects is paired with relevant land characteristics data. Metrics were chosen that have impacts on the local climate. Previous work has modeled air temperature and humidity using LANDSAT data (Shandas et al. 2019). By using more commonly understood metrics, the impacts of different kinds of land characteristics on local microclimates are better understood. All rasters have been sampled to a 10 m resolution. This research study selected a wider variety of land and environmental characteristics from different satellite-derived datasets.

Each of the variables in Table 2 has been demonstrated to impact the climate in urban areas in previous studies (Unger 2009; Yang et al. 2015; Tan et al. 2016; Eastin et al. 2018; Yuan and Bauer 2007). It could also be hypothesized that each of these variables could also have an impact on local dew point temperature and solar radiation (Hao et al., 2019). In addition, we create focal distance rasters of distances ranging from 30 to 990 m in increments of 30 m, similar to Shandas et al. 2019. Additionally, these are variables that make physical sense, allowing results to be easily disseminated to the public and to decision makers. They inform the kinds of environments that enhance or mitigate extreme WBGT values. In a focal distance raster, the value of an individual pixel is the value of the average of the surrounding pixels within the specified distance. E.g., in the 990 m tree canopy focal distance raster, the value of each pixel is the amount of tree cover for the surrounding 990 m. This technique accounts for the influence of the surrounding land characteristics, rather than only what is directly underneath each point.

Table 2 Variables used to train the machine learning random forest models for Ta, Td, and SR

Variable	Description	Source
Tree Canopy	Percent of tree canopy within a raster cell (%)	NLCD
Impervious Surface	Percent of impervious surface within a raster cell (%)	NLCD
Elevation	Elevation of a raster cell (m)	USGS DEM
Building Volume	Volume of building within a raster cell (m^3)	Pesaresi and Politis, 2023
Distance to a road	Distance of a Pixel to the nearest road (ft)	Orange County GIS
Sky View Factor	Fraction of sky that is visible from the ground	Calculated from DEM and DSM, Dirksen et al. 2019
Slope	Gradient of a pixel	USGS DEM
Slope direction	Slope aspect of a pixel	USGS DEM
Albedo	Reflectance of the surface within a pixel	LANDSAT, Liang 2001

Machine learning

Random Forest was chosen for this study because it has been successfully used in a wide variety of environmental modeling tasks, including microclimate and heat stress modeling (Shandas et al., 2019; Oukawa et al. 2022; Pouyan et al., 2022). Random Forest also contains a system of internal validation by using a split dataset. For our use case we trained the model on 90% of the data and made predictions on the other 10%. The R^2 and RMSE for both observation days from this test are shared in the results section below (see Fig. 5).

The land characteristic and focal distance raster data presented in Table 1 serve as the independent variables to train three separate Random Forest (RF) models that use temperature, dewpoint, and solar radiation as the respective dependent variables. This is done by using the XY coordinate data associated with each data point of atmospheric data (Ta, Td, SR) to extract the value of the underlying land characteristic raster and focal distance raster pixels and storing that in.csv format. The machine learning model is then trained using 90% of the points as a training dataset and 10% as a test to assess the accuracy of each model.

Random forest is a decision tree-based machine learning model. These are structures that make decisions by splitting data into branches based on certain feature (land characteristic) values, leading to a final prediction (Ta, Td, and SR). This series of decisions leads to a final predicted value of a respective atmospheric variable. RF has performed extremely well when used to model environmental conditions in the past, often resulting in R^2 values of greater than 0.95 (Shandas et al. 2019; Oukawa et al. 2022). There are several benefits to using Random Forest to perform environmental modeling. RF is non-linear and consistently outperforms linear models. The non-linear nature of RF allows it to place particular emphasis on independent variables that contain more influence when found in extreme values.

WBGT calculations

The formulas for WBGT calculation are provided by Liljegren et al. 2008, and are publicly available at: https://github.com/mdljts/wbgt/blob/master/src/wbgt.c. The RF models provide rasters for Ta, Td, and SR. Atmospheric pressure is calculated using the reference pressure at the NCEconet station and the hypsometric equation (Wallace and Hobbs 2006). Wind speed is calculated using the reference WS at

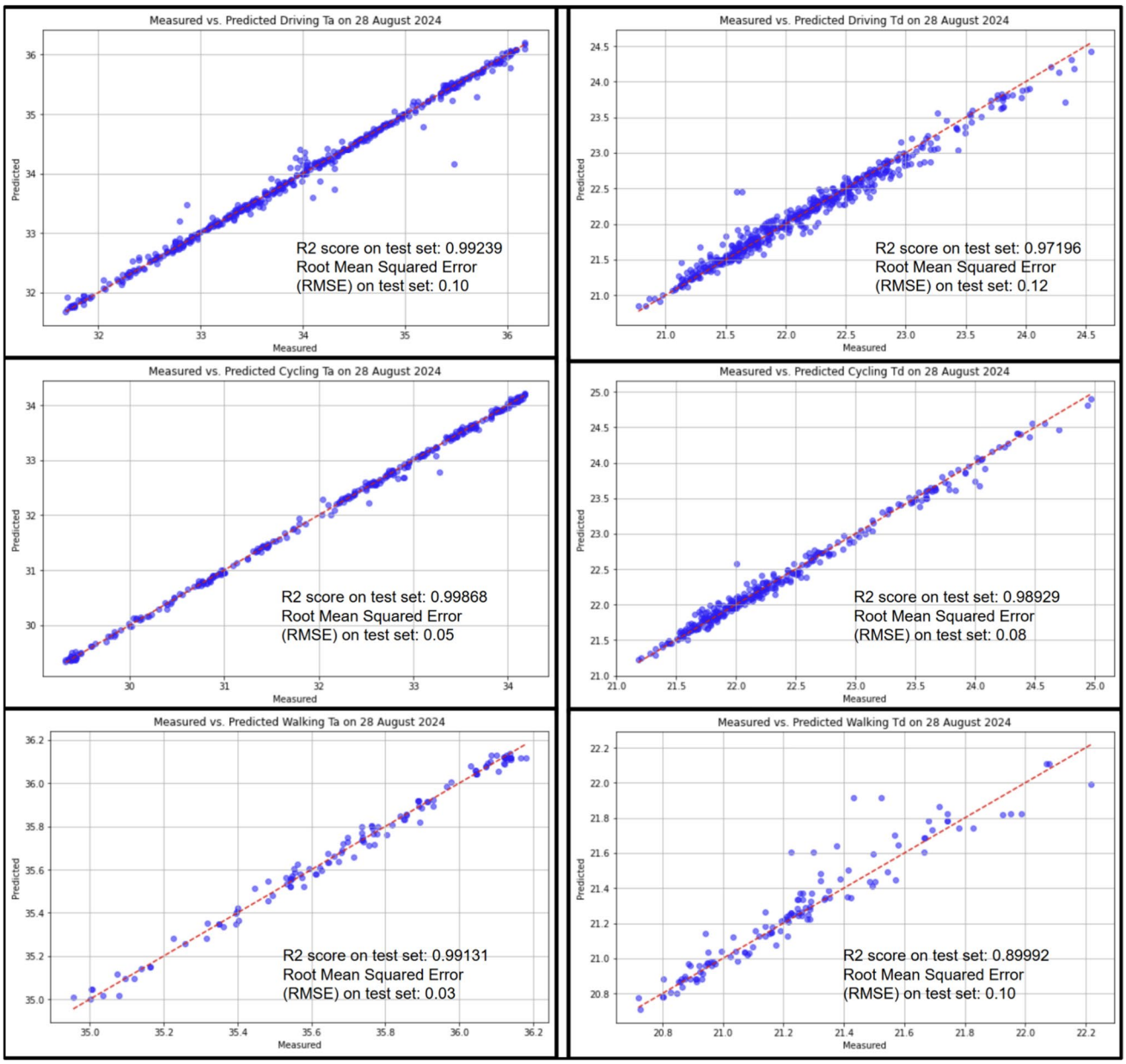


Fig. 5 The test data set produces highly accurate predictions of air temperature and humidity on 28 August 2024. The plots for 14 August 2024 look similar to this, with models that perform equally well

the NCEconet station and a surface roughness raster and formulas provided by Clark and Konrad (2024).

Transect performance

In order to evaluate the need for all three transects, Ta and Td rasters are created from all three transects and machine learning (ML) models. Then an RF model is used on the data from each individual transect, and the rasters produced are compared. It is hypothesized that each kind of transect will perform best in the spatial domain they are located in and worst in areas with environments that are not sampled by an individual transect. By combining all three transects to create a model, the most combinations of land characteristics are sampled.

Results

Results here are presented from two separate days: 14 August 2024 and 28 August 2024. Both days shared similar optimal meteorological conditions for UHI formation, including clear, sunny days with low wind speeds (Eastin et al. 2018; Robinson et al. 2024). During the observation period on

the 14th of August, the NC Econet station reported a wind speed of 8 kph at 10 m and 927 watts/m^2 of incoming solar radiation at 3 pm. On the 28th of August Intensive Observation Period (IOP), the wind speed was 9 kph, at 10 m, and there was 790 watts/m^2 of incoming solar radiation.

Modeling results

The RF models produced highly accurate predictions of local temperature along each transect route for both Ta and Td. R^2 values ranged from 0.89992 to 0.99868 with low mean squared errors. For the areas along each transect, the predictions from the models should be trusted given these statistically sound results. This extremely high predictive power is in line with previous studies using similar techniques (Shandas et al., 2019; Oukawa et al. 2022).

Spatial distribution

The results presented here detail the spatial distribution of air temperature and dew point temperature across the study area. When combined, the models produce a highly detailed map that captures the influence of the land characteristics across a broad spatial area (Fig. 6).

Important features such as the downtown Franklin Street/Jones Ferry corridor, the UNC campus and hospital, and the Eastgate Shopping Center (see Figs. 1 and 2) stand out in comparison with the cooler and more rural areas to the west and southeast of the urbanized area. Carolina North Forest also provides substantial cooling, despite being surrounded by rapidly developing areas. Interestingly, when combined together, the models from the three separate transects can resolve the influence of the impermeable I-40 interstate (located in the northeast portion of the maps here) without actually transecting that area. Figure 6 also displays the significant urban dry island formed by the dense development in Carrboro and Chapel Hill. This is due to the removal of trees, which causes a dramatic decrease in the evapotranspiration occurring in the area, lowering the water vapor in the atmosphere. Increased water runoff rates caused by impermeable surfaces could move stormwater out of the area at a much faster rate, decreasing evaporation into the atmosphere. Urban dry islands (UDI) have been documented in previous literature (Huang and Song 2023), and the numerical relationship with humidity and WBGT is clear (see Fig X, Liljegren et al. 2008), but their impact on the spatial distribution of WBGT within a city is still understudied (Fig. 7).

Transect spatial comparison

When combined, the mobile transects offer a clear picture of the UHI and UDI across the entire study area. However, the use of three separate mobile transects is labor-intensive and requires significant human resources and coordination (Fig. 8).

Figure 5 emphasizes the strengths and weaknesses of each kind of mobile transect. The predictions of each model are constrained by the environments they sample in. A simple random forest model cannot make predictions for the dependent variable outside of the conditions observed in the training dataset. This makes it vital to sample a wide range of environments during the IOPs (Fig. 9).

As seen in figure The driving transects are only able to capture data in a vehicle-friendly environment. This transect only went on paved surfaces, leading to a warm and dry bias when compared to the combined three-transect model. The bicycle transect is the most balanced of the three individual models, given that it was able to transect both off-road and forested environments in Carolina North Forest; however, due to the nature of the cycling transect, there are lots of areas where cycling is not safe and could not be captured. Most of these areas have a high concentration of impervious surfaces (e.g., Highway 54 along the south side of UNC's campus). The walking transect is the most spatially limited because of the restricted distance a walker can travel during the Intensive Observation Period (IOP). Due to the lack of spatial coverage on the walking transect and the location it was performed (Eastgate Shopping Center, see Figs. 2 and 3), there is a substantial warm bias when attempting to predict the air temperature and a dry bias when predicting dew point temperature across the rest of the spatial domain. Random forest models can not predict independent variable values outside of the observed range of values of air temperature and humidity, meaning it is vitally important to capture a wide range of environments if trying to map heat stress across a large area.

Correction for sample size

Figure 10 displays the importance of dispersed environmental sampling rather than large sample size when training these RF models. In order to ensure model performance was increased by including all transects, rather than just a larger sample size, the RF model used data from all three transects, rather than just one (Figs. 8 and 9), and trained on only ⅓ of the dataset and tested on the other ⅔. While model performance did decrease marginally when compared to Fig. 5, the predictive power was still greater than $R^2 = 0.93$ for each measurement.

Transect exclusion analysis

When comparing the temperature and humidity models created from two of the three transects, Fig. 11 shows

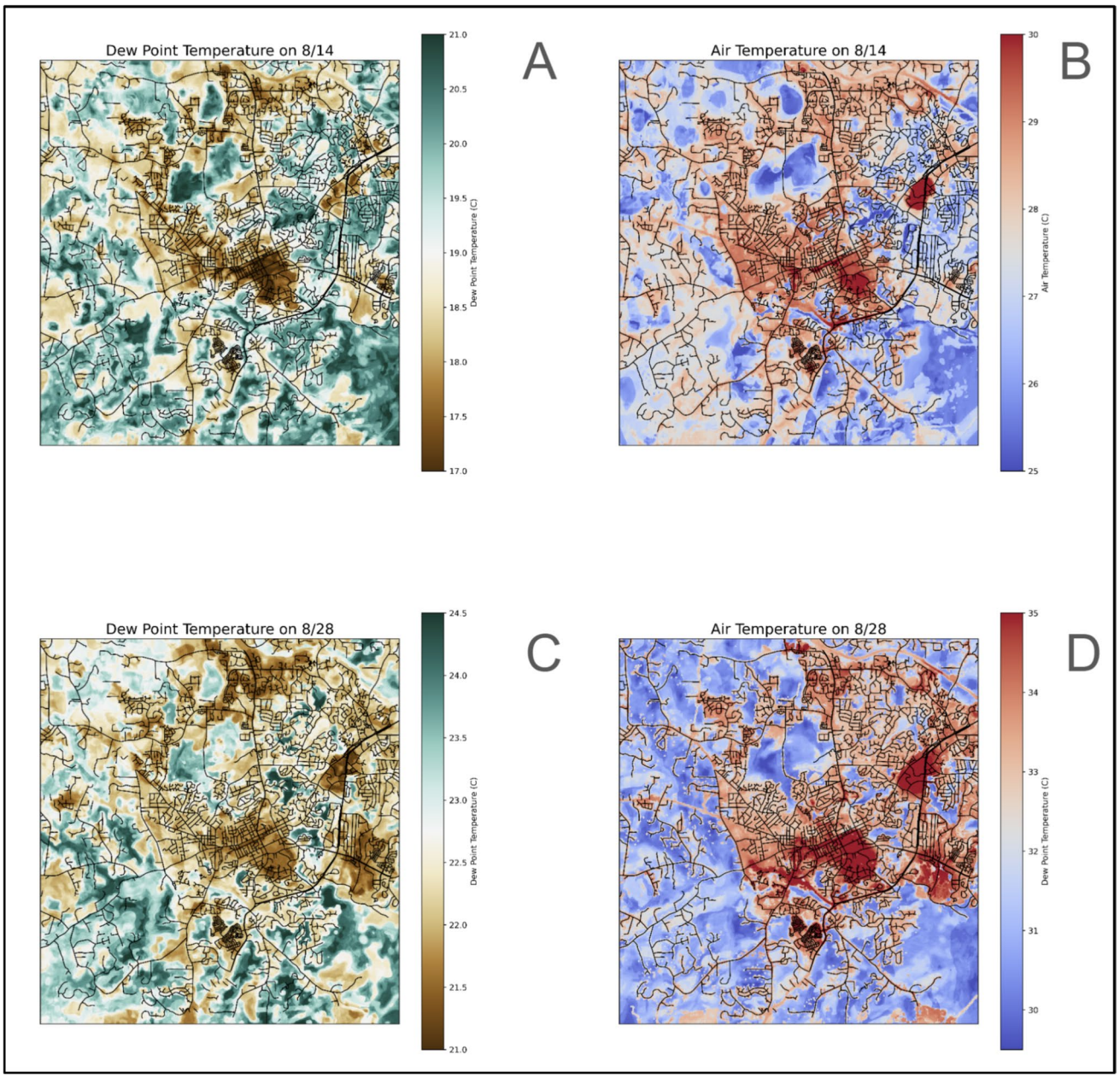


Fig. 6 The combined model output for all three kinds of transects on the two days of data collection. A—dew point on 8/14, B—air temperature on 8/14, C—dew point temperature on 8/28, D—air temperature on 8/28

numerically the bias shown spatially in Figs. 8 and 9. Transects trained primarily over impervious surfaces tend to overreport air temperature and underreport dew point temperature when compares to a model trained on a more balanced set of transects. The lower R^2 values of the models built on two transects and compared to the third indicate the importance of transecting different environments. For example, when the walking transect is excluded, the models underpredict the temperature in Eastgate Shopping Center (Fig. 1). Eastgate Shopping Center has the largest surface area and highest density of impermeable surfaces in our study area. Inversely, when analyzing the model Produced from the walking and driving transects and tested on the bicycle transect, the temperatures in cooler, more vegetated areas such as CNF are overpredicted. This is likely because the vehicle transect was limited to sampling over impermeable surfaces, and the walking transect also sampled in impermeable environments. These results support the use of a variety of transects that are able to adequately sample as many different kinds of environments as possible in order to produce the most accurate results. Studies using a limited number of in-situ stations to model air temperature,

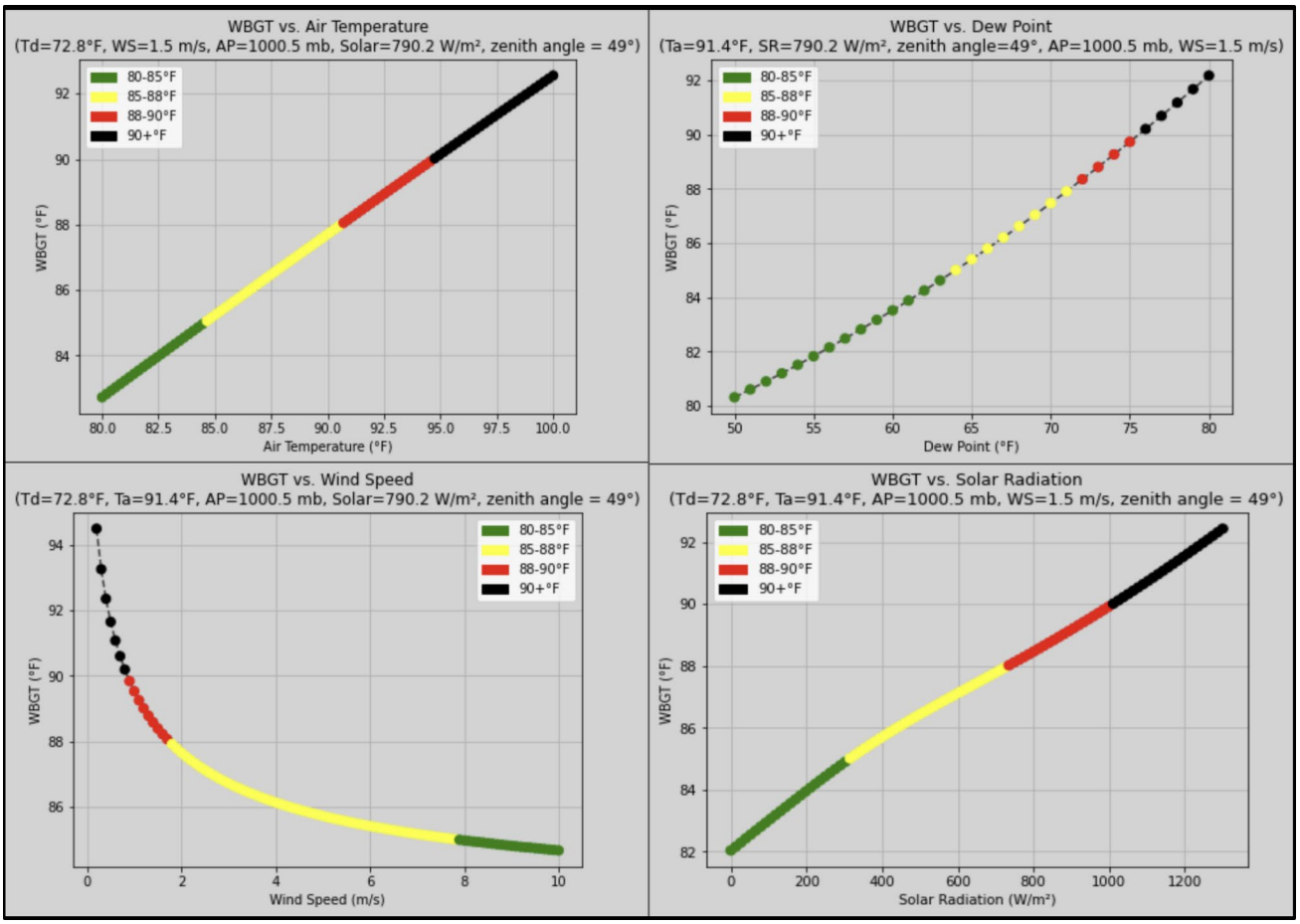


Fig. 7 Each panel of this figure shows the relationship that each major component that influences WBGT has on the metric. With all other variables being held constant, as air temperature rises, WBGT will increase almost linearly. The same is true for dew point and solar radiation. However, as wind speed approaches 0, heat stress increases exponentially. Conditions are from the 28 August IOP

humidity, or WBGT across a city are limited by the small spatial sampling. The models are extremely predictive where they sample (Fig. 5, Fig. 9), emphasizing the importance of sampling all kinds of environments, and particularly in places where people are concentrated and exposed to heat.

WBGT modeling

The Liljegren method is used to calculate WBGT across the spatial domain using air temperature (modeled using RF), humidity (modeled using RF), atmospheric pressure (calculated with Wallace and Hobbs 2006), and wind speed (Clark and Konrad 2024). The equations for WBGT calculation and the calculation of each variable are available in the appendix of this manuscript.

The maps in Fig. 12 show the importance of WBGT mapping in urban areas. There is a four-flag variation across the study area with a higher concentration of hotter pixels towards the more intensely developed areas. Each flag level has different safety precautions that are advised. For example, the North Carolina High School Athletic Association has published guidelines (found here: https://www.nchsaa.org/wp-content/uploads/2015/03/heat-guidelines_0.pdf) for each flag condition ranging from a 5-min water break each one-half hour of practice for green-flag conditions (80–84.9 WBGT), to completely suspending practice for black-flag conditions (>90 WBGT).

Discussion

Understanding spatial variations in heat exposure is important for assessing risk among vulnerable populations, as localized differences can significantly influence health outcomes. This work shows these variations are not small. As observed on 28 August 2024, there was a four-flag variation in heat risk across the study area, with each flag having separate advised safety precautions. Without a detailed map of heat risk, communities rely too heavily upon a sparse

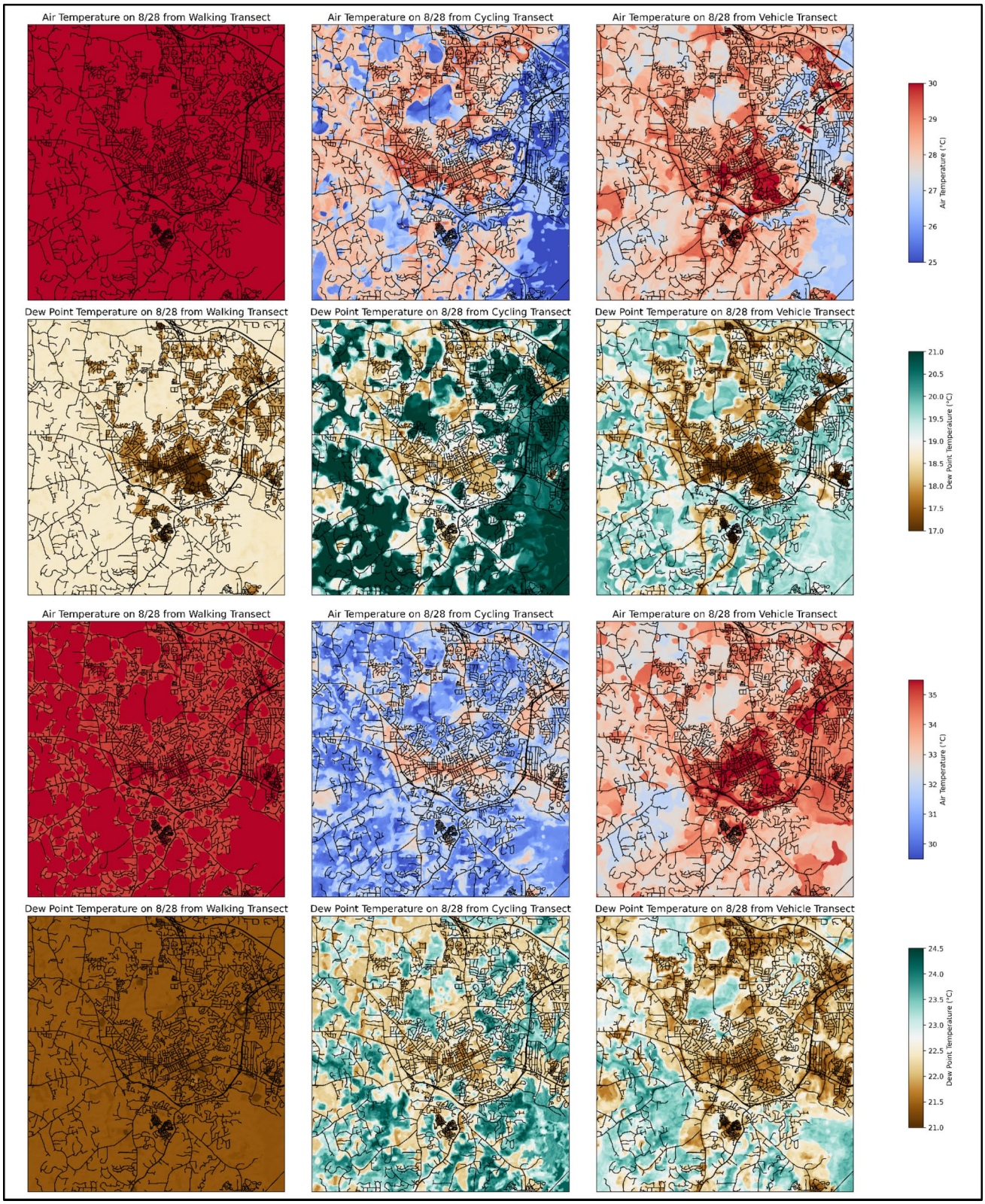


Fig. 8 The models created from each individual transect applied across the entire study area for both Ta and Td on 14 August and 28 August 2024

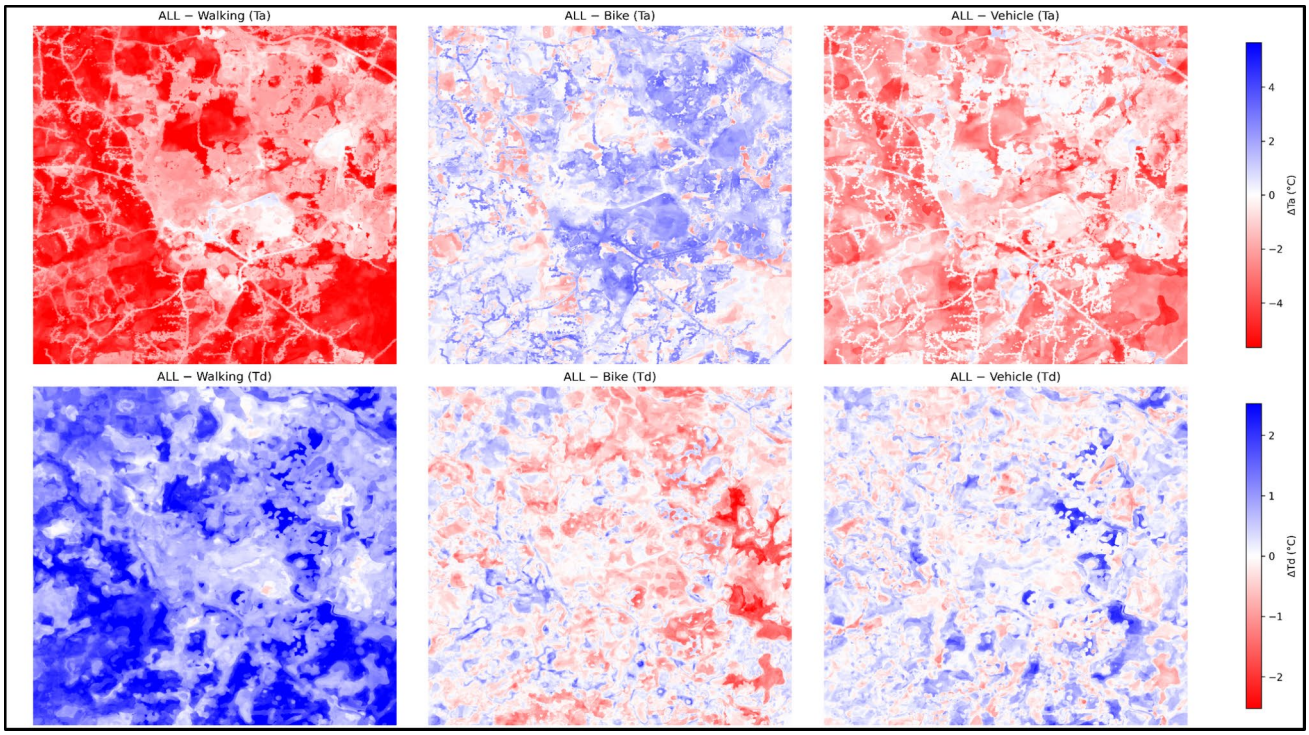


Fig. 9 This figure shows the differences on 28 August in air temperature and dew point temperature between the combined transect model and models created from individual transects. Areas in red are over-reported by an individual model; areas in white are correctly predicted by the individual model, and areas in blue are underreported by the individual model

network of in situ stations to provide heat exposure data. This work clearly indicates that a singular station may either under- or over-report conditions compared to the rest of a broader area, based on the land characteristics surrounding the station. This work provides a deeper understanding of the importance of different sampling techniques for mobile transects as well as a guide for adopting a more holistic heat stress metric.

Multiple kinds of transects are important for the accuracy of the results. Each transect in this study introduced its own kind of bias based on the sampling environment. A variety of environments should be sampled, and this is most easily done by using multiple transect methods. Vehicles will have a difficult time sampling over non-impermeable surfaces (e.g., away from roads) and in cool environments that are heavily treed. As more transects are introduced, more data can be fed into the model. With the non-linear nature of random forest, data from each transect can be factored in and be able to more accurately predict areas that are not sampled. Importantly, transects should take a "people first" approach. Measurements where people are outside and participating in outdoor activities are most important. If limited in resources, study areas should prioritize their transects towards areas where people are outside. This could be greenways, parks, bus stops, sidewalks, playgrounds, or parking lots. Practically, people will not often be outdoors in environments such as major highways or on rooftops, so these areas should not be sampled if resources are limited. But sampling these areas provides insight into how these features impact the ambient environment and how urban sprawl is impacting UHI formation.

The spatial scale of the study area should be considered when choosing transect methods. Each study area will be unique and present its own challenges. Larger study areas should consider more transects, as there are likely more kinds of local microclimates. Vehicle, cycling, and walking transects all cover different amounts of area within a 1-h transect observation period. Walking transects may be ideal for a neighborhood-scale mobile mapping campaign. Walking transects are the least expensive (no vehicle or bicycle required) and can transect areas where cars or bicycles cannot, such as walking-only paths in parks. Bicycle mobile transects offer a good middle-ground option for medium-sized study areas such as a college campus (Robinson et al. 2024). Bicycles can cover much more ground and access similar areas to walkers. For example, the bicycle transect was about ten times longer in distance than the walking transect and completed in about the same amount of time. The bicycle transect also covered off-road paths through CNF, which helped to sample some of the most natural areas of the study area. The vehicle transect is commonly used for large study areas in the Heat Watch mapping campaigns.

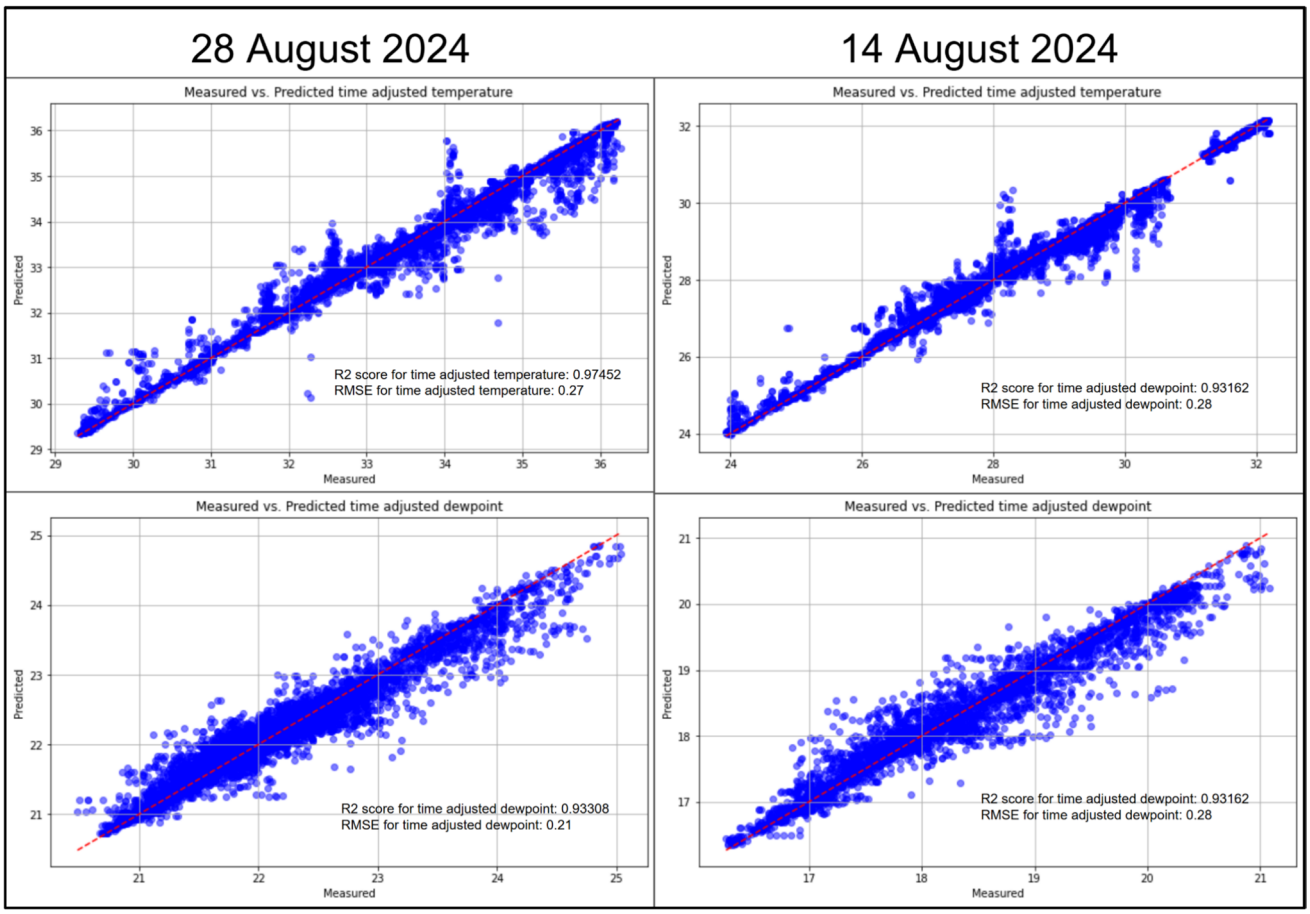


Fig. 10 Results of the RF model interval validation when trained on ⅓ of the data points and tested on ⅔ of the data points across all transects. The test data set produces highly accurate predictions of air temperature and humidity on 28 August 2024 and 14 August 2024, even with ⅓ of the data

These campaigns almost exclusively use vehicle transects. The heat watch campaigns are heavily funded and often cover entire cities or county-sized areas.

Mobile transect UHI mapping is not without limitation. This is a labor-intensive and but relatively inexpensive exercise when compared to passive methods of data collection such as using satellite imagery or in situ weather stations. Due to this, the temporal resolution of mobile transect UHI mapping is often limited, in almost every fully funded Heat Watch campaign, data collection is limited to one or two days. In this case we collected data during the climatological peak of heat in the diurnal cycle on two separate occasions. Satellite-based UHI analysis offers a longer temporal range with the ability to analyze historical UHI fingerprints. Station-based UHI analysis offers the highest temporal resolution by collecting data 24 h/7 days per week. Mobile transects are the best method for providing a snapshot of metrics most relevant to heat stress at high spatial resolution. Other limitations include limited spatial availability of wind speed data, but across the limited scale of our study area, this is not anticipated to be a significant factor, especially as Clark and Konrad (2024) were able to increase the accuracy of site-specific WBGT predictions using the vertical wind speed downscaling algorithm. Using the vertical downscaling did increase the accuracy of their results by removing a cool bias from elevated 10-m wind speeds. While temporally limited, this work is a significant step forward in heat stress modeling in complex urban environments due to the incorporation of multiple kinds of transects as well as solar radiation and wind speed data. When examining clear-day and peak extreme-heat conditions, this work presents a working model of heat stress prediction. In order to account for more variables, such as varying cloud patterns, or develop a model for the entire diurnal cycle, rather than the climatological peak of heat stress, a different study design would need to be implemented. In situ stations gathering all of the necessary variables set up in a dense network across all of the environments described in this manuscript would be recommended. This work justifies the need for further exploration and a longer study period. The scope of this study is to examine WBGT distribution on clear, extreme heat days where variability is limited.

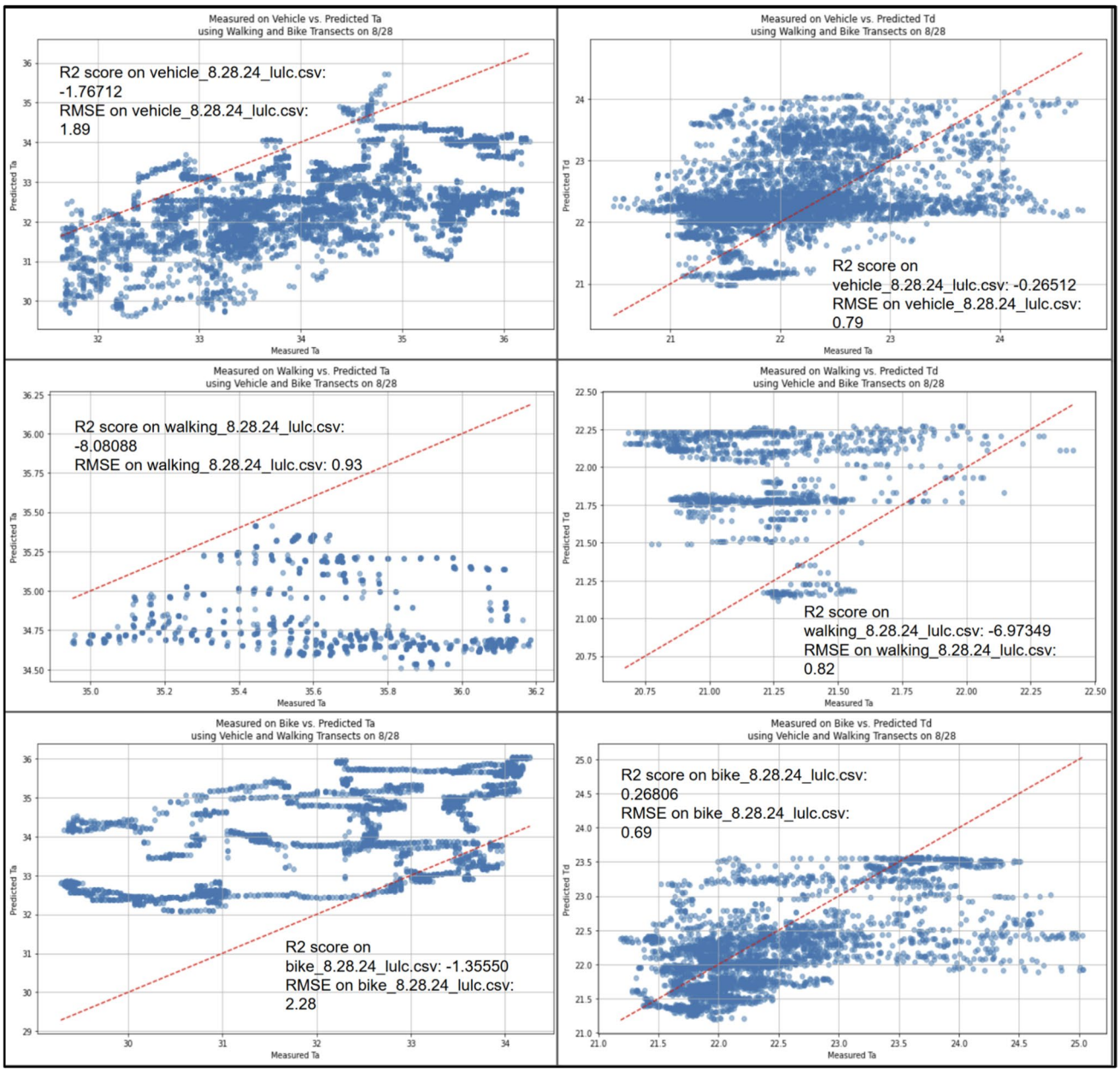


Fig. 11 For these results, an air temperature and a dew point temperature model were trained using a "leave one out" approach. The model was trained using two of the three mobile transect routes and tested on the third

Outside of the data produced, mobile transect design is critically important, and there are many considerations. Firstly, the safety of the citizen-scientist is the most important thing. The routes should be safe and not past an individual's skill level. For example, the cycling transect in this study traversed a small section of forest path, which may be more suitable for walking if the cyclist is not properly equipped. Also, most mobile transect UHI mapping studies will target the hottest days and also aim to sample the hottest places. Careful consideration for the safety of the citizen-scientists should be taken. People at increased risk for heat-related illness could still engage in citizen science by undertaking the driving transect from a vehicle with air conditioning. The walker and cyclist should both have plenty of water to ensure they do not overheat during the IOP. Often these transects are specifically used in areas with limited access (CNF, for example) where people are active. A citizen-scientist should understand the risks of being active in the heat.

In order to address these temporal limitations, there are plans for an extended mobile mapping campaign in Carrboro, Chapel Hill, and neighboring South Durham during the

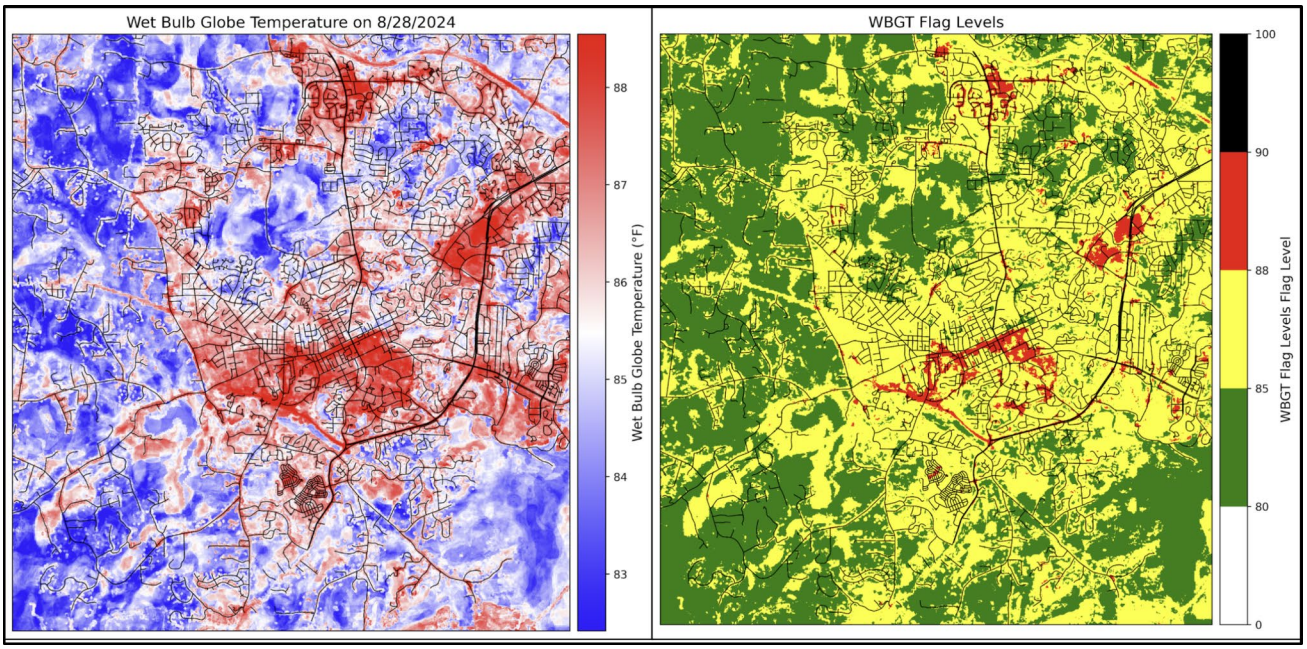


Fig. 12 The WBGT UHI in Carrboro and Chapel Hill, North Carolina, on 8 August 2024, as modeled and calculated by the formulas provided by Liljegren et al. 2008. The image on the right displays the WBGT warning flag level (as defined by the North Carolina High School Athletic Association). These were produced from the data of all of the transects

2025 heat season. This campaign is scheduled to collect data two to three days per week under a variety of conditions. The goal is to answer questions that our brief snapshots of data can't answer, such as how the UHI and WBGT UHI develop over time and how different kinds of weather impact the UHI intensity and spatial distribution. It can be hypothesized that due to varying sun angles and the "memory" of urban surfaces, the spatial distribution and differences between the urban and rural could change over the course of the summer. This has not yet been evaluated with mobile transects.

Citizen science-mapped mobile transects also provide the opportunity for community members to be engaged and invested in climate work in their own community. This mapping campaign has raised awareness for the Carrboro and Chapel Hill urban heat island and has been warmly received by the public. Public engagement with this work has allowed for collective learning about hot spots related to land characteristics and urban form. The goal is for people to make informed decisions about outdoor activities and for local entities to take steps to mitigate heat risk in our area.

Conclusions

We found significant variations in WBGT across the relatively small study area that can be attributed to differences in local land characteristics and their impacts on air temperature, humidity, solar radiation (via shading), and wind speed (via surface roughness). These variations crossed standard thresholds set by various organizations, including the North Carolina High School Athletic Association. We found that more developed areas contributed significantly to higher air temperatures but also formed an urban dry island, offsetting some heat stress. Areas with higher surface roughness, such as Carolina North Forest, had lower wind speeds. Overall, the more developed areas had higher WBGT, but it could be hypothesized that antecedent conditions and variable ambient conditions would impact this, and further investigation is needed.

This work outlines the instrumentation and procedures necessary to engage citizens and create a WBGT model for an extreme heat day(s). In the future, we would like to add temporal resolution by extending the study period to an entire heat season or perhaps even leveraging the data collected in different locations via Heat Watch to gather more information about how variable weather patterns and the diurnal cycle impact heat stress in different study areas. With data from enough heat season days and a range of air mass types, perhaps a predictive model could be developed to enhance heat stress forecasts across the study area and beyond.

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Authors' contributions Andrew Robinson (1): research conception, research design, instrumentation design, primary data collection, data management, data analysis, writing, and editing. Chris Fuhrmann (2):

project oversight, research conception, primary data collection, and editing. Charles Konrad (3): project oversight, research conception, and editing. Olivia Davis (4): primary data collection, and editing. Eric Kirk (4): primary data collection, and editing. David Parr (5): data analysis advising, and editing.

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Data availability All data used to produce this manuscript is available upon request from the corresponding author, Andrew Robinson (arobi120@unc.edu).

Code availability All code used to produce this manuscript was written in Python and will be made available upon request from the corresponding author, Andrew Robinson (arobi120@unc.edu).

Declarations

Ethics This study did not involve human participants, human data, or animals, and therefore did not require approval from an institutional review board or ethics committee. All data used in the study are publicly available or derived from observational and modeling techniques that do not involve any individual-level identifiers or interactions. The research complies with the journal's ethical standards.

Consent to Participate Not applicable. This study did not involve human subjects, and all fieldwork was undertaken by the authors, and therefore no consent to participate was required.

Consent for Publication Not applicable. This study does not contain any individual person's data in any form (including individual details, images, or videos), and therefore consent for publication is not required.

Competing interest This statement is to certify there are no competing or conflicting interests by any of the contributing authors in this work.

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