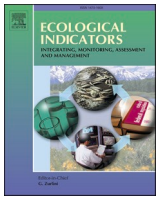
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Estimating the urban heat island effect with lichens and bryophytes: a citizen science protocol

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ABSTRACT

The urban heat island effect (UHI), whereby urban areas are warmer than the surrounding rural areas, has become an increasing threat to human health and affects biodiversity. Counteracting this public health concern requires large-scale monitoring of urban heat. One cost-effective way to obtain this data is by using bioindicators, such as lichens and bryophytes. They are well-known bioindicators readily available in the urban environment, and have proven to respond to the UHI. Gathering large amounts of data in a short time span may prove difficult for many institutes or municipalities, but can be resolved by incorporating citizen science. However, lichen and bryophyte species identification with no prior experience may prove problematic for citizen scientists. Therefore, we developed a citizen science protocol that requires scoring the presence of easily recognisable morphotypes of epiphytic lichens and bryophytes, instead of individual species. Data was collected in urban environments in the Netherlands by participants at three knowledge levels: an expert in lichenology and bryology, university biology students, and citizen scientists. Using the expert dataset, we trained a baseline multiple linear model (LM) and a random forest (RF) model, which predicted local UHI with low root-mean-square errors (RMSE = 0.29 °C and 0.20 °C, respectively). Prediction accuracy declined with decreasing participants' expertise. We conclude that a simplified protocol using morphotypes of lichens and bryophytes can be an effective, low-cost way of monitoring the UHI. However, some training or experience is required to obtain sufficiently accurate observations.

1. Introduction

The human population living in cities is expected to increase from 30 to 68% of the world's population between 1950 and 2050 (United Nations 2025). Urban expansion leads to a stronger urban heat island effect (UHI; Bassett et al., 2020; Mohajerani et al., 2017). The UHI is considered the temperature difference between the warmer urbanized areas and the cooler, more rural areas (Ulpiani, 2021). This temperature difference is caused by a combination of factors, including indirect solar heating and anthropogenic heat (Rizwan et al., 2008). These factors ultimately result in higher air and surface temperatures, lower air humidity, faster drainage of precipitation, and altered airflow patterns (Kuttler, 2008; Oke, 1995). Climate change will further accelerate these temperature differences, putting cities at the forefront of global warming (Grimm et al., 2008; Kalnay and Cai, 2003). Urban environments experience a more extreme climate regime than rural areas during heat waves, due to locally hindered evaporation and decreased wind speed (Bassett et al., 2020; Li and Bou-Zeid, 2013). The UHI has led to an increase in human health issues, especially for lower-income groups (Patz et al., 2005; Hsu et al., 2021). Advice to mitigate the UHI in growing cities has shifted from low-density urban development to promoting densification, whereby Nature-Based Solutions are incorporated on a local scale (such as green spaces) in urban planning to counteract the UHI (Steeneveld et al., 2011; Vuckovic et al., 2019; Doyle et al., 2026).

To guide UHI mitigation actions and improve urban planning in this regard, monitoring is essential, which requires a vast amount of city-

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wide data. One cost-efficient way to assess and map the UHI is by employing bioindicators (Parmar et al., 2016), especially when combined with citizen science (Thornhill et al., 2016). Their use provides many benefits, as they are able to identify environmental impacts, are often easily inventoried, and could be an economically viable alternative to traditional systems like sensors (Parmar et al., 2016). Two groups of organisms often used as bioindicators are lichens and bryophytes (Delves et al., 2023; Oishi and Hiura, 2017; Thakur et al., 2024). These are widespread groups which are relatively easy to detect, allowing for simplified procedures (Frati and Brunialti, 2023) and have a long-standing history as bioindicators starting in the 19th century (Nylander, 1866). Furthermore, because they absorb nutrients and pollutants directly through their surface, they are vulnerable to a range of ecological changes (Degtjarenko et al., 2016; Printarakul and Meeinkuirt, 2022; Thakur et al., 2024). Particularly, epiphytic lichens and bryophytes have proven to be effective indicators for air quality (e.g., nitrogen and sulphur pollution; Delves et al., 2023; Llop et al., 2012; Wiseman and Wadleigh, 2002; Edmondson et al., 2010; Oishi and Hiura, 2017), and can be used for climatic factors as well (Aptroot et al., 2021).

Munzi et al. (2014) were the first to report that lichens can be useful indicators for the UHI, as long as pollution levels are below the critical levels for plants established for Europe (APIS, 2013). Żołnierz et al. (2022) found that some epiphytic bryophyte species are positively correlated with the UHI, whereas other species are negatively correlated. Claerhout et al. (2025) investigated the specific thallus mass (STM) of urban lichens and found that STM increased significantly along a gradient of UHI, indicating that the UHI affects not only the species community but also the physiology of individual lichens. Our follow-up study (Claerhout et al., 2026) revealed that both lichens and bryophytes can be used as bioindicators for distinct levels of the UHI. Some acrocarpous bryophyte species were found to be correlated with a high UHI, grey foliose lichens with intermediate to a high UHI, green foliose as well as fruticose lichens with a low to intermediate UHI, and crustose and leprose lichens with a very low UHI. These findings are concordant with the correlation of functional traits with urbanization levels reported by Koch et al. (2019).

Citizen science, including volunteers with or without a scientific background, has the benefit of gaining many data points in a short period of time (Dickinson et al., 2010; Lepczyk et al., 2020) as well as raising awareness and educating citizens (Bonney et al., 2009; Dickinson et al., 2012; McKinley et al., 2017). The latter is especially important for lichens and bryophytes, which are generally little known to the general public, but receive growing interest (Munzi and Giovanetti, 2021). The success of citizen science is illustrated by the increasing amount of citizen science studies in the last few decades (Pocock et al., 2017; Finger et al., 2023). Citizen science can be incredibly useful if performed correctly (Thompson et al., 2023) and has already been applied to epiphytic lichens and bryophytes (Counoy et al., 2023; Derrien et al., 2020; Gilbert, 1974; Lõhmus et al., 2023; Martellos et al., 2024; Mira et al., 2024; Pescott et al., 2015; Tregidgo et al., 2013). Despite the value of citizen science in lichen and bryophyte research, there is a trade-off between data quantity and quality (Isaac et al., 2014; Tregidgo et al., 2013). Lichens and bryophytes are often cryptic, overlooked organisms where species identification comes with a steep learning curve (McMullin and Allen, 2022). This is especially true for untrained citizens. Therefore, the depth of data submitted by the citizen scientists should be calibrated to their knowledge level to maximize data quality and quantity (Lepczyk et al., 2020).

While previous research has revealed that individual lichen and bryophyte species shift along microclimatic and urban heat gradients (Munzi et al., 2014; Żołnierz et al., 2022; Claerhout et al., 2026), employing this knowledge for wide-scale monitoring faces several operational problems. On the one hand, traditional bioindication demands high-level taxonomic expertise, which cannot be provided to the extent and at the spatial resolution required for effective urban green infrastructure management. On the other hand, existing broad-scale citizen science initiatives sometimes run into the problem of lower data quality when dealing with obscure taxa (Tregidgo et al., 2013). As climate change is ramping up, there is an urgency to design simplified, non-expert protocols capable of incorporating citizen science to obtain climate-mapping tools which result in small-grain data but can be employed widespread.

To address these gaps, this study introduces a simplified citizen science protocol that clusters individual lichen and bryophyte species into five easily recognisable, morphological categories. We evaluate how participant knowledge levels impact model accuracy by addressing two guiding research questions:

1. To what extent can a simplified morphotype protocol accurately estimate UHI variations within an urban context?
2. How do differences in participant knowledge levels (expert vs. biology students vs. citizen scientists) affect data quality and model performance?

This work represents the first study globally to utilize citizen science data from lichens and bryophytes to model and map the UHI. By decoupling bioindication from species-level identification, this protocol provides municipalities and urban professionals a framework for cost-efficient urban heat assessment.

2. Materials and methods

2.1. Classifying indicator species into morphotypes

The citizen science protocol uses groups of lichen and bryophyte indicator species with similar and easily recognisable characteristics, such as growth form and colour in dry conditions (morphotypes). Indicator species for the UHI were obtained from Claerhout et al. (2026), based on an indicator species analysis (Dufrêne and Legendre, 1997) of lichen and bryophyte diversity on *Tilia* trees along a UHI gradient in Amsterdam, Leiden, and Rotterdam. The UHI gradient consisted of five UHI zones with different average temperature differences between city and rural environments in summer (dark blue (DB): 0–0.5 °C; blue (B): 0.5–1.0 °C; yellow (Y): 1.0–1.5 °C; orange (O): 1.5–2.0 °C; red (R): > 2.0 °C; for details see Claerhout et al., 2026). The indicator species analysis resulted in a list of 22 suitable indicators: 15 lichens, 5 bryophytes (all belonging to the morphological group of acrocarpous mosses), one alga (*Apatococcus ammoniophilus* Søchting, Friedl & Moestrup), and the total vegetation coverage (the latter as an indicator for both high and low UHI; Claerhout et al., 2026). Here, we grouped the lichen and bryophyte indicators into five morphotypes (hereafter referred to as types 1 to 5), based on their UHI sensitivity and morphological characteristics. A list of all indicators including a short description of their morphology, the type and UHI zone to which they belong, and their Ellenberg light and temperature indicator value (Sparrius et al., 2015) can be found in Appendix A. Type 1 consists of species belonging only to the UHI zones "DB" and/or "B" (very low to low UHI) and is characterized by crustose lichens with a photobiont belonging to the genus *Trentepohlia* or leprose lichen species from the genus *Lepraria.* Type 2 comprises species belonging to the UHI zones "B" and "Y" (low to intermediate UHI; excluding *Hypotrachyna revoluta* (Flörke) Hale and *Parmelia sulcata* Taylor) and is characterized by fruticose lichens like *Evernia prunastri* (L.) Ach. and the green shield lichens *Flavoparmelia caperata* (L.) Hale and *F. soredians* (Nyl.) Hale. Type 3 contains species from UHI zones "Y" and "O" (intermediate to high UHI), which corresponds to grey or blue shield lichens such as *Physconia grisea* (Lam.) Poelt, *Punctelia. jeckeri* (Roum.) Kalb, and *P. subrudecta* (Nyl.) Krøg, while also including *Hypotrachyna revoluta* and *Parmelia sulcata* from UHI zones "B" and "Y". These species were included into type 3, despite being also indicative for zone "B", as they share the characteristic morphology. Type 4 contains only species from UHI zones "O" and "R" (high to very high UHI). This type is characterized by

acrocarpous mosses such as *Dicranoweisia cirrata* (Hedw.) Lindb., *Grimmia pulvinata* (Hedw.) Sm., *Orthotrichum diaphanum* Schrad. ex Brid., and *Syntrichia papillosa* (Wilson) Jur. The fifth morphotype is not indicative of the UHI at all. This type contains species that are indicators of nitrogen pollution (Sparrius, 2007), including all yellow and fine grey lichens like *Candelaria concolor* (Dicks.) Arnold, *Candelariella* spp., *Xanthoria parietina* (L.) Beltr. and *Physcia* spp. Type 5 was included to provide a type for every lichen that may be found by citizen scientists. A search card (in Dutch) was made, including a selection of pictures of indicators for the UHI (Appendix A), and distributed to participants. By clustering different UHI indicators into morphotypes, we expect that these types exhibit a similar distribution as the individual indicators.

2.2. Citizen science protocol

Participants were instructed to assess bark coverage of the five morphotypes on roadside trees in the urban environment using the instructions on the project website (https://blwg.nl/stad). To start, participants had to look for groups or rows of five trees, which had to be free-standing or clustered within a 100 m area adjacent to roads in urban areas. The trees could not be slanting more than 10° and should have a diameter of at least 21 cm (corresponding to the width of the search card). Trees without any conspicuous epiphytic lichen or bryophyte growth at eye level (1.5–2 m above ground) and/or trees whose bark is overgrown by other plants, such as *Hedera helix* L., ought to be discarded. Furthermore, coniferous trees and trees from the genera *Aesculus* and *Platanus* ought to be excluded from sampling, because of their peeling bark. Participants were instructed to make observations during dry weather, since the lichen thallus colour might change when wet, potentially leading to misidentification of types 2 and 3. For each of the five trees, participants were instructed to estimate the cover of each morphotype on the bark at eye-level on the side of the tree with the highest coverage. If there is an equal amount of coverage on different sides of the tree, the side with the most different types should be chosen. Coverage estimations consisted of three possibilities: “high cover”, “little cover”, or “no cover”. “High cover” was selected for the dominant vegetation type. If there were multiple dominant types, more than one could be assigned to “high cover”. “Little cover” was chosen if the type was present, but not as the most dominant on the assessed tree. “No cover” was chosen if the vegetation type was not found on the assessed tree. The data and the corresponding location were submitted by the participants on the project website. When submitting the results, citizen scientists could use the GPS on their phone to immediately identify the correct location. All the data was anonymized.

2.3. Knowledge levels and locations

To assess the impact of different prior knowledge of lichens and bryophytes on the accuracy of the UHI evaluation, the study was conducted with participants from three different knowledge levels. The first knowledge level was citizen scientists (CS), who did not require prior knowledge of the studied groups of epiphytes in order to participate. To engage citizen scientists, we announced the project on a popular nature news website in February 2023. Instructions and a visual search card were sent by mail to about 500 respondents, of whom 250 attended a webinar or watched an instruction video. Furthermore, workshops and field excursions were organized in five Dutch cities, which typically consisted of a 15-min presentation and a 15-min explanation of the protocol in the field. CS who could not attend these activities could make use of an explanatory video on the project website. The second knowledge level was Dutch university students (US) who have been given an introduction to the protocol and to the morphotypes. This group can be subdivided into MSc students (MS) and BSc students (BS). MS consisted of two biology students at Leiden University, who received an extensive introduction to the biology of lichens and bryophytes, the morphotypes, and the collection protocol over multiple days. They collected data in March and April 2025 in The Hague (52°04′47.94“ N; 4°18’40.85” E) and Zoetermeer (52°03′27.00“ N; 4°29’35.02” E). BS consisted of six BSc students from the Erasmus University College Rotterdam, who had a short (one afternoon) introduction to the morphotypes and protocol. They collected data between April and June 2024 in Rotterdam (51°55′35.4612” N; 4°27′44.8416″ E). The third knowledge level was an expert (EX) in lichenology and bryology (Tim Claerhout, first author of this paper). We collected expert data in February and March 2025 in Leiden (52°09′29.99” N; 4°29′35.02″ E). The locations of the observations can be found in Fig. 1.

2.4. Modelling and statistical analysis

Field records were first pre-processed using QGIS v.3.44.3 and R v.4.5.0 (QGIS Development Team 2025; R Core Team, 2025). Observations that did not adhere to the protocol were removed manually. The remaining observations were linked to local values of the UHI, derived from Remme et al. (2017). Furthermore, the coverage of each morphotype per tree was given a numerical value. “No cover” was set to zero, “little cover” to one, and “high cover” to two. These values were summed for all five trees, leading to a score between zero and ten for each morphotype per observation.

To get insights into the abundance of each morphotype, a bar graph with the prevalence of little coverage and high coverage was created for the expert dataset. To confirm the expected distributions of each morphotype, a line graph with a generalized additive model (GAM) for the coverage of each type along the UHI was made. These insights led us to merge types 2 and 3 into one explanatory variable because of their similar distribution across the UHI range, even though they were separate in Claerhout et al. (2026). The data of these two types were merged by their highest numerical value found in either type on a single tree, since this method is most similar to observations made for the other types using the sampling protocol. Observations of this new type with high coverage were found in intermediate UHI areas, whereas observations with low coverage could be found in both very high and very low UHI areas, leading to overdispersion. Therefore, a sensitivity analysis was executed on the expert dataset (EX) to find the optimal cut-off value in the following set of values: three, four, and five. The cut-off point of four was chosen as this was the optimal value (i.e., lowest RMSE (root-mean-square error) and MAE (mean actual error); see further) to remove the observed overdispersion. As a result, all values within the new merged group below four were set to zero.

To estimate the accuracy of the protocol, the following steps were taken. To account for spatial autocorrelation, multiple observations within 50 m, were *ad random* reduced to one using the package “geosphere” (Hijmans et al., 2024). Because a random set of data points was selected, there might be a bias due to specific points being selected. Therefore, 1000 datasets were created from the full dataset, each with different randomly selected data points when closer than 50 m apart. To eliminate errors in analysis from randomly selected observations, all steps were repeated with all datasets. The expert (EX) dataset was split into a training subset containing 70% of the observations and a test subset containing the remaining 30% of the observations. The training dataset was used to make a multiple linear model (LM) and a random forest model (RF) using the “DHARMa” (used for checking residuals and assumptions), and “randomForest” package, respectively (Liaw and Wiener, 2014; Hartig, 2022), to estimate the UHI. The test dataset was used to calculate the accuracy of the model (see further).

Estimated UHI values (averaged values after spatial autocorrelation (n = 1000); see higher) were calculated for each knowledge level separately using both the LM and the RF model. The estimated UHI values for the expert were calculated using the test subset of the EX dataset. Regression plots were created for the full dataset, the CS, US, BS, MS, and EX datasets of the LM. Note that, although valuable, a mixed-effects model whereby the observer effect is included could not be applied to the CS dataset as the presence of anonymous data would lead

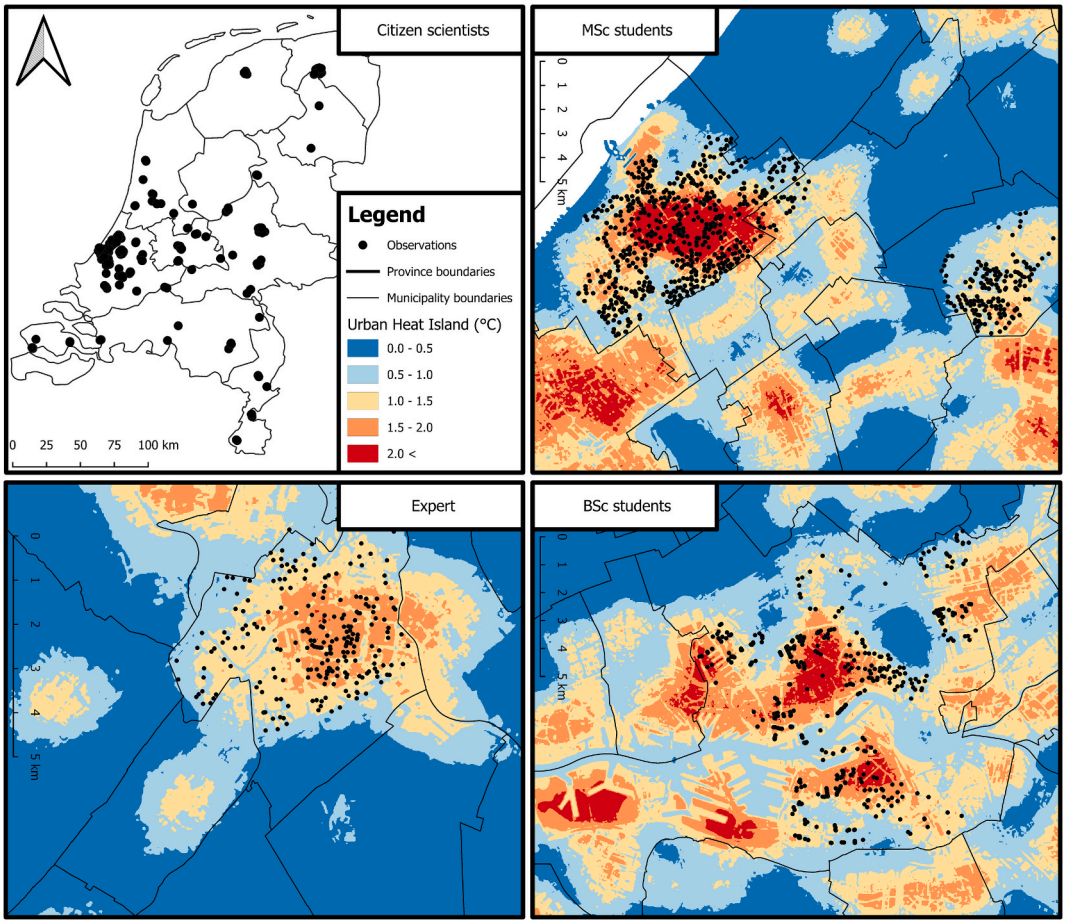


Fig. 1. Spatial distribution of the (valid) observations by the different knowledge levels. **Top left**. Data collected by citizen scientists (CS) in The Netherlands (CS). **Top right**. Data collected by MSc students from Leiden University (MS) in The Hague (left) and Zoetermeer (right). **Bottom left**. Data collected by the expert (EX) in Leiden. **Bottom right**. Data collected by BSc students from Erasmus University College (BS) in Rotterdam.

to potentially erroneous results. For both the LM and RF models, the accuracy of the data collected by each group was assessed by comparing the average root-mean-square error (RMSE) and the mean actual error (MAE) value (including standard deviations; Hodson, 2022) after accounting for spatial autocorrelation. Additionally, the slope of the regression line of the estimated UHI vs. real UHI was used as an extra accuracy assessor for the LM datasets, where a slope closer to one was deemed better. To illustrate the practical use of this data, a heat map of Leiden was created using an exponential decay function of the estimated UHI values from the expert dataset (EX) of the LM and RF models and their original UHI values from Remme et al. (2017). The function is as follows where "r" (the distance to the observation) could reach a maximum of 1000 and "L" (the e-folding length, i.e., the distance at which the temperature drops to approximately 37% ($\frac{1}{e}$) of its maximum value) was set to 100.

$$\Delta T(r) = \Delta T0 \cdot \exp\left(\frac{-r}{L}\right)$$

These values were chosen as they best represent the situation of a mid-sized city where the UHI drops quickly due to the high water surface area and low building density.

Second, to get insights into the manner of data collection by different knowledge levels, we ran the following analyses. By creating a bar graph of the abundance of every morphotype for the entire, the CS, the US, and the EX dataset, we were able to discern differences in type selection between knowledge levels. Furthermore, bar graphs showing the distribution of the total sum of all values across every sampled tree per observation and all morphotypes for every knowledge level (all, CS, US, BS, MS and EX), illustrated the differences in consistency of type coverage selection ("little cover" vs "high cover"). To confirm visual trends, pairwise differences using the mean and standard deviation were calculated.

3. Results

3.1. Survey overview

In total, 2483 observations were recorded by participants of all knowledge levels, of which 65 observations were removed because they did not follow to the protocol (49) or were not situated in the Netherlands (16 in Belgium). The raw, anonymized data can be found in Appendix B. In the cleaned dataset ($n = 2418$), 352 observations were uploaded by the citizen scientists, 251 by the expert, 1351 by the MSc students, and 464 by the BSc students. The citizen science data were collected by at least 132 volunteers (excluding 18 anonymous observations), of which 58% only uploaded one observation and a further 33% uploaded between two and five observations. Ten participants (9%) uploaded six or more observations. After spatial autocorrelation, the number of observations was reduced to 1463 (314 by CS, 232 by EX, 565 by MS, and 351 by BS), which formed the final dataset for subsequent analyses.

3.2. Exploration and validation of the protocol and the models

To explore the abundance of each morphotype across all observations, a bar graph with the percentage of each coverage type for each

morphotype was created (Fig. 2). Type 1 was the morphotype that was found the least, having the least data in both categories, "little cover" and "high cover" (Fig. 2). Type 5 was the most abundant type and the only one where "high cover" was selected more than "little cover".

The coverage of each morphotype along the UHI gradient was analysed based on the expert (EX) dataset, which was the only dataset where the protocol was followed perfectly. The morphotypes showed different distributions along a UHI gradient in Leiden according to their expected functioning as indicators. Type 1 showed a negative trend with UHI, whereas type 4 showed a positive one. Both type 2 and type 3 follow a unimodal trend with an optimum of UHI around 1.2 °C. Type 5 showed no correlation with UHI and was more common than all other types across all values of UHI within this range (Fig. 3).

Using the training subset of the EX dataset, a multiple linear model was made to estimate the UHI based on observations from our protocol. The results are shown in Table 1. All morphotypes have a significant influence when estimating UHI values, except for morphotype 5. The UHI estimations using this linear model and the random forest model (RF) can be found in Appendix B. Using these UHI estimations from both models, heat maps of Leiden were created (Fig. 4) bearing the purpose of a conceptual visualization.

3.3. Influence of knowledge levels

Using the models (LM and RF) that were trained on the EX dataset, estimated UHI values were also calculated using the dataset for each knowledge level (Appendix B). This allowed us to compare how the different knowledge levels influenced the quality of the UHI estimation. There is a difference in prediction error between the expert and the other knowledge levels (Table 2). The UHI can be estimated with an RMSE of 0.29 and 0.20 (corresponding to 0.29 °C and 0.20 °C) when employing the multiple linear model and random forest model, respectively. The RF model was closer to the real UHI value in 73% of the observations. When comparing the RMSE, MAE, and slope values between knowledge levels, the error in the EX dataset is lower, and the slope is higher than both the CS and student (US, MS & BS) datasets (Table 2). The RF model gives a model accuracy that is equal to or marginally better than the LM (Table 2). When plotting the estimated values of UHI against the actual values of UHI, there is a clear positive relationship for the data collected by the expert (EX) in both the LM and RF (slope of 0.42 and 0.47, respectively), whereas the positive relationship is less prominent for the data collected by the participants of the other knowledge levels (Fig. 5). Note that a perfect model would have slopes of "1", so even though the expert dataset yields the best results, they are not perfect. One reason for this is because higher UHI values are estimated more accurately by the multiple linear model based on expert data than lower UHI values, as the trendline is closer to the actual value (Fig. 5). Although RMSE and MAE are marginally lower for BS compared to MS, the slope is considerably higher for MS.

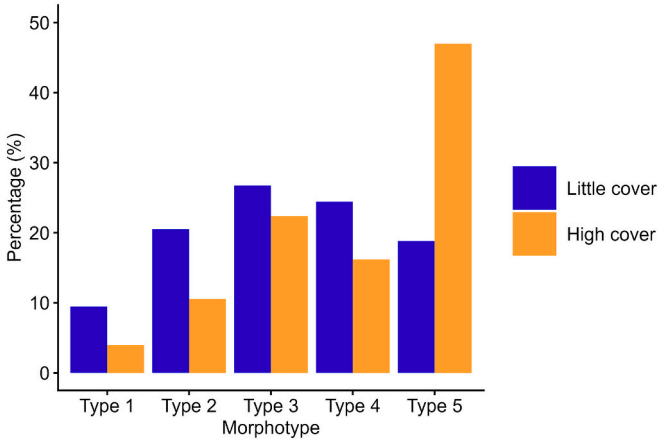


Fig. 2. Percentage of coverage estimations for all morphotypes and categories ("little cover" and "high cover") for all sampled trees (five per observation) across all knowledge levels (n_{Tree} = 12,090). Each bar represents the number of times "little cover", or "high cover" was selected.

To infer possible reasons for the differences in UHI estimation between the knowledge levels, bar graphs of the average value of each morphotype within each observation were made to see if the knowledge levels differed in morphotype identification (Fig. 6) or coverage selection (Fig. 7). In Fig. 6, we see that observations collected by CS contained type 1 and type 4 more frequently, relative to the expert and the students. Furthermore, in Fig. 7, CS and US (including MS and BS) had a wider spread compared to EX. The total sum ranged between 5 and 30, whereas expert and students had most scores between 15 and 30, and 10 and 25, respectively (the max value is 50: five morphotypes × five trees per observation × the max coverage value (= 2); Fig. 7). The significant pairwise differences between the different knowledge groups can be found in Appendix C. The R-script used for the statistical analyses is available in Appendix D.

4. Discussion

4.1. Theoretical and practical implications

This project describes a new cost-efficient way of mapping the urban heat island effect (UHI), by engaging citizen scientists to collect data using a protocol where lichen and bryophyte bioindicators of the UHI are clustered into five easily recognisable morphotypes. The advantages as well as the limitations of this method have become apparent during our research. There is a clear correlation between the occurrence of the lichen and bryophyte morphotypes and the strength of the UHI (Fig. 3, Table 1), proving their potential for biomonitoring the UHI in the Netherlands. The alignment of type 1 with low-UHI areas, and types 2 and 3 with intermediate UHI, is in line with Koch et al. (2019), who found that crustose lichens were negatively correlated, and foliose lichens positively correlated, with the UHI. Additionally, the strong positive correlation between type 4 (acrocarpous bryophytes) and high-UHI areas is in line with results from Claerhout et al. (2026) and Żołnierz et al. (2022), because of their tolerance to high temperatures and dryness (Green et al., 2011; Stark, 2017; Oliver et al., 2020). Indeed, type 4 indicators have morphological adaptations to withstand increased temperatures and desiccation, such as leaves containing hair-points and/or leaves that are able to curl up when dry (Tao and Zhang, 2012; Zheng et al., 2011).

Practically, the model based on the expert dataset achieved a predictive fidelity for estimating the UHI with a 0.29 °C prediction error using the multiple linear model (LM) and a 0.20 °C error for the random forest (RF) model (Table 2). This practical use of the expert dataset has been demonstrated in Fig. 4 for the municipality of Leiden. It shows that the protocol to estimate the UHI can result in a small-grained, informative end-product which can be used in policy and urban green management across the Netherlands or countries with a similar climate (e.g., Doyle et al., 2026).

4.2. Limitations and influence of knowledge level

The abovementioned prediction error based on the expert model may partly be the result of limited data. The error is mainly apparent in the lower UHI values and may be explained by the lower number of observations in areas with a UHI less than one degree Celsius (Fig. 5). Therefore, including more observations in lower-UHI areas to recalibrate the models could improve the accuracy of the estimated UHI values.

Two limitations related to the methodology stem from the inclusion of specific indicator species into the morphotypes and the coverage estimations. Firstly, there are look-alike species that resemble the UHI

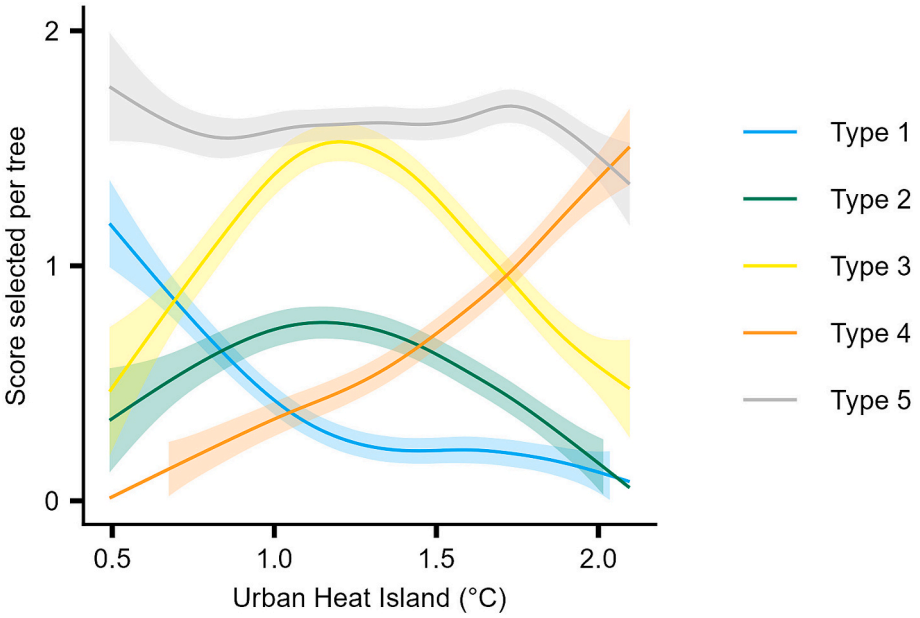


Fig. 3. Distribution of coverage estimation for each morphotype across an urban heat island effect (UHI) gradient (Remme et al., 2017) on single trees within an observation. Distributions are displayed using a generalized additive model (GAM) distribution based on the expert dataset (n_{Tree} = 1165).

Table 1
Multiple linear regression summary of a linear model estimating UHI based on morphotypes of lichens and bryophytes. AIC_{model} = 102.4. ***: *p*-value <0.05.

	Estimate	SE	*p*-value
(intercept)	1.665	0.106	***
Type 1	−0.065	0.011	***
Type 2 & 3	−0.033	0.007	***
Type 4	0.041	0.008	***
Type 5	−0.016	0.008	N·S.

indicator species, but are not indicative of the UHI themselves. One example is the fruticose *Ramalina* species that are not indicative for any UHI zone, but resemble the type 2 indicator species *Evernia prunastri* and may, therefore, also be counted as type 2 due to their similar external characteristics. Secondly, coverage estimations ("high cover", "little cover", "no cover") were not defined based on a linear scale, but on the presence of a dominant type and potential other less abundant types. Therefore, it is likely that some incongruences regarding coverage selection among participants arose. Moreover, it is important to note that, in relation to the previous limitation (indicator species inclusion in morphotypes), type 1 species (crustose lichens) are inherently smaller and are therefore hardly present with a high coverage (Fig. 2). This may be an additional factor in explaining the underestimation of low UHI values (Fig. 5).

Finally, different knowledge levels of participants limit the accuracy of the UHI estimations (Fig. 5, Table 2). These differences may be explained by prior knowledge and the consistency in applying the sampling protocol. Increasing prior knowledge level through extensive training may increase the data quality and consistency (Aivelo, 2024), but can also increase the threshold for citizen scientists to participate (Toffolo et al., 2026), thereby lowering the desired data quantity. Moreover, other studies report that citizen science data is not necessarily substandard and that every project should be judged individually, depending on the project design and application (Kosmala et al., 2016; Toffolo et al., 2026).

Firstly, the knowledge difference would explain why the estimations calculated using the data from the MSc students, who had a more extensive introduction, had a stronger correlation (i.e., higher slope) with the actual UHI values than the BSc students, who had a significantly shorter introduction to the context and protocol of the citizen science project (Fig. 5E vs. 5F). Moreover, citizen scientists selected type 4 more often than the participants from the other knowledge levels (Fig. 6). This could suggest that the distinction between acrocarpous and pervasive, non-indicative pleurocarpous bryophytes may be difficult for citizen scientists. These pleurocarpous bryophytes, especially *Hypnum* spp., can be dominant in nitrogen-enriched areas (van Herk, 2019). Although the differences between these two groups of bryophytes were explained on the project website, they were not explained on the instruction card, nor were the non-indicative pleurocarpous bryophytes given their own morphotype as we did with non-indicative lichens in type 5. This may have led to an overestimation of type 4 by the citizen scientists. Secondly, the consistency in sampling protocol may be an additional factor in explaining the gap in prediction errors between the expert and other knowledge levels. Since the expert data was collected by a single participant, there is no bias induced by multiple people collecting the same type of data (adherence bias). This adherence bias is much greater in the CS data as this dataset was assembled by at least 132 participants. The wider spread in the observations between the citizen scientists and the expert illustrates this (Fig. 7). Furthermore, this adherence bias may also have led to an overestimation of the total selected morphotypes (Fig. 6).

Data quality differences between the data collected by the citizen scientists and the expert were also found in previous citizen science research (Counoy et al., 2023), although the protocol used in our study was simpler (i.e., it was not required to identify individual indicator species). Another study with a simplified protocol had similar results when assessing nitrogen pollution and could not obtain sufficiently accurate results using citizen science data on a smaller scale. Nevertheless, large-scale differences were picked up by the protocol (Tregidgo et al., 2013).

4.3. *Participant motivation and feedback*

The collected data from the participants of the citizen scientist group can provide information about their motivation. The outreach to the general public was successful, with at least 132 participants willing to contribute to the project (the majority did not provide a unique identifier such as their name). Moreover, citizens were willing to be educated about the research behind the project and lichens and bryophytes in

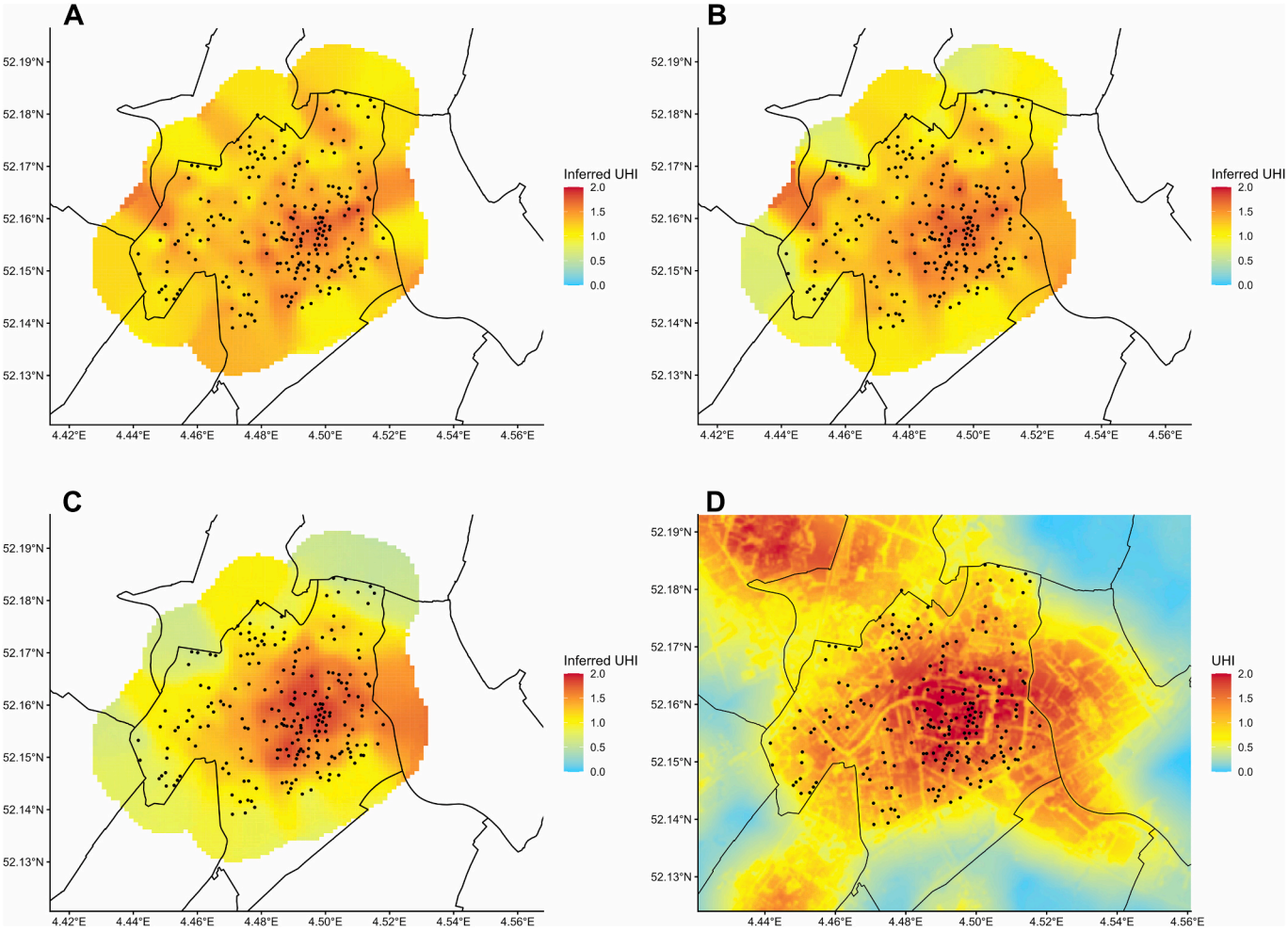


Fig. 4. Heat maps of Leiden (NL) using an exponential decay interpolation method of the estimated urban heat island effect (UHI) values (averaged values after spatial autocorrelation ($n = 1000$)) from the expert dataset (EX; black points). Black lines indicate the municipality borders with Leiden in the centre. **A.** Heat map based on the interpolated estimated UHI values of the linear model. **B.** Heat map based on the interpolated estimated UHI values of the random forest model. **C.** Heat map based on the interpolated original UHI values from Remme et al. (2017). **D.** Heat map of the raw (i.e., not interpolated) UHI values as depicted in Remme et al. (2017). Areas further than 1000 m from observations were not depicted on the map.

Table 2
Average root-mean-square error (**RMSE**), mean actual error (**MAE**) and regression slope (**Slope**) and their respective standard deviations (**SD**) for the estimated urban heat island effect (UHI) values derived from the linear model and the random forest model across participants from different knowledge levels ($n = 1000$). The knowledge levels (**KL**) represented are the full dataset (ALL), the citizen scientists (CS), MSc students from Leiden University (MS), BSc students from Erasmus University (BS), all university students (US) and the expert in the field of lichenology and bryology (EX).

Linear model							Random forest model					
KL	**RMSE**	**SD**	**MAE**	**SD**	**Slope**	**SD**	**RMSE**	**SD**	**MAE**	**SD**	**Slope**	**SD**
ALL	0.47	<0.01	0.37	<0.01	0.11	0.02	0.46	<0.01	0.36	<0.01	0.13	0.01
CS	0.52	<0.01	0.42	<0.01	0.08	0.01	0.55	<0.01	0.44	<0.01	0.05	0.02
US	0.48	<0.01	0.39	<0.01	0.10	0.02	0.46	<0.01	0.37	<0.01	0.09	0.01
BS	0.47	<0.01	0.38	<0.01	0.04	0.02	0.44	<0.01	0.35	<0.01	0.039	0.03
MS	0.48	<0.01	0.39	<0.01	0.11	0.01	0.48	<0.01	0.40	<0.01	0.11	0.01
EX	0.29	0.02	0.23	0.01	0.42	<0.01	0.20	0.01	0.15	0.01	0.47	<0.01

general. This could be explained by the overall increase in interest from people in lichens (Munzi and Giovanetti, 2021). Indeed, 25 out of 29 participants who filled in a questionnaire, which was sent around between October and December 2024 to infer participants' experiences with the method, rated the overall project with a 4/5 or 5/5. Furthermore, only one participant rated the overall aim of the research as "bad" from the options "bad", "average", "good" and "excellent". However, it is important to note that the response rate of 22% (29 out of 132 participants) is quite low and should not be overgeneralised. Despite the overall positive response of the participants who filled in the questionnaire, 62% of the citizen scientists collected only a single observation, and 35% collected two to five observations, meaning that only a few citizen scientists collected a higher amount of data. This is in line with Lõhmus et al. (2023), who found that less than 5% of participants collected most of the lichen data. In our project, some participants indicated they found collecting data too difficult and overwhelming because they had to distinguish between too many different types of organisms, which they had little previous knowledge of (pers. obs.).

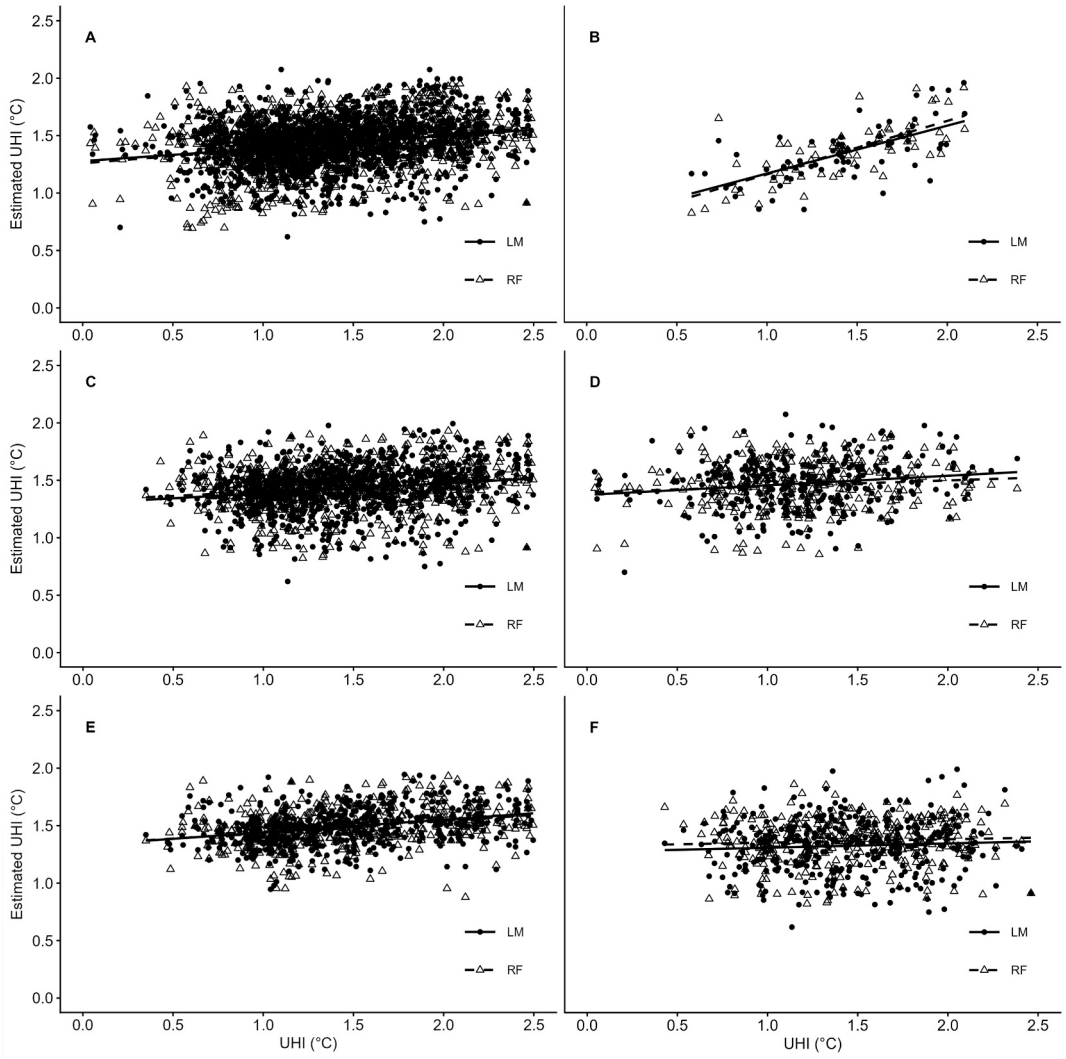


Fig. 5. Regression plots between the actual urban heat island effect (UHI) values derived from Remme et al. (2017) and the estimated UHI values (averaged values after spatial autocorrelation ($n = 1000$)) derived from the multiple linear model (LM) and random forest model (RF). Regressions were made for the entire dataset (**A**; $n = 1463$), the expert (EX) dataset (**B**; $n = 70$), the student (US) dataset (**C**; $n = 916$), the citizen scientist (CS) dataset (**D**; $n = 314$), the MSc student (MS) dataset (**E**; $n = 565$) and the BSc student (BS) dataset (**F**; $n = 351$).

They indicated that the difference between types 2 and 3 was quite difficult because of their similar shape and comparable colour, especially in humid weather. The few citizen scientists who collected a higher amount of data may have been motivated by their experience of contributing to science (Day et al., 2022). Indeed, we noticed a higher intrinsic motivation from participants who were already part of nature associations (pers. obs.). Motivational data from a citizen science project studying pavement plants found that people who contribute data are more keen to assist research than people who follow the project through social media ("followers"). Nonetheless, these followers had an equal or more positive attitude towards urban flora compared to people who did contribute data (Beets et al., 2025). Both groups can play a pivotal role in outreach and education of citizen science projects.

4.4. Protocol modifications and future directions

Despite the overall success of the citizen scientist protocol, certain adjustments are necessary to increase the data accuracy for future iterations. The collection process would have to be improved by making instructions clearer and by simplifying the process:

1. Merge types 2 and 3 into one category in the collection protocol.

Both contain species with similar shape and thallus colour that can be difficult to distinguish for people who have no prior experience in lichen identification, and both indicate intermediate UHI levels (Fig. 3).

2. Give pleurocarpous bryophytes their own morphotype and explain the differences between acrocarpous and pleurocarpous species on the search card, not only in the instructions on the website.

This ought to increase the quality of the observations and remove the difference in the selection of type 4 between citizen scientists and other knowledge groups (Fig. 7).

3. Remove the possibility of submitting observations with any number of trees other than five, and to submit trees without any of the types selected.
4. Change the cover estimations from a relative scale to an absolute scale with predefined cut-offs.

These should streamline the data collection and would lead to higher data quality. As a possible side effect, it could increase the motivation of participants to collect more data.

We propose that future research focuses on the applicability of the

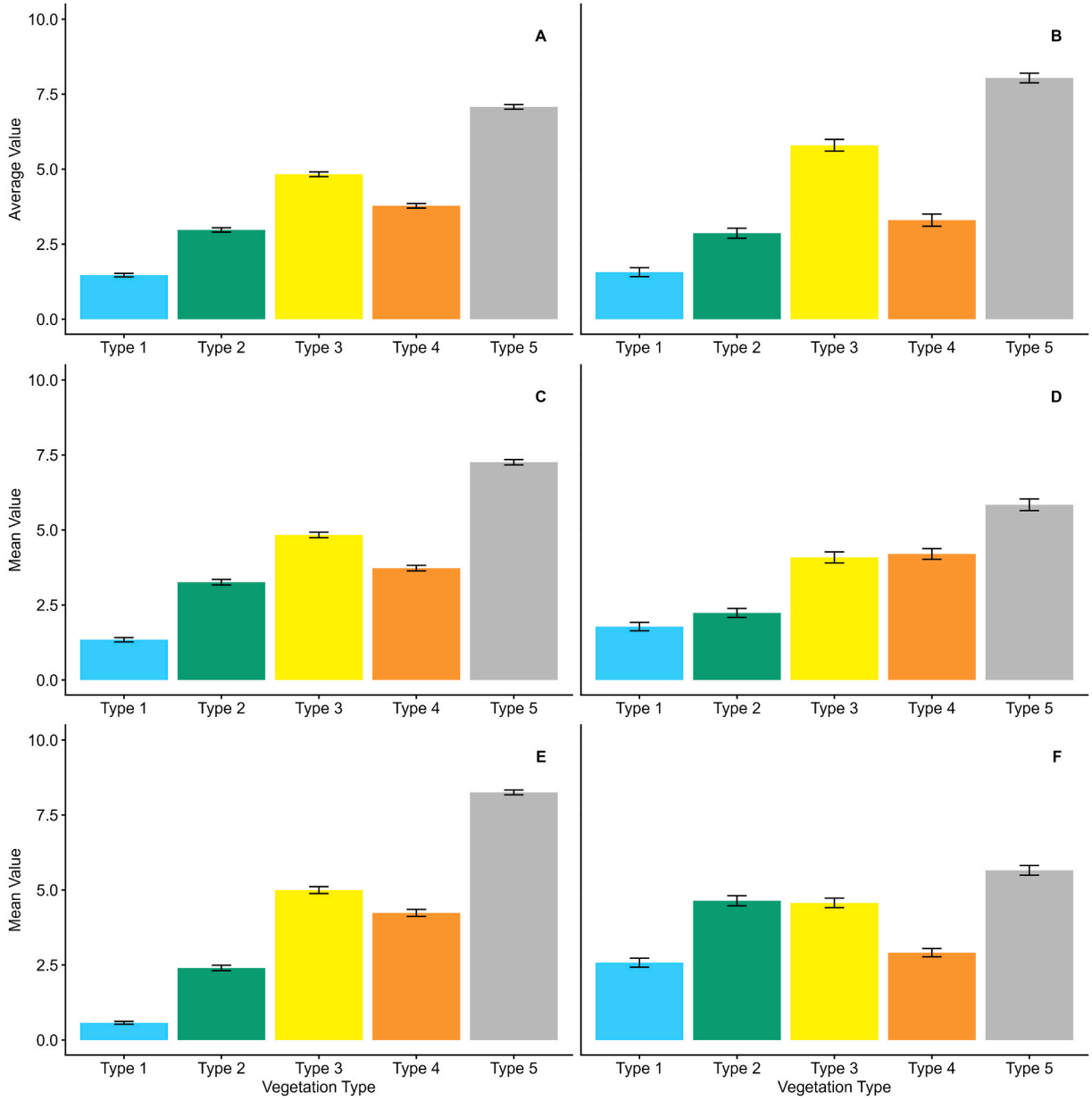


Fig. 6. Bar graphs for every knowledge level showing the sum of cover estimations (where "little cover" equals 1 and "high cover" equals 2) for every morphotype across all trees in every observation. Bar graphs were made for the entire dataset (**A**; $n = 1463$), the expert (EX) dataset (**B**; $n = 232$), the university student (US) dataset (**C**; $n = 916$), the citizen scientist (CS) dataset (**D**; $n = 314$), the MSc student (MS) dataset (**E**; $n = 565$) and the BSc student (BS) dataset (**F**; $n = 351$).

model in other climates where (most) UHI indicators are present (e.g., continental climate in Europe).

5. Conclusion

The present study assessed the possibility of monitoring the urban heat island effect (UHI) using clusters of easily recognisable epiphytic lichens and bryophytes (morphotypes) as an alternative to biomonitoring at the species level. We found that the morphotypes employed in this protocol are indicative of distinct levels of the UHI and can therefore be utilized effectively to create predictive models to estimate the UHI. Heat maps were created using the estimated UHI and proved informative, allowing different institutes, like municipalities and urban practitioners, to monitor the UHI using a cost-effective protocol. Morphotype data was collected by participants from three different knowledge levels (expert, students (BSc and MSc), and citizen scientists) to investigate the influence of prior knowledge on the data quality. We found that data could be collected more accurately by an expert in the research field than by the other knowledge levels. However, estimations made by MSc students were more accurate than those from BSc students who received a shorter introduction. Thus, a higher prior knowledge level does increase the data quality. Changes and additions to the protocol (instructions) are proposed to improve the data quality in future versions. Furthermore, we highlighted the strengths and pitfalls regarding the use of citizen science in biomonitoring using obscure species groups.

CRediT authorship contribution statement

Tim Claerhout: Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jeroen Barendse:** Writing – review & editing, Writing – original draft, Visualization, Validation, Investigation, Formal analysis, Data curation.

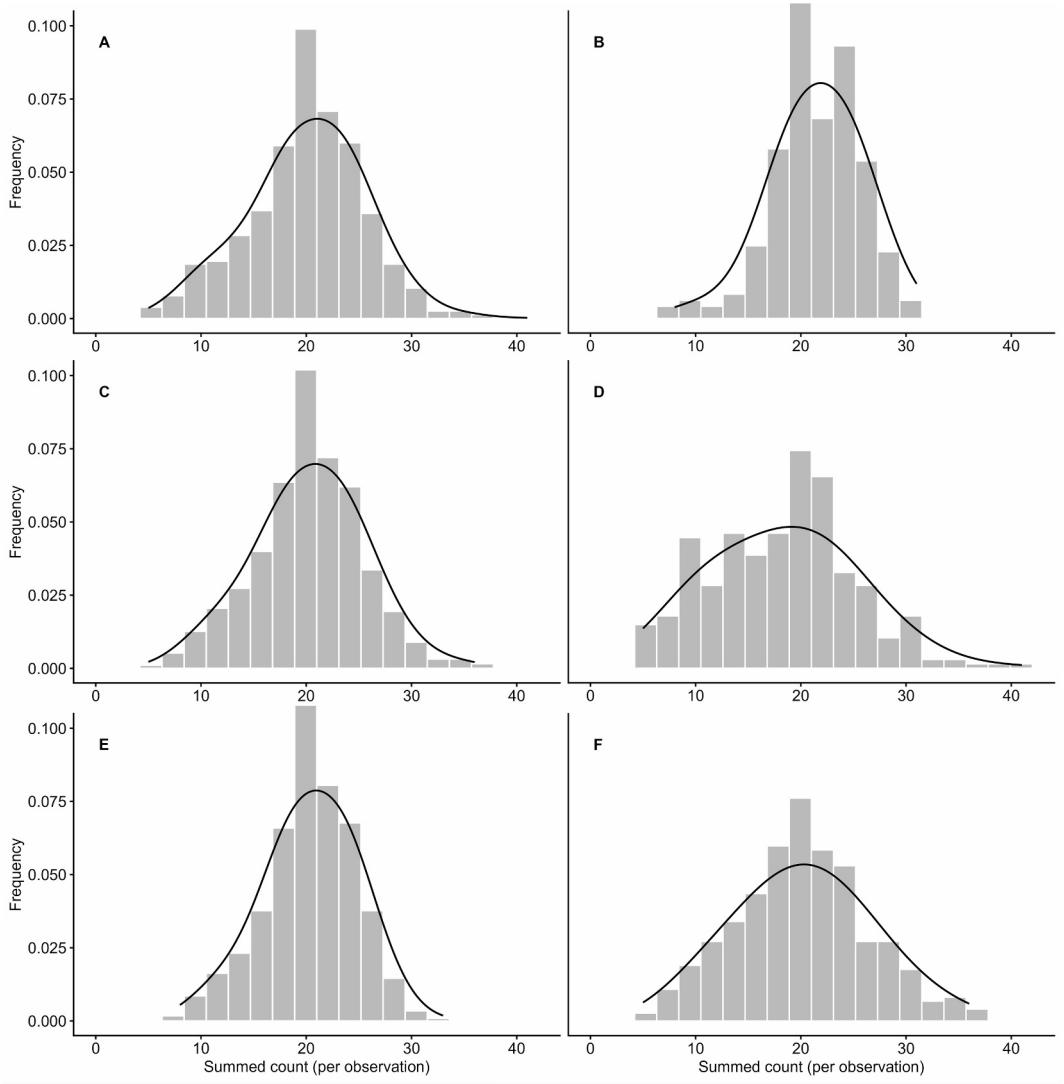


Fig. 7. Bar graphs indicating the frequency of the total sum of the coverage estimations (where "little cover" equals 1 and "high cover" equals 2) for all observations. Bar graphs were made for the entire dataset (**A**; $n = 1463$), the expert (EX) dataset (**B**; $n = 232$), the university student (US) dataset (**C**; $n = 916$), the citizen scientist (CS) dataset (**D**; $n = 314$), the MSc student (MS) dataset (**E**; $n = 565$) and the BSc student (BS) dataset (**F**; $n = 351$).

Michael Stech: Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Paul J.A. Keßler:** Writing – review & editing, Supervision, Funding acquisition. **Laurens B. Sparrius:** Writing – review & editing, Visualization, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

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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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Appendices

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2026.115766.

Data availability

The authors confirm that the data supporting the findings of this study are available within the article and its appendices.

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