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A School-Based Citizen Science Network as a Distributed Observation Infrastructure for Urban Biodiversity in the Athens Metropolitan Area

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Abstract

Fine-scale urban biodiversity data remain uneven across metropolitan regions, limiting cities' ability to monitor ecological change and support climate-resilient planning. This study evaluates whether a formal school network can operate as a distributed observation infrastructure for urban biodiversity, using the ARSINOE Educational Community in the Athens Metropolitan Area, Greece, implemented through the MINKA platform. We define observation infrastructure operationally as an institutionally coordinated network of spatially distributed school nodes that generate georeferenced biodiversity observations through a shared digital platform and community-based validation workflow. At the locked snapshot, the initiative contained 9,784 georeferenced observations, of which 6,363 reached Research Grade. Inferential analyses used a core subset of 9,425 observations from January–May 2024 and January–May 2025. Participation was highly uneven: the five largest contributors produced 70.2% of core observations and the ten largest 85.8%. Recording extended beyond formal school hours; among records with a parsable hour, 61.9% were outside weekday 08:00–15:00, and 32.6% of all core observations were made at weekends. Research Grade attainment was associated mainly with taxonomic group, with a smaller association with submission mode and no clear association with recording time. The Research Grade subset was plant-dominated but multi-taxon. School-based citizen science can therefore complement urban biodiversity monitoring by producing spatially distributed, community-validated occurrence records, provided that unequal effort, taxon-specific validation differences and opportunistic sampling are explicitly accounted for.

Keywords: citizen science; urban biodiversity; observation infrastructure; school-based monitoring; community validation; Athens Metropolitan Area

1. Introduction

Urban biodiversity supports ecosystem services that contribute to human well-being and climate resilience, including microclimate regulation, runoff mitigation, recreation, and other cultural and regulating benefits (Langemeyer & Gómez-Baggethun, 2018; Aronson et al., 2017). At the same time, biodiversity is declining globally under the combined pressures of land-use change, climate change, pollution, and invasive alien species (IPBES, 2019). Cities are therefore increasingly recognized as critical settings in which biodiversity must be monitored, managed, and integrated into planning and resilience strategies (Aronson et al., 2017). Recent syntheses further emphasize that urban biodiversity research increasingly requires integrative, cross-taxon, and planning-relevant approaches that connect ecological evidence with urban decision-making (Rega-Brodsky et al., 2022).

Monitoring urban biodiversity remains challenging at the spatial and temporal resolution needed to capture the complexity of heterogeneous metropolitan landscapes (Norton et al., 2016). Species-occurrence datasets are also often affected by spatial, temporal, and taxonomic biases that can compromise ecological interpretation if they are not carefully addressed (Boakes et al., 2010; Troudet et al., 2017; Díaz-Calafat et al., 2024). Recent work in Athens has shown the value of combining citizen-science and remote-sensing data to assess biodiversity patterns at metropolitan scale, highlighting both the need for fine-scale local evidence and the opportunity to strengthen urban biodiversity assessment in the region (Ziliaskopoulos & Laspidou, 2024).

Citizen science (CS) offers a practical way to address these challenges by engaging distributed observers and expanding data collection across large areas, including places that are difficult for professional researchers to access on a regular basis (Dickinson et al., 2010). Its value also extends beyond research. At the policy level, CS already contributes, or has the potential to contribute, to around

one-third of the UN Sustainable Development Goal indicators, with particularly strong relevance to SDG 15 (Life on Land) and SDG 11 (Sustainable Cities and Communities) (Fraisl et al., 2020). In urban settings, citizen science can help build, refine, and complement biodiversity datasets for monitoring and conservation, while opportunistic observations can reveal multi-taxon patterns across urbanisation gradients (Voigt-Heucke et al., 2023; Callaghan et al., 2020).

School-based CS is especially promising because standardised protocols can be deployed across multiple schools and students can generate ecologically useful records when tasks are matched to their skills and supported by training and verification procedures (Saunders et al., 2018; Schuttler et al., 2019; Castagneyrol et al., 2020). However, previous school-based studies have more often focused on particular taxa, specific ecological tasks, data quality, or learning outcomes than on formal school systems as metropolitan-scale biodiversity observation infrastructures in their own right (Saunders et al., 2018; Schuttler et al., 2019; Castagneyrol et al., 2020).

This study addresses that gap through the ARSINOE Educational Community, a school-based citizen science initiative developed within ARSINOE Case Study 1, "Greening the Athens metropolitan area," and implemented through the MINKA citizen observatory (ARSINOE Project, 2022; Liñán & Piera, 2024). Using a locked dashboard snapshot and an observation-level export, we evaluate whether a formal network of schools can function as a distributed observation infrastructure for urban biodiversity in the Athens Metropolitan Area. Specifically, we assess (i) network scale and participation, (ii) the temporal and validation patterns of submitted observations, and (iii) the taxonomic breadth and diversity output captured by the Research Grade subset. Given the unequal contribution levels typical of distributed citizen-science networks, the analysis emphasises descriptive taxonomic-output summaries together with sampling-completeness diagnostics, rather than treating raw school-level counts as directly comparable estimates of local biodiversity.

In this article, the term "distributed observation infrastructure" is used operationally rather than to imply a fully standardised ecological monitoring scheme. It refers to an institutionally coordinated network of spatially distributed school nodes that repeatedly generate georeferenced biodiversity observations through a shared digital platform and community-based validation workflow. We therefore evaluate the ARSINOE Educational Community as a complementary observation infrastructure: one capable of expanding urban biodiversity records across everyday metropolitan environments, but still constrained by opportunistic sampling, uneven participation, and taxon-specific validation differences.

2. Methods

2.1 Study area and project design

This study was conducted in the Athens Metropolitan Area (Attica, Greece), a densely urbanised region where fragmented green spaces, extensive impervious surfaces, and strong anthropogenic pressures create persistent challenges for biodiversity monitoring and climate-resilient planning (ARSINOE Project, 2022; Ziliaskopoulos & Laspidou, 2024). The initiative was developed within ARSINOE Case Study 1, "Greening the Athens metropolitan area", which links urban greening, biodiversity protection, climate adaptation, and public participation within a broader metropolitan resilience framework (ARSINOE Project, 2022).

Within this context, the ARSINOE Educational Community was organised as a distributed school-based observation network involving 55 schools listed in the project dashboard across Attica, including 49 secondary schools and 6 primary schools. The network was developed according to the quintuple helix model of innovation (Carayannis et al., 2012), adapted to citizen science projects (Liñan et al. 2022), involving different communities as indicated in Figure 1. Each school contributed through a dedicated sub-project nested within a central umbrella project on the MINKA platform, allowing observations to

be organised and examined at both school and network level. MINKA is a participatory citizen observatory developed within ARSINOE that supports georeferenced observations, project-based data organisation, and community validation through web and mobile interfaces (Liñán & Piera, 2024).



Figure 1. *Example* of the interactions between the communities involved in the ARSINOE Educational Community, following the quintuple helix model. Teachers and students, as members of the participatory community, provide field observations; research institutions support the MINKA platform and data-quality control; the Centre of Education for the Environment and Sustainability, acting as mobiliser, coordinates school participation; and the "Antonis Tritsis" Metropolitan Park supports activities within the park.

For the purposes of this study, analyses focused on two winter-spring monitoring windows, from January to May 2024 and from January to May 2025. These periods coincided with key spring phenological stages and favoured the observation of flowering plants and associated fauna. The campaign followed an opportunistic but structured design, with students and teachers recording observations in schoolyards, nearby streets, neighbourhood green pockets, urban parks, and peri-urban sites through repeated participation across school-based observation nodes.

2.2 Participant engagement and data collection protocol

Before each monitoring period, participating teachers were introduced to the aims of the initiative and received practical guidance on field observation and on the use of the MINKA platform. Students were then invited to record biodiversity observations during organised school activities, such as schoolyard explorations, neighbourhood walks, and field excursions, and, where appropriate, during informal observations outside regular school hours.

The recording protocol was designed to maximise participation while ensuring that each observation included the minimum metadata required for subsequent validation and quantitative analysis. Participants were asked to upload one or more photographs for each observation together with the observation date, time, and geographic location. Observations were submitted through the MINKA web interface or mobile application, which support georeferenced reporting and project-based organisation of contributions (Liñán & Piera, 2024).

Each participating school contributed through its own sub-project within the umbrella project "ARSINOE Educational Community", making it possible to examine contributions at both school and network level. The protocol encouraged participants to document a broad range of visible taxa encountered in everyday urban and peri-urban environments rather than focusing on a single taxonomic group. Because the initiative was conceived as a distributed urban observation effort rather than a standardised ecological survey, sampling intensity was not fixed across schools. This design favoured broad participation and spatial coverage, while also requiring later consideration of uneven contribution levels across school nodes. Participating students contributed observations through teacher-led activities. Registration to the MINKA platform and submission of observations were managed by the responsible teachers for each school, who uploaded the records and associated metadata through the relevant school sub-project. Where appropriate, observations made outside regular school hours were also included through the same supervised, teacher-mediated workflow.

2.3 Data acquisition and validation on MINKA

All records considered in this study were submitted through the MINKA platform within the umbrella project "ARSINOE Educational Community" and, at the platform level, through corresponding school sub-projects. The study drew on two complementary data products derived from the same locked project record. First, a locked project dashboard snapshot was used to report the overall scale and validation status of the initiative. Second, an observation-level export was used for record-level temporal and validation analyses. The dashboard snapshot and observation-level export were frozen on 20 December 2025. All observation counts, taxonomic assignments, validation statuses, and Research Grade classifications reported in this manuscript refer to this frozen version of the project record; subsequent changes on the MINKA platform are not reflected in the analyses.

At the time of analysis, the public dashboard snapshot included 9,784 observations, 1,505 taxa, 54 observers, 52 identifiers, and 16,143 identifications, of which 6,363 observations (65.03%) had reached Research Grade status. The downloaded observation-level export contained one additional record with obscured coordinates; this record was excluded before analysis so that all record-level analyses used public georeferenced records. The full analytical export therefore contained 9,784 observations. For each record, the analytical export included the observation identifier, observer/account identifier, observation date and time, taxonomic assignment, geographic coordinates, source/device indicator, and validation status, but it did not retain row-level school-node/sub-project membership. School-node contribution summaries and node-level diversity summaries were therefore derived separately from the dashboard sub-project/node audit, using the same locked snapshot and the same core spring and Research Grade filters where applicable. This separation avoids treating the observation-level export as the source of school-node membership for the GEE validation model.

The date and time fields refer to the recorded observation date and time rather than the upload timestamp. Because records were submitted through a teacher-mediated workflow, some observations may have been uploaded after they were made; temporal analyses therefore characterise the timing of recorded observations, not platform-use activity. In the full export, observations spanned 13 April 2022 to 30 October 2025. For inferential analyses, a core analytical subset was defined using the observation date field and restricted to records collected during January–May 2024 and January–May 2025 (n = 9,425 observations). MINKA uses a community-based validation workflow in which uploaded observations can receive taxonomic identifications from other users, and each observation is assigned a community taxon reflecting the consensus emerging from these identifications; observations that meet the platform's quality criteria can subsequently reach Research Grade status (Liñán & Piera, 2024).

2.4 Analytical framework and statistical analysis

The analytical workflow proceeded in five steps, combining descriptive network metrics, count-based regression, clustered logistic modelling, and effort-aware diversity estimation. The locked dashboard snapshot was used to report the scale and validation profile of the initiative, whereas inferential analyses were conducted on the core spring subset. Diversity analyses focused on the Research Grade component of this subset.

Step 1: Data preparation and variable construction.

From the observation-level export we derived observation date, calendar day, month, year, day of week, hour of day, observer/account identifier, source/device type, quality grade, and broad taxonomic group. School-node identifiers and node-level contribution totals were derived from the dashboard node audit and used for the school-level descriptive summaries. Off-hours recording was coded as 1 for any observation made outside weekday school hours (08:00–15:00) and 0 otherwise. Weekend days were coded as Saturday or Sunday. The taxonomic grouping used in the Research Grade model distinguished birds, plants, insects, reptiles, and other identified taxa. Observations remaining unresolved or identified only at high taxonomic rank were summarised descriptively.

Step 2: Descriptive network summaries and inequality assessment.

Participation across school nodes was summarised using observation totals, cumulative contribution shares, and the Gini coefficient (Gini, 1912). Cumulative contribution shares were calculated as the proportion of total observations contributed by the top k ranked school nodes. Inequality in node-level contribution was then summarised using the Gini coefficient:

$$G = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}|x_i - x_j|}{2n\sum_{i=1}^{n} x_i} \quad (1)$$

where x_i denotes the number of observations contributed by node i, and n is the number of active school nodes. Values closer to 1 indicate stronger concentration of observations among fewer nodes. Associations between node-level observation totals, the number of Research Grade taxa, and node-level Research Grade success were evaluated using Spearman's rank correlation coefficient (Spearman, 1904). These summaries underpin the concentration results reported in Figure 3.

Step 3: Temporal modelling of daily observation activity.

Daily observation counts were computed for all calendar days in the two monitoring windows, including days with zero observations. The resulting day-level dataset contained 303 days: 152 days from January–May 2024 and 151 days from January–May 2025. Let Y_d denote the number of observations recorded on day d. Daily counts were modelled using negative binomial regression with a log link because the counts were overdispersed relative to a Poisson model (Ver Hoef & Boveng, 2007). Overdispersion was assessed using the Pearson residual dispersion ratio from an initial Poisson model. The Poisson model showed strong overdispersion (dispersion ratio = 41.5), and the negative binomial model provided a substantially better fit than the corresponding Poisson model (AIC = 2,221 vs 7,749). The negative binomial specification was therefore retained for the day-level count model. The model assumes:

$$Y_d \sim NB(\mu_d, \kappa) \quad (2)$$

with variance:

$$Var(Y_d) = \mu_d + \frac{{\mu_d}^2}{\kappa} \quad (3)$$

where μ_d is the expected daily count and κ is the dispersion parameter. The log-linked linear predictor was specified as:

$$log(\mu_d) = \beta_0 + \beta_1 Weekend_d + \sum_m \beta_m Month_{md} + \beta_y Year2025_d \quad (4)$$

where $Weekend_d$ is a binary indicator for weekend days, $Month_{md}$ represents month-specific indicator variables with January as the reference level, and $Year2025_d$ indicates whether the record belonged to the 2025 monitoring window, with 2024 as the reference year. Model coefficients were exponentiated and reported as incidence-rate ratios:

$$IRR_k = e^{\beta_k} \quad (5)$$

with corresponding 95% confidence intervals. The same subset was also aggregated by day of week and hour of day to produce the temporal heatmap shown in Figure 4; regression outputs are reported in Table 2. This model was used to characterise temporal patterns in observation activity within the campaign. Because participation intensity and the number of active school nodes were not standardised across dates and years, model coefficients are interpreted as differences in campaign recording activity rather than as direct indicators of biodiversity dynamics or interannual ecological change.

Step 4: Modelling Research Grade attainment.

The probability of reaching Research Grade status was analysed using a marginal logistic model estimated with generalized estimating equations (GEE; Liang & Zeger, 1986). Starting from the core spring subset (n = 9,425), records were excluded sequentially if they were unresolved, identified only at coarse taxonomic rank, or lacked a parsable observation hour. The final GEE dataset contained 8,153 observations, representing 86.5% of the core spring subset, from 40 observer/account clusters, and was restricted to observations assigned to one of five identifiable broad taxonomic groups: birds, plants, insects, reptiles, and other identified taxa. The model therefore estimates Research Grade attainment conditional on an observation having an identifiable broad taxonomic group and sufficient timestamp information to classify school-hours/off-hours recording; it should not be interpreted as a model of validation outcome for all submitted records.

Observer/account ID was treated as the clustering variable to account for repeated submissions from the same account. We used an independence working correlation structure and robust sandwich standard errors. The model was specified as:

$$\log\left(\frac{p_{ij}}{1-p_{ij}}\right) = a_0 + a_1 Year2025_{ij} + a_2 OffHours_{ij} + a_3 Web_{ij} + \sum_g a_g TaxonGroup_{g,ij} \quad (6)$$

where $Year2025_{ij}$distinguishes 2025 from 2024, $OffHours_{ij}$identifies observations made outside weekday school hours (08:00–15:00), Web_{ij}denotes web-based submission, with app submission as

the reference category, and $TaxonGroup_{g,ij}$represents broad taxonomic-group indicators. The bird group was used as the taxonomic reference level because it showed the highest raw validation success. Model coefficients are reported as odds ratios with 95% confidence intervals. The corresponding model estimates and effect plot are shown in Table 3 and Figure 5, respectively.

The observer/account clustering was used because the observation-level export available for record-level validation modelling did not retain a row-level school-node identifier; school-node information was therefore used for descriptive node-level summaries rather than for the GEE validation model.

Step 5: Effort-aware diversity and sampling completeness.

Node-level diversity was calculated from the dashboard sub-project/node audit rather than from the observation-level export used for the GEE model. For each school node, Research Grade records in the core spring subset were grouped by community taxon ID before estimating Hill numbers and sample coverage (Hill, 1973; Chao & Jost, 2012; Chao et al., 2014). For $q \neq 1$, the general Hill-number expression is

$$ {}^{q}D = (\sum_{k=1}^{S} p_k^q)^{\frac{1}{1-q}} \tag{7} $$

where S is the number of taxa and p_k is the relative frequency of taxon k, defined as:

$$ p_k = \frac{n_k}{N} \tag{8} $$

with n_k denoting the number of Research Grade observations assigned to taxon k and $N = \sum_{k=1}^{S} n_k$. For q = 1, the Hill number is given by:

$$ {}^{1}D = \exp(-\sum_{k=1}^{S} p_k \ln p_k) \tag{9} $$

The three diversity orders used in this study therefore correspond to taxon richness ($q = 0$), the exponential of Shannon diversity ($q = 1$), and inverse Simpson diversity ($q = 2$). Sampling completeness was summarised using sample coverage. Following the abundance-based estimator used in the coverage-based rarefaction and extrapolation framework, sample coverage was estimated as:

$$ \hat{C} = 1 - \frac{f_1}{n} \times \frac{(n-1)f_1}{(n-1)f_1 + 2f_2} \tag{10} $$

where n is the total number of records in the sample, f_1 is the number of singletons, and f_2 is the number of doubletons (Chao & Jost, 2012; Chao et al., 2014). When $f_2 = 0$, the bias-corrected form implemented in the same framework was used. These metrics were interpreted as record-based taxonomic diversity and sampling completeness rather than as direct estimates of organism abundance.

Comparative discussion in the main text emphasised school nodes with at least 100 Research Grade observations. This threshold was used as a pragmatic screening rule to reduce instability in completeness estimates for very small samples and should not be interpreted as a formal inferential cutoff. Because estimated sample coverage differed substantially among school nodes, node-level Hill numbers are interpreted as descriptive measures of Research Grade taxonomic output rather than as direct between-school comparisons of local biodiversity. Because frequently recorded organisms on the platform may remain identified at different taxonomic ranks, all frequency-based summaries are reported as taxa rather than species. Diversity estimates and estimated coverage values are reported in Table 4 and summarised graphically in Figure 6.

2.5 Ethics, privacy and data availability

The initiative was implemented through participating schools as a teacher-coordinated educational citizen-science activity within the ARSINOE Educational Community and the MINKA platform. School participation and field activities were coordinated by responsible teachers in accordance with applicable school procedures. Students did not create or manage individual MINKA accounts for the purposes of this study; registration, upload, and management of observations were handled by responsible teachers through the relevant school sub-projects.

The study did not collect, analyse, or report personally identifiable information about students. The analytical dataset consisted of de-identified biodiversity occurrence records exported from MINKA, including observation metadata, taxonomic assignment, validation status, observation date and time, geographic coordinates, source/device type, and anonymous observer/account identifiers. Observer/account identifiers were used only as clustering variables in the Research Grade model and are not reported. No student names, student ages, student photographs, classroom-level identifiers, individual learning records, or other personal student data were analysed.

School-level results are reported at the school-node/sub-project level because these project nodes are publicly visible in the MINKA dashboard. No student-level or classroom-level information is reported. The underlying observations and associated media remain hosted on the MINKA platform under its applicable licensing and citation guidelines.

Formal ethics approval was not required because the study analysed de-identified project-level biodiversity records generated through a teacher-mediated educational citizen-science activity and did not involve the collection or analysis of personal student data.

The dashboard snapshot and observation-level export used in this study were frozen on 20 December 2025. All counts, validation statuses, taxonomic assignments, and analyses reported in this manuscript refer to this frozen version of the project record. Data fields that could identify individual students, teachers, or sensitive school-level information are not released. Public observations remain accessible through the MINKA platform subject to platform licensing and citation guidelines.

3. Results

3.1 Network scale, participation, and validation profile

The observation-level export corresponding to the locked project snapshot comprised 9,784 observations spanning 13 April 2022 to 30 October 2025. Of these, 6,363 observations (65.03%) had reached Research Grade status. The locked dashboard snapshot additionally reported 54 observers, 52 identifiers, and 1,505 taxa. For inferential analyses, we defined a core spring subset restricted to observations recorded during January–May 2024 and January–May 2025 (n = 9,425 observations),

including 6,161 Research Grade observations (65.37%). Because 359 observations fell outside this analytical window, all regression-based and effort-aware diversity analyses reported below refer to the core spring subset. A summary of these project-level metrics is provided in Table 1, and the quality-grade composition of the full locked snapshot and the core spring subset is shown in Figure 2

Table 1. *Project-level summary metrics for the locked dashboard snapshot and the core spring subset.*

Metric	Value
Schools listed in dashboard	55
School nodes with observations in locked dashboard/node audit	36
Schools with observations in core spring subset	31
Locked dashboard snapshot observations	9,784
Locked dashboard snapshot taxa	1,505
Observers / identifiers / identifications	54 / 52 / 16,143
Research Grade observations in locked snapshot	6,363 (65.03%)
Observation date span in full export	13 Apr 2022 - 30 Oct 2025
Core spring subset observations	9,425
Research Grade observations in core spring subset	6,161 (65.37%)

The comparison between the full locked snapshot and the core spring subset indicates that the project's validation profile remained highly consistent after restricting the data to the two focal monitoring windows. In both datasets, approximately two-thirds of observations had reached Research Grade status, while the remainder consisted mainly of records still awaiting identification, with only a small fraction classified as casual (Figure 2).

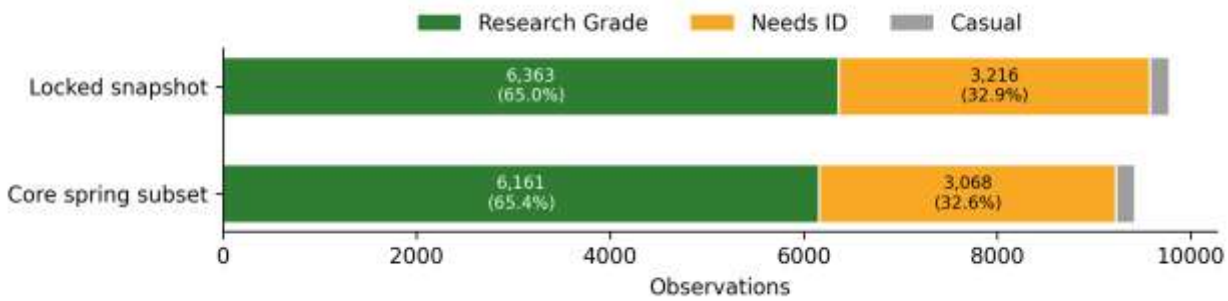


Figure 2. *Quality-grade composition of the locked project snapshot and the core spring subset.*

3.2 Uneven contribution across school nodes

Of the 55 schools listed in the dashboard, 36 contributed at least one observation to the full export and 31 contributed to the core spring subset. Participation was highly concentrated across school nodes: the five largest contributors accounted for 70.2% of all core observations, and the ten largest contributors accounted for 85.8% (Figure 3). The corresponding Gini coefficient was 0.696, indicating a strongly unequal distribution of contribution across the school network.

Based on the dashboard sub-project/node audit, filtered to the same locked snapshot and core spring subset, the largest contributing school nodes were the 3rd Gymnasium of Nea Filadelfeia (n = 2,088), the 2nd Gymnasium of Nea Filadelfeia (n = 1,717), the Music Gymnasium of Ilion (n = 1,064), the 11th Gymnasium of Ilion (n = 1,060), and the 1st General Lyceum of Acharnes (n = 690). The rank-order distribution of observations showed a steep decline after the first few nodes, followed by a long tail of lower-contributing schools (Figure 3). Observation totals were almost perfectly correlated with the number of Research Grade taxa recorded per node (Spearman's $\rho = 0.990$, $p < 0.001$), indicating that nodes with higher observation effort also generated substantially greater taxonomic output. By contrast, node-level observation totals were not associated with Research Grade success ($\rho = 0.045$, $p = 0.812$), suggesting that larger contributors did not systematically achieve higher validation rates.

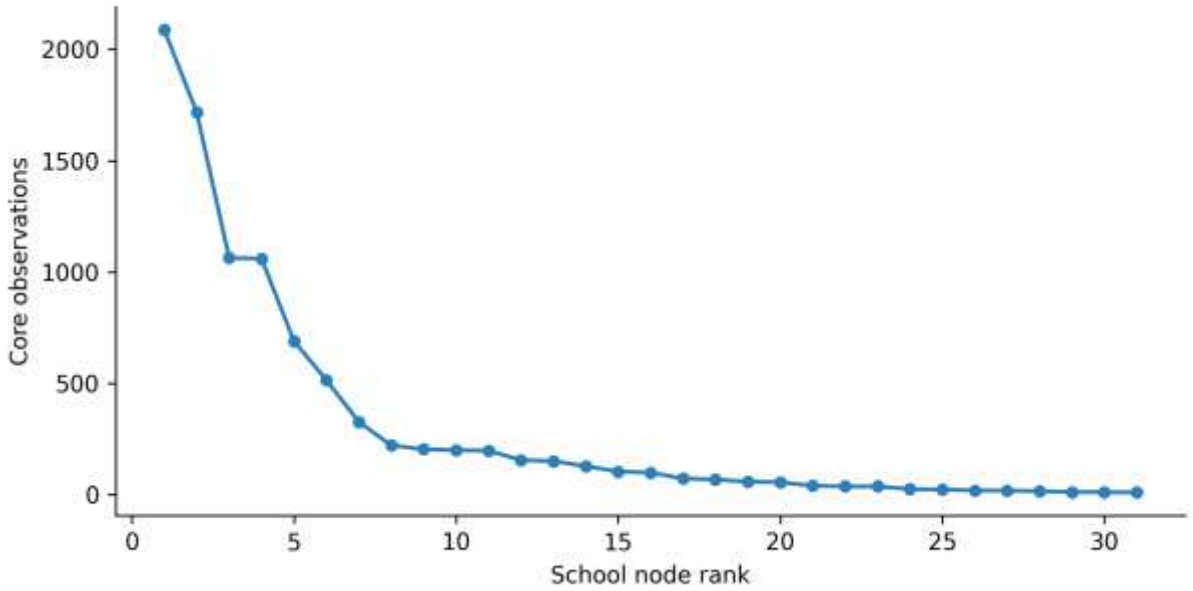


Figure 3. *Rank-order distribution of observations across school nodes in the core spring subset. The five largest school nodes accounted for 70.2% of all observations and the ten largest accounted for 85.8%.*

3.3 Temporal participation patterns

Observation activity in the core spring subset was concentrated around late morning but extended well beyond formal school hours. Among records with a parsable observation hour, only 38.1% of observations were recorded during weekday school hours (08:00–15:00), whereas 61.9% were recorded outside this interval. In addition, 32.6% of all core observations were made at weekends, with Sunday alone accounting for 19.8% of the total (Figure 4).

The most active recording hours were 10:00 (n = 938), 11:00 (n = 862), 12:00 (n = 780), 17:00 (n = 751), and 21:00 (n = 667), indicating a dual participation pattern combining organised school-based activity with substantial recording during afternoons and evenings. The day-by-hour heatmap further showed particularly strong peaks on Tuesday at 11:00 and Sunday at 10:00 and 17:00 (Figure 4). A negative binomial model of daily observation counts indicated higher weekend activity in magnitude, but this effect was not statistically significant at the 0.05 level after accounting for month and year (IRR = 1.40, 95% CI 0.98–2.00, $p = 0.068$; Table 2). Relative to January, daily counts were substantially higher in February, March, and April, whereas May did not differ significantly from January. Daily observation activity was markedly lower in 2025 than in 2024 (Table 2). Given the opportunistic design of the campaign and the lack of standardised sampling effort across school nodes and dates, this year

effect is interpreted as a difference in campaign recording activity between the two monitoring windows rather than as evidence of lower biodiversity in 2025.

Table 2. *Negative binomial regression of daily observation counts in the core spring subset. Reference categories were weekday, January, and 2024. IRR values > 1 indicate higher daily observation activity within the campaign relative to the reference category.*

Predictor	IRR	95% CI low	95% CI high	p
Weekend vs weekday	1.40	0.98	2.00	0.068
February vs January	4.38	2.61	7.36	<0.001
March vs January	5.59	3.37	9.29	<0.001
April vs January	5.16	3.09	8.60	<0.001
May vs January	1.05	0.63	1.77	0.845
2025 vs 2024	0.16	0.12	0.22	<0.001

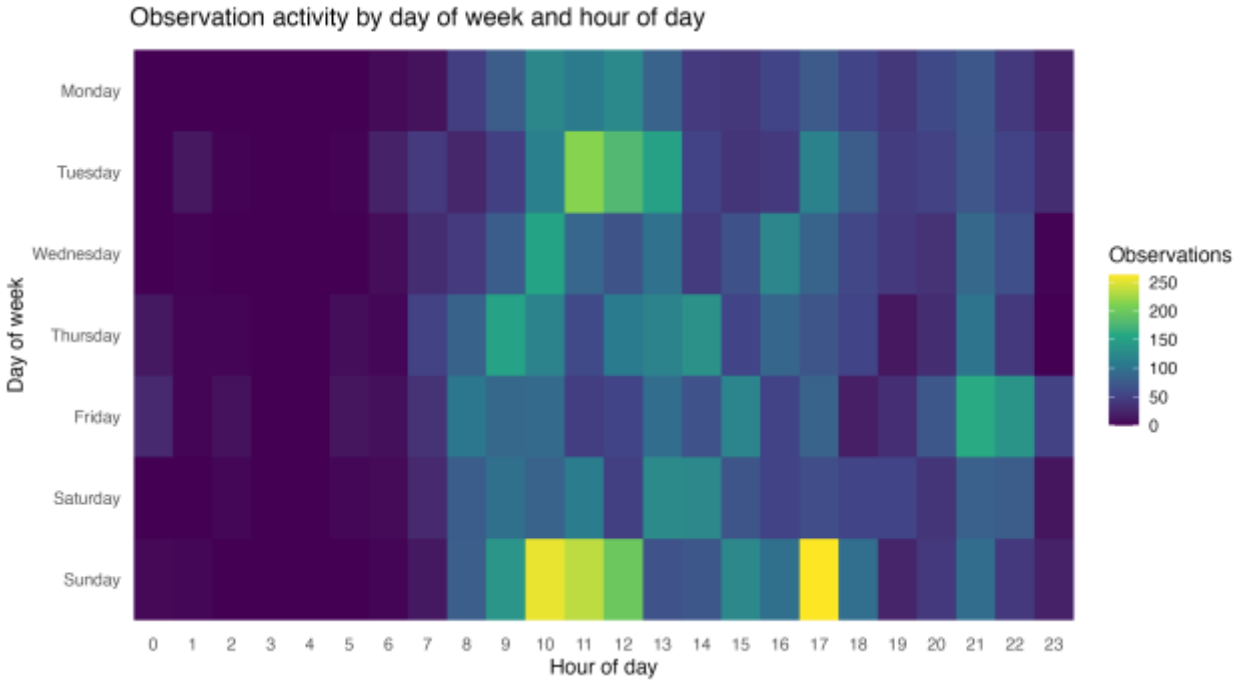


Figure 4. *Observation activity by day of week and hour of day in the core spring subset.*

3.4 Research Grade attainment

Of the 9,425 observations in the core spring subset, 8,153 observations were included in the GEE model of Research Grade attainment. Excluded records consisted of observations that were unresolved or identified only at coarse taxonomic rank, and records without a parsable observation hour. The model results therefore describe validation patterns among observations assigned to one of the five broad taxonomic groups used in the regression and with sufficient timestamp information to classify school-hours versus off-hours recording.

Table 3. *Observer/account-clustered GEE logistic model of Research Grade attainment in the core spring subset. Reference categories were birds, app submission, school-hours recording, and 2024. OR values > 1 indicate higher odds of reaching Research Grade status relative to the reference category.*

Predictor	OR	95% CI low	95% CI high	p
Year: 2025 vs 2024	1.15	0.918	1.447	0.221
Web vs app	0.83	0.696	0.984	0.032
Off-hours vs school-hours	1.02	0.872	1.193	0.804
Plants vs birds	0.13	0.086	0.199	<0.001
Insects vs birds	0.08	0.054	0.134	<0.001
Reptiles vs birds	0.29	0.136	0.601	<0.001
Other taxa vs birds	0.03	0.019	0.052	<0.001

Research Grade attainment was most strongly associated with taxonomic group rather than with recording time. In an observer/account-clustered GEE logistic model, year did not significantly affect the probability of reaching Research Grade status (OR = 1.15, 95% CI 0.918–1.447, p = 0.221), and off-hours recording was also not significant (OR = 1.02, 95% CI 0.872–1.193, p = 0.804). Web-based submission showed a small but statistically significant negative association relative to app submission (OR = 0.83, 95% CI 0.696–0.984, p = 0.032), although this effect was much weaker than the taxonomic-group differences.

Clear taxonomic differences emerged. Birds showed the highest raw validation success (95.7%), followed by reptiles (86.5%), plants (74.4%), insects (66.1%), and other identified taxa (41.0%). Relative to birds, the odds of reaching Research Grade were significantly lower for plants (OR = 0.13, 95% CI 0.086–0.199, $p < 0.001$), insects (OR = 0.08, 95% CI 0.054–0.134, $p < 0.001$), reptiles (OR = 0.29, 95% CI 0.136–0.601, $p < 0.001$), and other identified taxa (OR = 0.03, 95% CI 0.019–0.052, $p < 0.001$). Observations remaining unresolved or identified only at coarse taxonomic rank were excluded from the regression model and are described descriptively.

The corresponding effect plot indicates that the strongest association with Research Grade attainment was taxonomic group, consistent with differences in identifiability across recorded organisms (Figure 5).

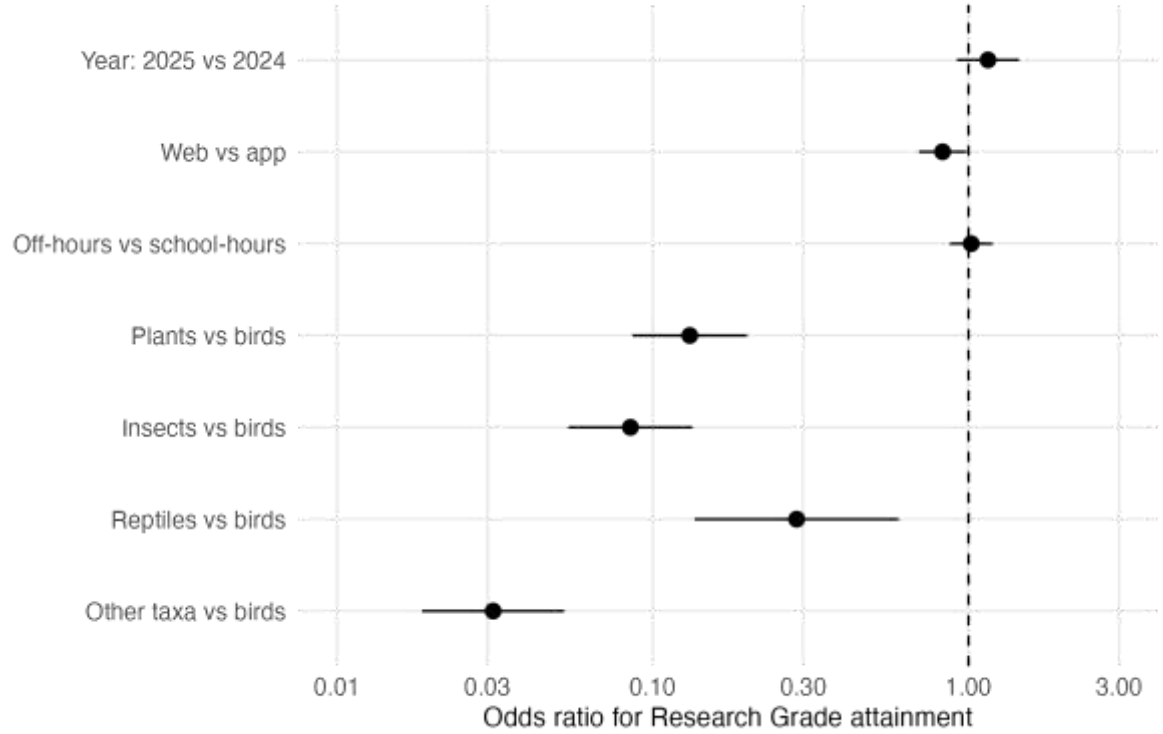


Figure 5. *Odds ratios from the observer/account-clustered GEE model of Research Grade attainment in the core spring subset. The dashed vertical line indicates OR = 1; birds were used as the taxonomic reference group. The x-axis is shown on a logarithmic scale.*

3.5 Taxonomic breadth and diversity output of the Research Grade subset

Table 4. *Descriptive node-level Research Grade taxonomic output and observed sample coverage for named school nodes with at least 100 Research Grade observations.*

School node	RG observations	Hill q=0	Hill q=1	Hill q=2	Observed sample coverage
3rd Gymnasium of Nea Filadelfeia	1338	606	455.8	348.4	0.750
2nd Gymnasium of Nea Filadelfeia	1284	466	292.9	169.3	0.816
Music Gymnasium of Ilion	617	220	115.6	59.7	0.789
11th Gymnasium of Ilion	526	263	196.5	142.5	0.702
Varvakeio Model Gymnasium	413	196	140.6	98.0	0.715
1st General Lyceum of Acharnes	330	187	151.0	117.3	0.652
3rd Gymnasium of Ilion	263	185	158.4	126.0	0.480
1st General Lyceum of Nea Filadelfeia	159	139	131.5	121.0	0.227
7th General Lyceum of Acharnes	148	119	111.3	102.4	0.374
6th General Lyceum of Athens	144	108	98.0	87.1	0.432
1st Gymnasium of Aspropyrgos	114	90	82.0	72.2	0.362
3rd General Lyceum of Zografou	112	80	70.8	60.9	0.475
5th Laboratory Center of East Attica	104	92	87.0	79.5	0.203

The Research Grade core subset contained 6,161 observations representing 1,225 unique taxon IDs. Plants dominated the subset (81.1%), followed by animals (18.9%) and fungi (0.05%). Within iconic taxonomic groups, birds accounted for 10.8% of Research Grade observations and insects for 5.5%. These proportions indicate that the network generated a predominantly plant-based but clearly multi-taxon biodiversity signal. The most frequently recorded Research Grade taxa were *Oxalis pes-caprae* (n = 95), *Lantana camara* (n = 87), *Malva sylvestris* (n = 76), *Columba livia domestica* (n = 71), and *Cairina moschata* (n = 68). Because records on the platform may remain resolved at different taxonomic ranks, these summaries are interpreted as patterns in recorded taxa rather than as strict species-level rankings.

Node-level diversity output varied markedly across the network (Table 4, Figure 6). Among nodes with at least 100 Research Grade observations, observed sample coverage ranged from 0.20 to 0.82, indicating substantial differences in sampling completeness. The highest observed Research Grade taxonomic output was recorded by the 3rd Gymnasium of Nea Filadelfeia (Hill q = 0: 606; Hill q = 1: 455.8; observed sample coverage: 0.750) and the 2nd Gymnasium of Nea Filadelfeia (Hill q = 0: 466; Hill q = 1: 292.9; observed sample coverage: 0.816). Other high-output nodes included the 11th Gymnasium of Ilion, the Music Gymnasium of Ilion, and the Varvakeio Model Gymnasium. Notably, diversity output and sampling completeness were not perfectly aligned: some nodes achieved very high richness despite only moderate coverage, whereas others showed comparatively high completeness with lower overall richness (Figure 6).

Taken together, these results indicate substantial variation in Research Grade taxonomic output across nodes. Because sample coverage varied widely, between-school comparisons should be interpreted cautiously and not as directly comparable estimates of local biodiversity.

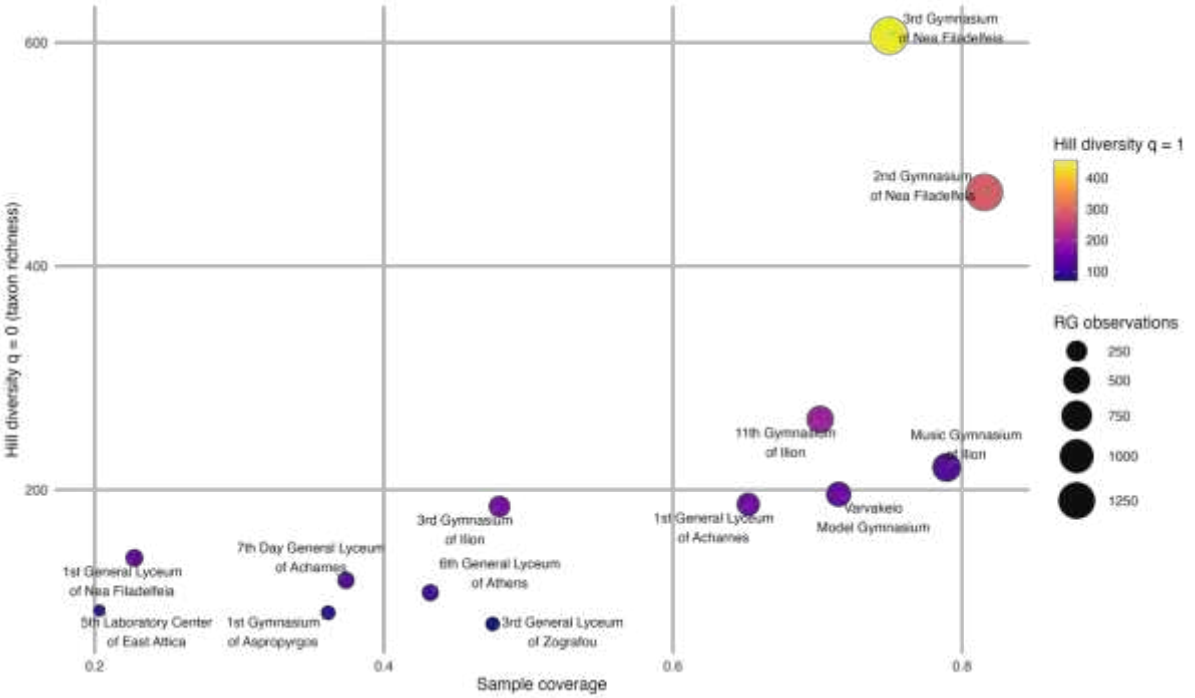


Figure 6. *Descriptive Research Grade taxonomic output and observed sample coverage across named school nodes with at least 100 Research Grade observations. Point size is proportional to the number of Research Grade observations, and point colour indicates Hill q = 1 diversity. Values should not be interpreted as direct comparisons of local biodiversity among schools.*

4. Discussion

4.1 Schools as distributed observation nodes for urban biodiversity

The ARSINOE Educational Community shows that a formal network of schools can operate not only as a setting for environmental education, but also as a distributed observation infrastructure for urban biodiversity at the metropolitan scale. In the locked project snapshot, the initiative produced nearly 10,000 georeferenced biodiversity observations, of which approximately two-thirds reached Research Grade status. This level of output suggests that school-based citizen science, when supported by an appropriate digital platform and a community-driven validation process, can generate a substantial body of quality-filtered biodiversity records. In doing so, the study builds on previous work in school-based citizen science, which has often centred on particular taxa, predefined ecological tasks, or educational outcomes, by shifting attention to the capacity of schools themselves to function as a spatially distributed observation system across the urban landscape (Saunders et al., 2018; Schuttler et al., 2019; Castagneyrol et al., 2020).

The contribution of the present study, therefore, lies less in showing that students are able to document biodiversity, a point that is already well established, and more in demonstrating that schools can serve as stable, place-based nodes embedded within diverse urban neighbourhoods. From this perspective, the ARSINOE Educational Community differs from many volunteer-based biodiversity initiatives because it combines the continuity and institutional anchoring of formal school participation with the spatial reach typically associated with citizen science networks. Such a configuration is particularly valuable in metropolitan regions, where biodiversity data are frequently uneven, concentrated around well-known green spaces, or insufficiently detailed to capture ecological patterns at fine spatial scales (Boakes et al., 2010; Troudet et al., 2017; Ziliaskopoulos & Laspidou, 2024).

4.2 Strong participation inequality, but broader temporal coverage than school hours alone

A central finding of the study is the pronounced inequality in contributions across school nodes. A relatively small number of schools generated the majority of observations, while the Gini coefficient confirmed a highly concentrated pattern of participation. This unevenness is not unusual in citizen science projects, where levels of contribution often depend on local coordination, participant motivation, teacher facilitation, and the practical opportunities available for field recording (Dickinson et al., 2010; Saunders et al., 2018). In the present case, the strong association between the total number of observations and the number of Research Grade taxa further suggests that differences in taxonomic output were shaped largely by unequal recording effort, rather than by underlying differences in biodiversity alone.

Importantly, however, participation was not confined to the formal school timetable. Among records for which the observation hour could be parsed, more than 60% of observations in the core spring subset were made outside weekday school hours, while nearly one-third of all core observations were recorded during weekends. This temporal distribution indicates that engagement continued beyond scheduled school activities. In practical terms, this extended the temporal coverage of the network and increased its monitoring capacity beyond the limits of classroom- or timetable-based participation. For urban biodiversity monitoring, such spillover is particularly significant, as it strengthens the ability of school-based networks to operate as semi-structured citizen observatories rather than as narrowly defined school-hour sampling schemes. The lower coefficient observed in 2025 should therefore be interpreted primarily as a campaign-participation effect within an opportunistic recording design, rather than as evidence of an ecological trend between the two monitoring windows.

4.3 Research Grade attainment was more strongly associated with taxonomic group than with recording context

The results show that Research Grade attainment was driven primarily by taxonomic group, with only a small additional association with submission mode. Birds had the highest probability of reaching Research Grade status, whereas plants, insects, reptiles, and other taxa showed progressively lower odds relative to birds. This pattern is consistent with a broader principle in citizen science data quality: validation success often depends on how easily an organism can be photographed, recognised, and resolved to a sufficiently specific taxonomic level, rather than on simple participation intensity alone (Dickinson et al., 2010; Castagneyrol et al., 2020).

In this dataset, the lower Research Grade success of plants and insects does not imply that these observations were uninformative. Rather, it reflects the greater identification difficulty associated with diverse or morphologically similar taxa, especially when records are contributed opportunistically by non-specialists. The role of the MINKA validation workflow is therefore particularly important. Community-based identification and Research Grade assignment appear to have filtered a large proportion of observations into a scientifically reusable subset, while still preserving the broader pool of non-Research Grade records as a potential resource for later expert review or educational use (Liñán & Piera, 2024). For future school-based observatories, these results suggest that clearer identification guidance, taxon-specific training, and improved photo protocols may improve validation outcomes more effectively than stricter scheduling rules.

4.4 A plant-dominated but clearly multi-taxon signal from everyday urban and peri-urban environments

The Research Grade subset was dominated by plants, but it also contained a meaningful animal component, including birds, insects, and reptiles. This taxonomic structure is consistent with the visibility and accessibility of urban vegetation, while also showing that the network did not simply capture a narrow botanical inventory. Instead, it produced a recognisably multi-taxon biodiversity signal from everyday urban and peri-urban settings. The frequent detection of common urban and synanthropic taxa further suggests that participants were engaging with the ecological reality of the metropolitan landscape rather than selectively documenting only rare or charismatic organisms.

Importantly, node-level diversity output and sampling completeness varied strongly across the network. Some schools achieved very high richness with only moderate coverage, whereas others combined lower richness with comparatively higher completeness. Raw taxon counts alone would have overstated between-school differences and risked conflating taxonomic output with recording intensity. The use of Hill numbers and sample coverage therefore strengthens the description of node-level taxonomic output within this opportunistic dataset, but it does not eliminate comparability limits created by uneven effort, mixed taxonomic ranks, and variable completeness (Chao & Jost, 2012; Chao et al., 2014).

From the perspective of urban green-space monitoring, these findings are important because they suggest that schoolyards, neighbourhood streets, nearby green pockets, parks, and peri-urban sites can help reduce fine-scale blind spots in metropolitan biodiversity information. Recent work in Athens has already highlighted the value of combining citizen-science and spatial data to assess biodiversity patterns across the city (Ziliaskopoulos & Laspidou, 2024). The present study complements that perspective by showing that school-based networks can contribute a dense layer of localised observations from urban green resources and everyday micro-sites that may be underrepresented in more conventional datasets.

This is consistent with urban biodiversity assessment frameworks that combine citizen-science observations with urban habitat classification to strengthen fine-scale ecological assessment in cities (Li et al., 2019). Recent work has also shown that citizen-science-driven species distribution models can be informative in urban ecosystems when data limitations and uneven sampling effort are explicitly addressed (Bührs et al., 2024). Because the Research Grade subset is both spatially dense and predominantly plant-dominated, it may also provide a useful complementary fine-scale input for future urban biodiversity modelling, species distribution analyses, and spatial prioritisation of greening actions, provided that its opportunistic nature and uneven sampling effort are explicitly accounted for.

4.5 Educational value as a co-benefit, not the primary evaluated outcome

Although this paper does not directly measure learning outcomes, the observed participation pattern is consistent with educational co-benefits alongside biodiversity recording. The extension of observation activity beyond formal school hours, the sustained contribution of some schools across the monitoring windows, and the engagement with multiple taxonomic groups all indicate that the project functioned as more than a one-off recording exercise. Previous studies have shown that school-based citizen science can support student engagement with authentic scientific practice and can strengthen connections between local environments, observation, and ecological understanding (Saunders et al., 2018; Schuttler et al., 2019).

However, these educational dimensions should be interpreted cautiously in the present article. Because no formal pre/post evaluation, interview dataset, or structured learning assessment was analysed here, educational impact is best treated as a plausible co-benefit rather than as a directly measured result. This distinction is important methodologically and helps keep the contribution of the present paper focused on biodiversity monitoring and observation-network performance.

4.6 Limitations and directions for future work

Several limitations should be acknowledged. First, the dataset was generated through an opportunistic rather than standardised ecological sampling design. As a result, the study cannot be interpreted as a complete inventory of biodiversity in Attica, nor can differences among school nodes be attributed solely to ecological variation. Second, participation was strongly uneven across nodes, meaning that some parts of the school network functioned as highly active monitoring hubs while others contributed only minimally. Third, the analyses were based on occurrence records and record-based diversity metrics, not on abundance data or repeated detection histories. This limits the kinds of ecological inference that can be drawn. Fourth, the observation-level export used for the Research Grade model did not include row-level school-node membership. The GEE validation model therefore used observer/account clustering rather than school-node clustering, while school-node information was used for descriptive node-level summaries. Future exports linking each observation directly to its school sub-project would allow validation dynamics to be modelled at the school-node level.

Future work could strengthen the monitoring value of the network by combining the existing citizen-science workflow with light standardisation. For example, repeated surveys within defined schoolyard plots, simple habitat metadata, or targeted observation challenges for selected taxonomic groups could improve comparability across schools without undermining participation. A parallel evaluation stream could also be developed to assess learning outcomes, environmental attitudes, or biodiversity literacy more systematically. Such additions would make it possible to separate the ecological and educational contributions of the initiative more explicitly in future publications.

Beyond these ecological and educational extensions, school-based biodiversity observation networks may also have longer-term relevance for integrated environmental-health monitoring. Although the present study does not assess human or animal health outcomes directly, the observation infrastructure described here could contribute to broader environmental-health monitoring by generating spatially distributed biodiversity observations and local ecological signals. In the longer term, similar citizen-science networks could complement One Health frameworks that connect environmental, animal, and human health dimensions, particularly where interoperable cross-domain monitoring systems are being developed across urban and coastal contexts (Ioannou et al., 2025a,b).

4.7 Implications for urban biodiversity monitoring and urban greening

Overall, these findings suggest that school-based citizen science can make a meaningful complementary contribution to urban biodiversity monitoring when supported by transparent validation workflows and effort-aware interpretation. The ARSINOE Educational Community did not replace standardised biodiversity surveys, nor was it designed to do so. Its value lies in expanding fine-scale georeferenced observations across dispersed and often overlooked urban locations while also building a socially grounded monitoring network. Related work has shown that citizen-science occurrence data can also be used to define and track restoration targets in urban areas, highlighting their potential relevance for future greening and restoration priorities (Callaghan et al., 2019).

At the same time, any future use of these data for modelling, restoration planning, or greening prioritisation should treat them as opportunistic and effort-sensitive occurrence data rather than as a standardised basis for direct comparison of local biodiversity across sites. Within those limits, school-based observation networks appear to be a promising but still underused component of urban citizen observatories.

5. Conclusions

The ARSINOE Educational Community shows that a formal school network can operate as a distributed observation infrastructure for urban biodiversity in a metropolitan region. Through the MINKA platform, the initiative generated a substantial body of georeferenced observations, many of which reached Research Grade status through community-based validation. This demonstrates that school-based citizen science can produce scientifically useful biodiversity records at meaningful scale when supported by an appropriate digital and validation framework.

At the same time, the study makes clear that these data must be interpreted with care. Contribution across school nodes was strongly uneven, and biodiversity output was closely tied to recording effort. Research Grade attainment was driven primarily by taxonomic group, with a smaller additional association with submission mode and no clear association with recording time. For this reason, effort-aware diversity metrics and sampling-completeness estimates were essential to avoid treating raw taxon counts as directly comparable across schools. In other words, the value of the network lies not simply in the number of observations collected, but in the ability to interpret those observations critically and within the limits of an opportunistic sampling design.

Although the resulting biodiversity signal was dominated by plants, the network clearly documented multiple taxonomic groups and captured records from schoolyards, neighbourhood streets, green pockets, and peri-urban settings that are often underrepresented in conventional datasets. This is one of the main strengths of the initiative.

The study does not suggest that opportunistic school-based observations can replace standardised ecological surveys, nor does it attempt to measure educational outcomes directly. Its contribution is different, but still important: it shows that formal school systems can function as stable, spatially distributed monitoring nodes that complement conventional urban biodiversity assessment. With appropriate support, transparent validation workflows, and realistic analytical interpretation, school networks could become a valuable component of future urban biodiversity observatories.

Credit author statement:

Alexandra Ioannou: Conceptualization, Methodology, Investigation, Formal analysis, Visualization, Writing – Original Draft
Jaume Piera: Coordination of the MINKA observatory development, Writing – Review & Editing
Ana Álvarez: Dashboard project Visualization Software, Writing – Review
Chrysi Laspidou: Conceptualization, Supervision, Project Administration, Funding Acquisition, Writing – Review & Editing

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Declaration of generative AI and AI-assisted technologies in the manuscript preparation process:

During preparation of this manuscript, the authors used ChatGPT only for language editing and readability improvements. The authors reviewed, edited, and verified all content and take full responsibility for the final manuscript.

Data availability

Project observations and visual analytics are publicly available through the MINKA dashboard for the "ARSINOE Educational Community" at https://dashboard.minka-sdg.org/arsinoe/. The study is based on a locked dashboard snapshot and an observation-level export derived from the same project record on 20 December 2025. Use of MINKA data and media should follow the platform's applicable citation guidelines. Processed input tables and analytical scripts used to generate the figures and statistical outputs are available from the corresponding author upon reasonable request.

Declaration of competing interest

The authors declare no competing interests.

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