Development and implementation of a passive surveillance system for *Aedes albopictus* in Emilia-Romagna, Italy

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Abstract

The invasive Asian tiger mosquito (*Aedes albopictus*) has become an important public health concern in Italy, particularly in the Po Valley area, where its biting behaviour and nuisance have contributed to multiple outbreaks of mosquito-borne diseases over the last two decades. To address this growing threat, the Emilia-Romagna region has conducted intensive mosquito monitoring efforts since 2010, generating a rich observational database.

Taking advantage of this rich oviptrap dataset, we implemented a stacked machine learning approach to predict the distribution and abundance of *Ae. albopictus*, based on ovitrap data and environmental covariates from 2010 to 2023. A spatio-temporal sensitivity analysis was carried out to determine the amount of data necessary to train a reliable model. Our results revealed that models trained on fewer years of data but with broader spatial coverage statistically outperformed those trained on longer time frames. This indicates that including data from diverse environmental settings improves model performance more than simply increasing the temporal depth of the training set. Models that incorporated a larger number of sampling locations were also more effective at capturing complex environmental influences on mosquito populations. Despite underestimating peak summer abundance in 2023, the model effectively and consistently predicted the seasonal trends and the spatial distribution of *Ae. albopictus*.

These findings highlight the potential of such models to inform public health strategies and optimise mosquito control interventions to mitigate vector-borne disease risks and nuisance, besides emphasising the importance of long-term and spatially extensive data in improving model performance.

Keywords: Ecological forecasting, invasive mosquito, public health, species distribution modelling, vector-borne diseases.

1 Introduction

The Asian tiger mosquito, *Aedes albopictus* (Skuse, 1894), is a vector of arboviruses such as Chikungunya, Dengue, and Zika, and it is also one of the most rapidly spreading invasive species in the world (Benedict et al. 2007; Delatte et al. 2008; Boes et al. 2014; Kraemer et al. 2015). Due to its ability to establish in new environments and transmit pathogens (Benedict et al. 2007), its rapid spread across Italy has raised significant public health concerns and required robust surveillance and control strategies (Rezza et al. 2007; Venturi et al. 2017; Brady et al. 2019; Barzon et al. 2021; De Carli et al. 2023; Branda et al. 2024; Sacco et al. 2024). The urgency of this issue was exemplified by the response of the Emilia-Romagna region to the 2007 Chikungunya outbreak, which underscored the need for efficient and targeted monitoring systems to prevent future epidemics (Canali et al. 2017; Angelini et al. 2008). However, implementing such systems using traditional surveillance methods requires substantial financial and logistic resources, increasing the demand for cost-effective and scalable approaches (Caputo et al. 2020).

To address these challenges, statistical modelling has emerged in the past two decades as an effective tool for predicting the geographic distribution and phenology of the species (Lippi et al. 2023). Spatio-temporal analysis, in particular, plays an important role in vector-borne disease surveillance by enabling decision-makers to allocate resources effectively and respond to outbreaks (Desjardins et al. 2018). Among the various statistical approaches, ecologists often employ correlative models to infer species phenology and spatial-temporal variations. These models establish statistical relationships between a response variable (e.g., species abundance or presence-absence) and predominantly abiotic covariates (Guisan et al. 2017; Edwards et al. 2021; Torina et al. 2023).

Existing models for estimating *Ae. albopictus* distribution vary in scope and complexity. Some models generate predictions without explicitly accounting for temporal and seasonal variability, not necessarily capturing population dynamics over time (Ding et al. 2018). Furthermore, many others focus on large-scale or global predictions (for example, see Kraemer et al. (2015) and Ding et al. (2018)), which, while valuable for broad epidemiological insights, may lack the spatial resolution necessary for practical, localised interventions. In our study, we aim to overcome both limitations by developing a model that incorporates temporal variability in its predictions and operates at a more localised regional scale. This approach enhances its applicability for targeted vector control and public health planning (Purse et al. 2015; Khatchikian et al. 2011).

Although statistical models have extensively advanced mosquito surveillance, their predictive accuracy remains sensitive to biases, which can arise from uneven data collection, assumptions in model structure, or constraints in parameter estimation, potentially leading to inaccuracies in spatial and temporal predictions (Benkendorf et al. 2020; Bazzichetto et al. 2023; Da Re et al. 2023). In this context, the work by Carrieri et al. (2023) represents a valuable contribution to the field, as it is one of the first attempts to apply a rigorous statistical framework to model *Ae. albopictus* egg abundance in the Emilia-Romagna region. Their study applied a Bayesian multi-model linear regression to estimate seasonal densities of *Ae. albopictus* eggs in the Emilia-Romagna region. While this approach relies on predefined equations and prior knowledge, requiring careful parameter estimation to ensure accuracy, it may be constrained by its underlying model structure. In contrast, our study adopts a data-driven approach by leveraging machine learning (ML) to infer *Ae. albopictus* egg abundance. Unlike parametric models that impose predefined relationships, ML identifies patterns directly from the data, potentially reducing bias and improving predictive performance.

Recent advancements in ML techniques have provided powerful alternatives to conventional statistical models, particularly for capturing complex, nonlinear relationships between environmental factors and mosquito population dynamics. Indeed, ML-based models have shown superior performance in predicting species distributions, identifying ecological niches, and modelling seasonal fluctuations (Chen et al. 2019; Bonannella et al. 2022; Ceia-Hasse et al. 2023; Oeser et al. 2024; Da Re et al. 2025). However, despite these advantages, ML models remain sensitive to biases in sampling locations, the complexities of hyperparameter tuning, and variability introduced by different algorithmic choices (Benkendorf et al. 2020; Bazzichetto et al. 2023; Da Re et al. 2024). Given that different algorithms may yield different results, model selection plays a fundamental role in predictive accuracy (Araújo et al. 2007; Pearson et al. 2006; Marmion et al. 2009). To address these challenges, ensemble learning techniques have emerged as an effective strategy to enhance model robustness and accuracy. While traditional aggregation methods, such as simple and weighted averaging, have been widely used (Marmion et al. 2009; Hao et al. 2019), studies suggest that stacking, or stacked generalisation, offers superior performance (Araújo et al. 2005; Araújo et al. 2007).

This study aims to develop a model that could support regional mosquito control efforts. Recognising the challenges posed by sampling issues such as variability in data availability, spatial coverage, and temporal depth, we seek to explore how these factors influence the reliability of machine learning-based predictions. To address this, we utilise a georeferenced database of *Ae. albopictus* egg observations collected between 2010 and 2023 and we explored how varying data quantities and distributions impact model performance. More specifically, this study aims to evaluate how variations in temporal depth and spatial coverage influence the sensitivity and reliability of the model, ultimately improving surveillance strategies for *Ae. albopictus*. In this context, we pursue three objectives: (1) identifying the optimal temporal span and (2) spatial coverage required for reliable model performance, and (3) generating short- and medium-term forecasts of mosquito egg distribution and abundance to support public health preparedness. Our results are especially relevant for regions seeking to implement similar surveillance models, as they offer valuable insights into the required effort and data collection needed for reliable predictions. Consequently, this work advances the development of data-driven decision-making tools for vector surveillance and control.

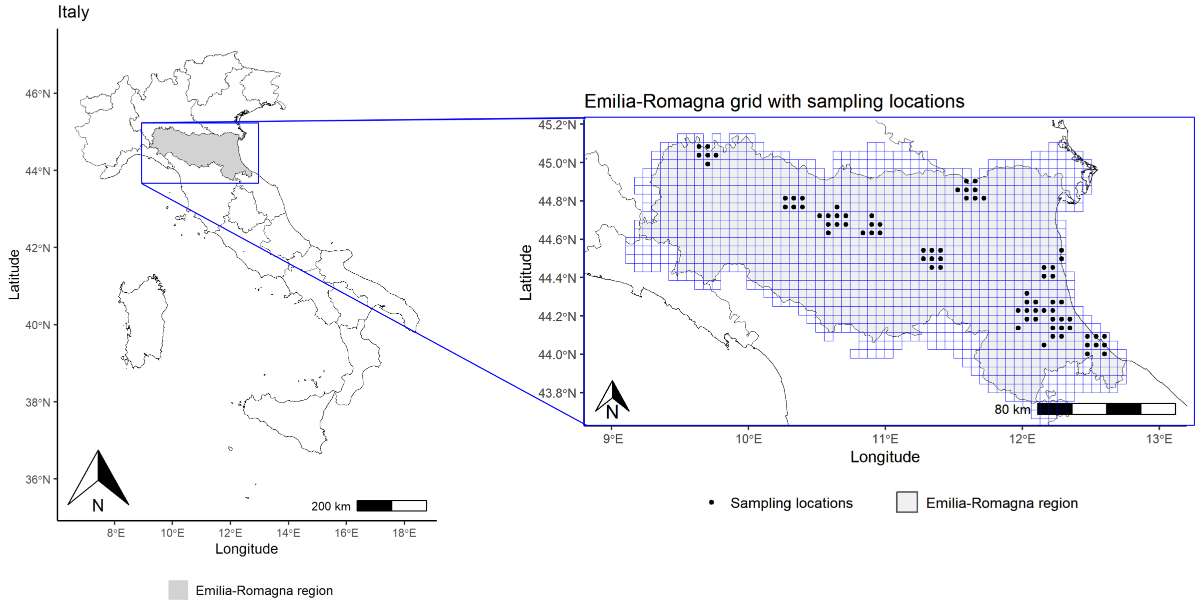


Figure 1: Left: Location of Emilia-Romagna within Italy. Right: Grid used for aggregating ovitrap data, matching the resolution of the climatic datasets (approximately 5×5 km). Black dots indicate the sampling locations (SLs), representing the aggregated ovitrap data.

2 Methodology

2.1 Ovitrap data

This study focuses on the Emilia-Romagna region in northern Italy, situated in the Po Valley (Figure 1). Since 2010, regional authorities have monitored *Ae. albopictus* populations using ovitraps, which are dark water-filled containers equipped with a surface for mosquito egg deposition. These traps are inspected biweekly following standardised local protocols. Egg counts provide a reliable measure of mosquito activity and serve as a key tool in the region's surveillance efforts.

Mosquito monitoring in Emilia-Romagna is coordinated by Local and Regional Public Health departments, with municipalities responsible for operational activities (Carrieri et al. 2011). The program involves ten municipalities deploying a total of 755 georeferenced ovitraps annually from late May (week 21) to early October (week 40). The locations of all the ovitraps are shown in Figure S1. During each survey, the status of each ovitrap is evaluated following the Regional Surveillance Operative protocol (Di Luca 2022). If a trap is found dry or overturned, its deposition substrate (a masonite stick) is excluded, and the data point is recorded as missing (NA). The collected sticks are sent to the Regional Environmental Protection Agency laboratories, where mosquito eggs are identified and counted using a stereomicroscope. A quality control process is then applied to the egg count data (Carrieri et al. 2017). After passing the quality check, the data are published on the regional portal www.zanzaratigreonline.it.

For data integration into the machine learning model, the egg counts of *Ae. albopictus* collected through ovitraps were set as the target variable. Temporal resolution was standardised to a weekly period using the `spreader` function from the *dynamAedes* R package (Da Re et al. 2022). The spatial resolution (approximately 5x5 km) was set consistently with the meteorological dataset. Ovitrap data were aggregated accordingly, with a similar pre-processing pipeline as the one described in Da Re et al. (2025), where the median egg count is calculated for each grid cell, referred to as a *sampling location (SL)* throughout this study. Each SL is identified by a unique numerical ID and represents the average egg observations within the grid cell. A total of 79 SLs are distributed across the study area.

2.2 Covariates

The study incorporates key environmental factors known to influence mosquito activity and development. Three primary covariates were included: air temperature, photoperiod (the number of daylight hours), and precipitation (Toma et al. 2003; Roiz et al. 2010; Roiz et al. 2011; Cruz Ferreira et al. 2017; Becker et al. 2020; Romiti et al. 2021; Carrieri et al. 2023). Daily air temperatures and precipitation data were extracted from ERG5, a meteorological dataset developed by the HydroMeteoClimate Service of Emilia-Romagna Regional Environmental Protection Agency (ARPAE). Currently, ERG5 covers the period from 2001 to the present and provides several spatially interpolated climate variables at a 5×5 km resolution based on data from ARPAE's meteorological network (Antolini et al. 2015), which is the standard adopted by the regional environmental authority for operational and environmental monitoring planning purposes.

To account for the delayed and cumulative effects of environmental conditions on mosquito populations, we derived rolling averages of each covariate, following the methodology of Da Re et al. (2025). Specifically, covariates were represented using rolling means to account for short-term temporal integration. Temperature and photoperiod variables were summarized as the median across the focal week (i) and the preceding one or two weeks (i–1, i–2), while precipitation variables were computed as the cumulative total over the same periods.

In addition to environmental variables, we incorporated seasonality and cyclic patterns using a Fourier series. This approach captures annual and short-term seasonal trends through sine and cosine harmonic waves (Hyndman et al. 2018). Four harmonics were included: two representing interannual variability and two capturing seasonal fluctuations.

To factor in the influence of urbanisation on mosquito distribution (Perrin et al. 2022) and to mitigate spatial sampling bias (Gutierrez-Velez et al. 2020; Whitford et al. 2024), since monitoring sites are primarily located in major cities (Figure S1), we included a urbanisation index derived from the ESA CCI Land Cover database (www.esa-landcover-cci.org, Defourny et al. (2012)). This dataset provides annual gridded maps with 22 global land cover classes. Urban areas are coded as value 190, based on data from the Global Human Settlement Layer (Pesaresi et al. 2016) and the Global Urban Footprint (Esch et al. 2017). To construct the urbanisation index, we first extracted all pixels labeled as urban (value 190) to create a binary map (1 = urban, 0 = non-urban). We then rescaled this map from its original 1 km resolution to 5 km, calculating the proportion of urban cover within each grid cell using the `terra::zonal` function. The resulting index assigns each grid tile a value between 0 (completely non-urbanised) and 1 (fully urbanised), with annual updates reflecting changes over time.

Given that (Phillips et al. 2009) argued that spatial sampling bias may not compromise model performance if sampled locations adequately represent the full range of covariate conditions, this assumption may not hold in highly urbanised regions like Emilia-Romagna. Ovitraps in our study were concentrated in densely populated cities, leading to over-representation of anthropogenic environments and potential under-representation of rural or peri-urban settings. Including a dynamic urbanisation index addressed this imbalance, both by improving ecological relevance and reducing spatial bias. This correction is particularly important given the well-established influence of urbanisation on *Ae. albopictus* distribution (Li et al. 2014; Manica et al. 2016; Westby et al. 2021; Torina et al. 2023), and the known risks that uncorrected spatial bias poses to model generalisability and inference (Reddy et al. 2003; Kadmon et al. 2004; Anderson et al. 2011; Kramer-Schadt et al. 2013; Yackulic et al. 2013).

2.3 Modelling framework

Stacking is an ensemble learning technique that combines predictions from multiple base models to mitigate overfitting and improve generalisability (Wolpert 1992; Marmion et al. 2009). Unlike bagging or boosting, which focus on reducing variance or bias, stacking integrates diverse models, allowing a meta-learner to determine the optimal way to merge their outputs (Bonannella et al. 2022; Bonannella et al. 2023; Oeser et al. 2024). Building on the methodology established in Da Re et al. (2025), we implemented a stacked model using four machine learning algorithms as base learners: XGBoost (Chen et al. 2016), Random Forest (Breiman 2001), Gradient Boosting

Machine (Friedman 2001), and Cubist (Kuhn et al. 2024). These models were then combined into a unified ensemble using a linear meta-learner, specifically a regularised linear regression model trained to optimally weight the base learners' predictions. This meta-model was implemented using the `mlr3` library (Bischl et al. 2016; Lang et al. 2019). The overall ensemble architecture is illustrated in Figure 2a.

To ensure consistent configuration across all base models, hyperparameters were optimised once using 10-fold cross-validation with 10 evaluations. However, we acknowledge the potential for overfitting by using this approach, particularly when training models on smaller datasets. These limitations are further explored in the "Discussion" section.

Once the ensemble was constructed and optimised via hyperparameter tuning, it underwent training, validation, and testing (Figure 2b). Each base learner's predictions were assigned varying weights, reflecting their relative contributions to the final model output.

2.4 Spatio-temporal sensitivity analysis

To assess how model performance varies with training data quantity, we applied a systematic spatio-temporal subsampling strategy. This involved iteratively selecting subsets of the dataset to create multiple training sets of varying sample sizes for each model, determined by the total years of data used for training and the fraction of SLs. The training process covered four periods, the longest spanning from 2011 to 2022, followed by progressively narrower timeframes (2015-2022, 2019-2022, and 2021-2022). For each period, five spatial fractions of the sampling locations (SLs), 0.10 (7 SLs), 0.25 (19 SLs), 0.50 (38 SLs), 0.75 (58 ± 1 SLs), and 0.90 (70 ± 1 SLs), were randomly sub-sampled from the full dataset. Each combination of training period and spatial fraction was replicated five times to ensure result robustness and consistency.

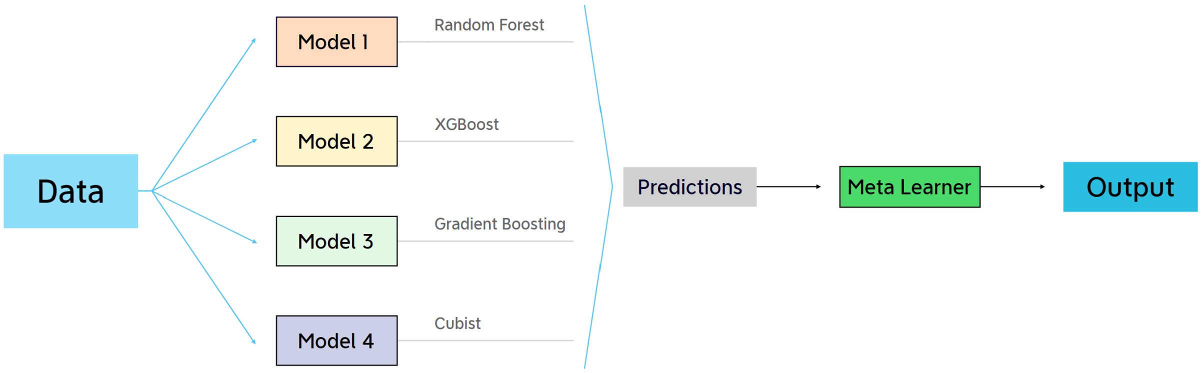
To validate the model, an internal validation was performed using 10-fold cross-validation within the training dataset; then, a spatial test was conducted on a separate dataset, using SLs that were excluded from training. For evaluating temporal transferability, model predictions were tested on all the available data from 2023, which was entirely withheld from the training of all 100 models.

2.5 Model performance evaluation

To quantify model performance, Root Mean Squared Error (RMSE) was computed for the internal, spatial, and temporal validations. The model yielding the lowest RMSE was selected to generate prediction maps for *Ae. albopictus* abundance and distribution in 2023.

To further analyse RMSE variations, we applied linear regression models, assessing main effects and interaction effects separately. The response variable in the linear model was the mean RMSE, while the explanatory variables were the training years, the fraction of sampling locations and their interaction. An Analysis of Variance (ANOVA) was then conducted using a two-way model to evaluate statistical significance. Model comparisons were based on the Akaike Information Criterion (AIC) (Table S1), and descriptive statistics were calculated for RMSE across training periods and spatial fractions. Finally, Tukey's Honestly Significant Difference (HSD) test was performed for post-hoc comparisons.

(a)



(b)

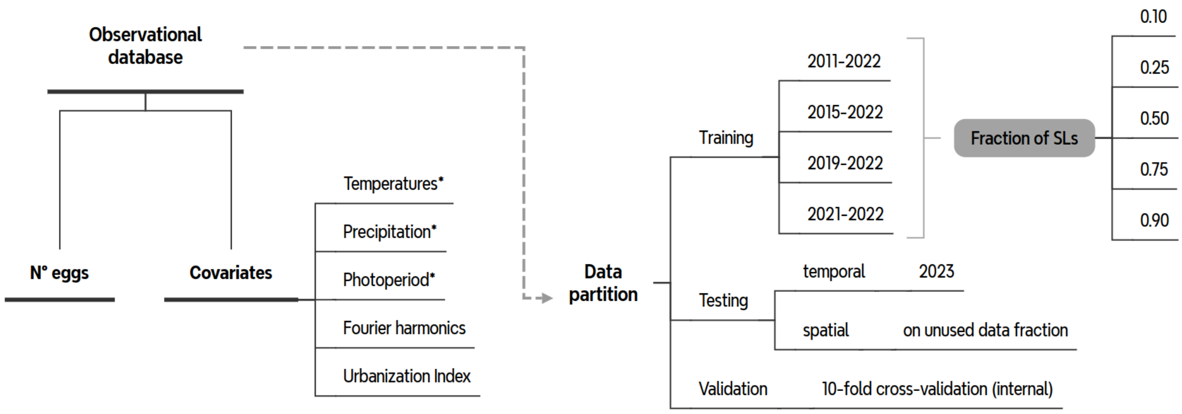


Figure 2: (a) Stacked model architecture. (b) Map illustrating the components of the observational database and subsequent data splitting.

3 Results

Among the base learners, the predictions from the Random Forest model had the largest positive influence on average, followed by GBM, XGBoost and Cubist (Figures S2 and S3). Temperature-related variables consistently emerged as the most influential factors across the models (Figure S4). These were followed by photoperiod variables, a Fourier harmonic, urbanisation, and precipitation with a 3-week lag. Ranked lower in importance were, in order, another Fourier harmonic, precipitation, and two additional Fourier harmonics.

3.1 Internal cross-validation

For the internal 10-fold cross-validation set, which was used for hyperparameter tuning of the base models, the RMSE values generally decreased as the fraction of sampling locations increases, but this trend was not consistent across all cases (Table 1). When comparing across training year ranges, models trained on longer periods generally performed better, too. Furthermore, the associated standard errors were smaller at higher sampling fractions and longer training years.

Cross-validation was not performed for the 0.10 sampling fraction (7 SLs) due to insufficient data. When executing the resampling procedure, an error was returned during model training and evaluation, which indicated that, for at least one fold, the resampling split produced an empty set. The issue arose because the resampling instance was instantiated on a task with too few rows to satisfy the requirements of the cross-validation strategy, leading to a failure in retrieving the necessary data from the backend.

Table 1: RMSE values with standard errors (±) for different training years and fractions of sampling locations for the internal cross-validation.

	2021 - 2022	**2019 - 2022**	**2015 - 2022**	**2011 - 2022**	**mean**
0.25	90.48 ± 6.51	84.28 ± 1.29	81.70 ± 4.59	88.06 ± 3.72	86.13 ± 2.18
0.50	89.49 ± 3.38	85.58 ± 2.64	82.24 ± 1.00	79.41 ± 2.70	84.18 ± 1.47
0.75	88.24 ± 0.75	84.38 ± 1.91	88.63 ± 0.47	80.64 ± 1.66	85.47 ± 0.97
0.90	87.29 ± 0.91	85.06 ± 0.72	85.32 ± 0.94	79.41 ± 0.90	84.27 ± 0.78
mean	88.87 ± 1.73	84.82 ± 0.83	84.47 ± 1.27	81.88 ± 1.41	

3.2 Spatial validation

Across all training periods and fractions of SLs, the models demonstrated consistent performance on the spatial validation, with a comparable range and scale of the error (Table 2). When comparing the errors for models trained with different quantities of training years, it emerged that the model trained on only two years achieved the overall lowest RMSE, on average (mean RMSE: 94.15). This is considerably lower than the RMSEs for other training periods such as 2019-2022 (105.40), 2015-2022 (102.69), and 2011-2022 (102.25) (Table 2). Specifically, the model trained on 2021-2022 with a 0.75 fraction of SLs (58 ± 1 SLs) achieved the lowest median RMSE of 73.00 ± 5.15 (Table 3), outperforming models with longer training periods. However, the model trained on data from 2011 to 2022 with a 0.90 fraction of SLs (70 ± 1 SLs) scored the lowest mean RMSE of 85.22 ± 4.94 (Table 2).

We have also computed the Relative Root Mean Square Error (rRMSE), a dimensionless metric that expresses the RMSE as a percentage of the observed data range, providing a scale-independent measure of model prediction error. By normalising the RMSE to the variability inherent in the observations, rRMSE allows for more meaningful comparisons of model performance across different datasets and scales. An rRMSE below 20% is generally considered indicative of good predictive performance, reflecting that the model error is relatively small compared to the natural variation in observed abundance (Li et al. 2013; Despotovic et al. 2016; McGough et al. 2017). In our

Table 2: RMSE values with standard errors (±) for different training years and fractions of sampling locations for the spatial validation.

	2021 - 2022	**2019 - 2022**	**2015 - 2022**	**2011 - 2022**	**mean**
0.10	101.49 ± 2.84	120.43 ± 2.88	106.71 ± 2.26	111.94 ± 2.39	110.15 ± 1.31
0.25	92.06 ± 2.68	97.91 ± 2.85	106.28 ± 2.91	100.92 ± 2.39	99.35 ± 1.36
0.50	89.02 ± 3.01	96.85 ± 3.58	99.23 ± 3.33	96.37 ± 3.32	95.41 ± 1.66
0.75	85.66 ± 5.15	97.69 ± 5.41	88.48 ± 3.76	89.95 ± 4.32	90.41 ± 2.35
0.90	90.30 ± 5.10	88.06 ± 8.08	93.79 ± 7.42	85.23 ± 4.94	89.35 ± 3.25
mean	94.15 ± 1.54	105.40 ± 1.69	102.69 ± 1.46	102.25 ± 1.41	

case, the rRMSE values ranged approximately from 16% to 24% across different training periods and sampling fractions (see Table S2).

We then employed a linear model to evaluate overall trends across various combinations of training years and fractions of sampling locations (Figure 3). An important observation is that all linear models exhibited a negative slope, indicating a clear decreasing trend in RMSE as the fraction of data increases. Notably, the model trained on 2 years of data had the lowest RMSE overall. However, for larger fractions of data (> 0.75), its performance became comparable to the model trained on 12 years of data, with overlapping RMSE values. Interestingly, for a fraction of 0.9, the 12-year model outperformed the 2-year model.

Table 3: Median RMSE results and quantiles 0.25 and 0.75 (Q1, Q3) for different training years and fractions of sampling locations used. The median values were calculated based on the mean RMSE obtained for each combination of training years, sampling fraction, iteration, and ID.

	2021 - 2022	**2019 - 2022**	**2015 - 2022**	**2011 - 2022**
0.10	89.34 (64.41, 125.76)	111.96 (83.52, 141.42)	99.98 (76.76, 125.90)	101.63 (83.22, 128.18)
0.25	85.30 (59.65, 116.12)	90.93 (66.47, 113.64)	96.58 (69.72, 129.58)	93.74 (71.11, 118.48)
0.50	83.53 (56.44, 113.12)	87.48 (65.72, 111.70)	89.12 (67.57, 112.24)	84.86 (63.02, 116.53)
0.75	73.00 (54.32, 107.13)	91.42 (65.15, 111.46)	77.67 (63.16, 103.67)	82.06 (59.33, 108.44)
0.90	85.58 (64.05, 110.74)	75.27 (56.55, 101.40)	88.65 (67.23, 100.08)	81.91 (56.09, 105.85)

Fractions of 0.10 and 0.25 generally show higher RMSE values, with a wider spread (i.e., larger interquartile range and more outliers). This indicates more variability and less accuracy when fewer SLs are used for training. Fractions of 0.75 and 0.90 consistently yield lower median RMSE values, with narrower boxplots (Figure S5) and fewer outliers, indicating better model performance and stability (Table 2).

The effect of SLs used in the training process is highly statistically significant ($p < 0.001$), as confirmed by the analysis of variance (ANOVA) (Table 4). The mean RMSE decreased as the fraction of SLs increased. Indeed, the lowest RMSE occurred for the 0.90 fraction (mean RMSE: 89.35). This is better than all other fractions, with a clear trend of decreasing RMSE as the fraction increased (Table 2). The Tukey test for pairwise comparisons of the main effects on mean RMSE (Table 6) confirmed that all fractions outperform with statistical significance fraction 0.10 (p-value is < 0.05). Additionally, the difference between 0.75 and 0.25 is also statistically significant. The difference between 0.90 and 0.25 is not statistically significant, with p-value = 0.085. Alternatively, the fractions 0.50 and 0.75 compared to 0.90 show no significant difference in performance, with adjusted p-values of 0.57 and 0.99, respectively (Table 6). The largest difference occurs between 2021-2022 and longer training years, particularly for lower fractions of SLs (Table 5 and Table 6).

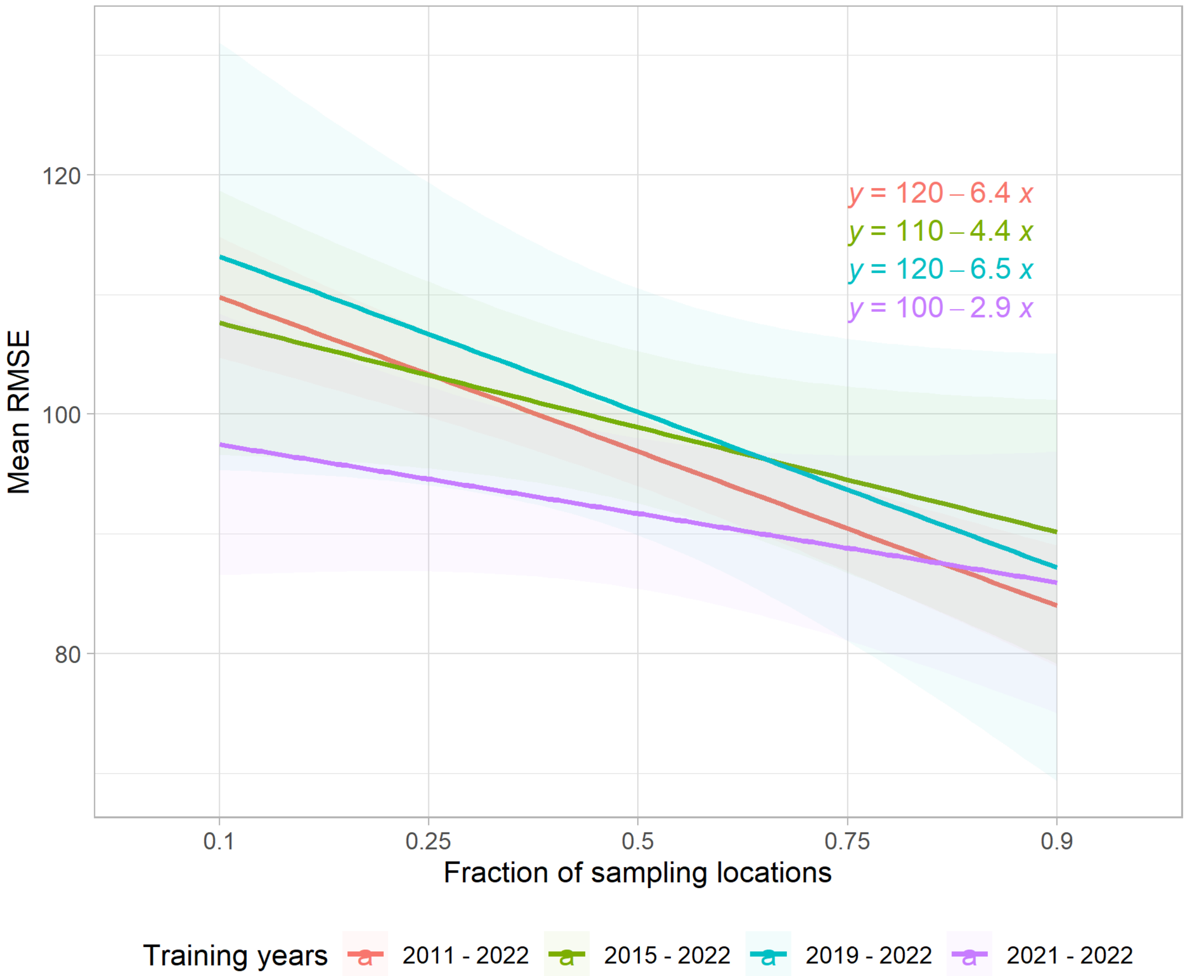


Figure 3: Linear model plot showing the relationship between the fraction of sampling locations and the mean RMSE for different training year sets (2011-2022, 2015-2022, 2019-2022, and 2021-2022). C.I. is 95%. The trend is similar across the four training year groups: as the fraction of sampling locations increases, the mean RMSE consistently decreases across all training year sets, indicating that higher fractions of sampling locations improve model accuracy.

Table 4: Analysis of variance (two-way ANOVA) for the linear model where the response variable is mean RMSE and the explanatory variables are the years of training and fraction of SLs.

	Degrees of Freedom	Sum of Squares	Mean Square	F-value	p-value
Training years	3	67581	22527	10.23	< 0.001
Fraction of SLs	4	210176	52544	23.986	< 0.001
Residuals	3877	8538979	2202		

Table 5: Tukey HSD test results for pairwise comparisons of the training years on mean RMSE, based on a two-way ANOVA model.The comparisons were conducted with a 95% confidence level. The lower and upper confidence intervals are reported in brackets (LCI, UCI).

Training years	difference (LCI, UCI)	p-value
2015-2022 - 2011-2022	0.43 (-4.99, 5.86)	1.00
2019-2022 - 2011-2022	3.15 (-2.30, 8.60)	0.45
2021-2022 - 2011-2022	-8.10 (-13.55, -2.65)	< 0.001
2019-2022 - 2015-2022	2.71 (-2.77, 8.20)	0.58
2021-2022 - 2015-2022	-8.54 (-14.02, -3.05)	< 0.001
2021-2022 - 2019-2022	-11.25 (-16.76, -5.74)	< 0.001

3.3 Predictions on the test set

The testing performed using the 2023 dataset showed similar error patterns across models trained with different periods and SL fractions (Figures 4 and 5). Overall, the models tended to underestimate *Ae. albopictus* egg abundance in 2023, particularly during the peak summer months. This systematic underestimation was observed in both short-term (2021-2022) and longer-term models, though the timing of the seasonal peak was predicted accurately. Predictions for off-season months (e.g., late autumn) displayed relatively low variability for egg counts, expected to be 0, particularly for models trained on 12 years of data (Figure 4). These longer-term models predicted fewer than 10 eggs per ovitrap in off-season months. The model trained on two years (2021-2022) demonstrated comparable performance to those trained on longer periods, underscoring its ability to capture general seasonal dynamics despite using less historical data.

Table 6: Tukey HSD test results for pairwise comparisons of the fraction of SLs on mean RMSE, based on a two-way ANOVA model.The comparisons were conducted with a 95% confidence level. The lower and upper confidence intervals are reported in brackets (LCI, UCI).

Fraction of SLs	difference (LCI, UCI)	p-value
0.25 - 0.10	-10.81 (-15.89, -5.73)	< 0.001
0.50 - 0.10	-14.75 (-20.48, -9.02)	< 0.001
0.75 - 0.10	-19.76 (-27.08, -12.43)	< 0.001
0.90 - 0.10	-20.79 (-31.46, -10.11)	< 0.001
0.50 - 0.25	-3.94 (-9.88, 1.99)	0.37
0.75 - 0.25	-8.95 (-16.43, -1.46)	< 0.05
0.90 - 0.25	-9.98 (-20.76, 0.81)	0.085
0.75 - 0.50	-5.01 (-12.95, 2.93)	0.42
0.90 - 0.50	-6.04 (-17.14, 5.07)	0.57
0.90 - 0.75	-1.03 (-13.04, 10.98)	0.99

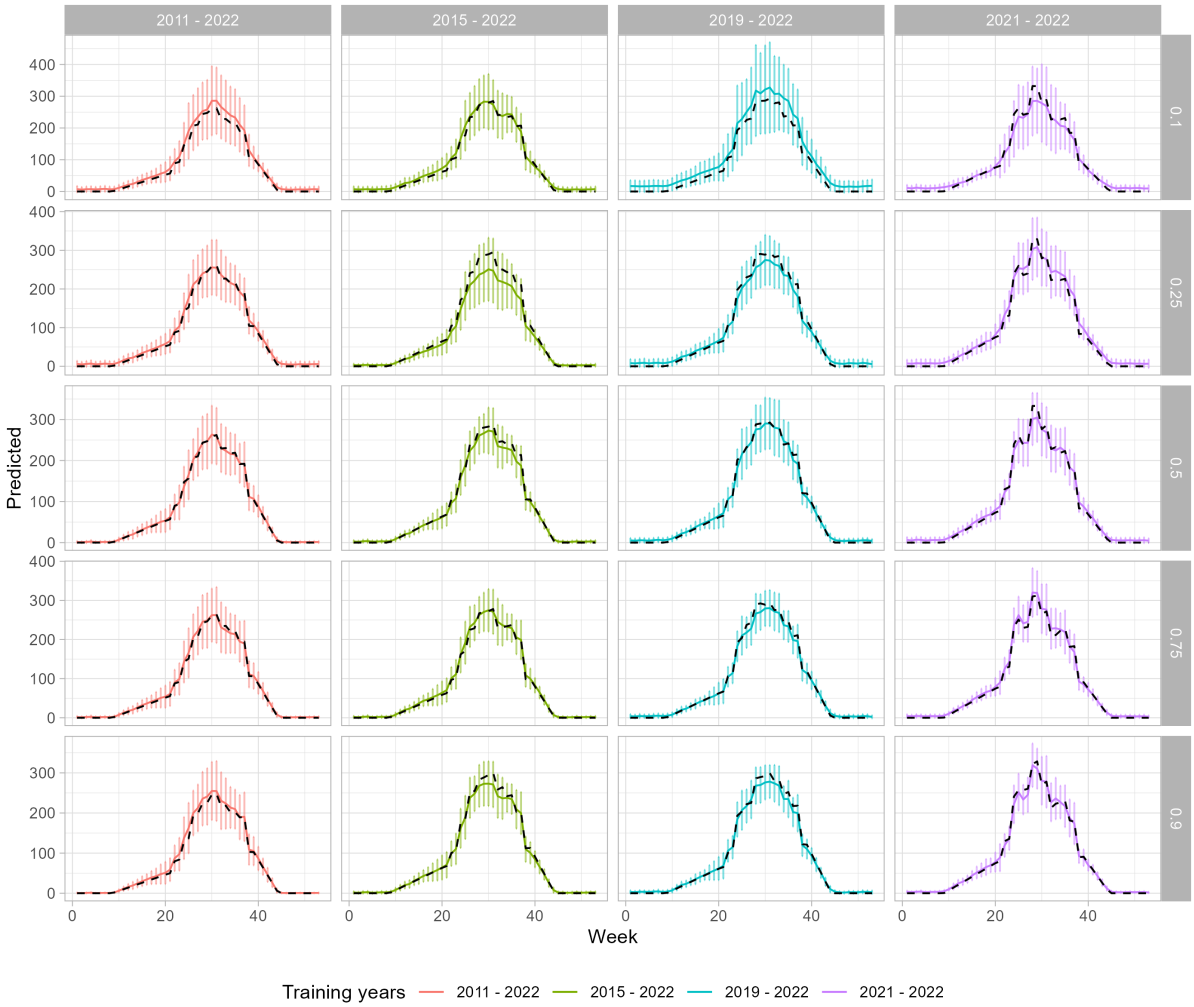


Figure 4: Mean predicted (coloured lines) and mean observed (dashed lines) *Ae. albopictus* egg abundance for the spatial validation set across four training periods (2011-2022, 2015-2022, 2019-2022, and 2021-2022) and five data fractions (0.10, 0.25, 0.50, 0.75, and 0.90).

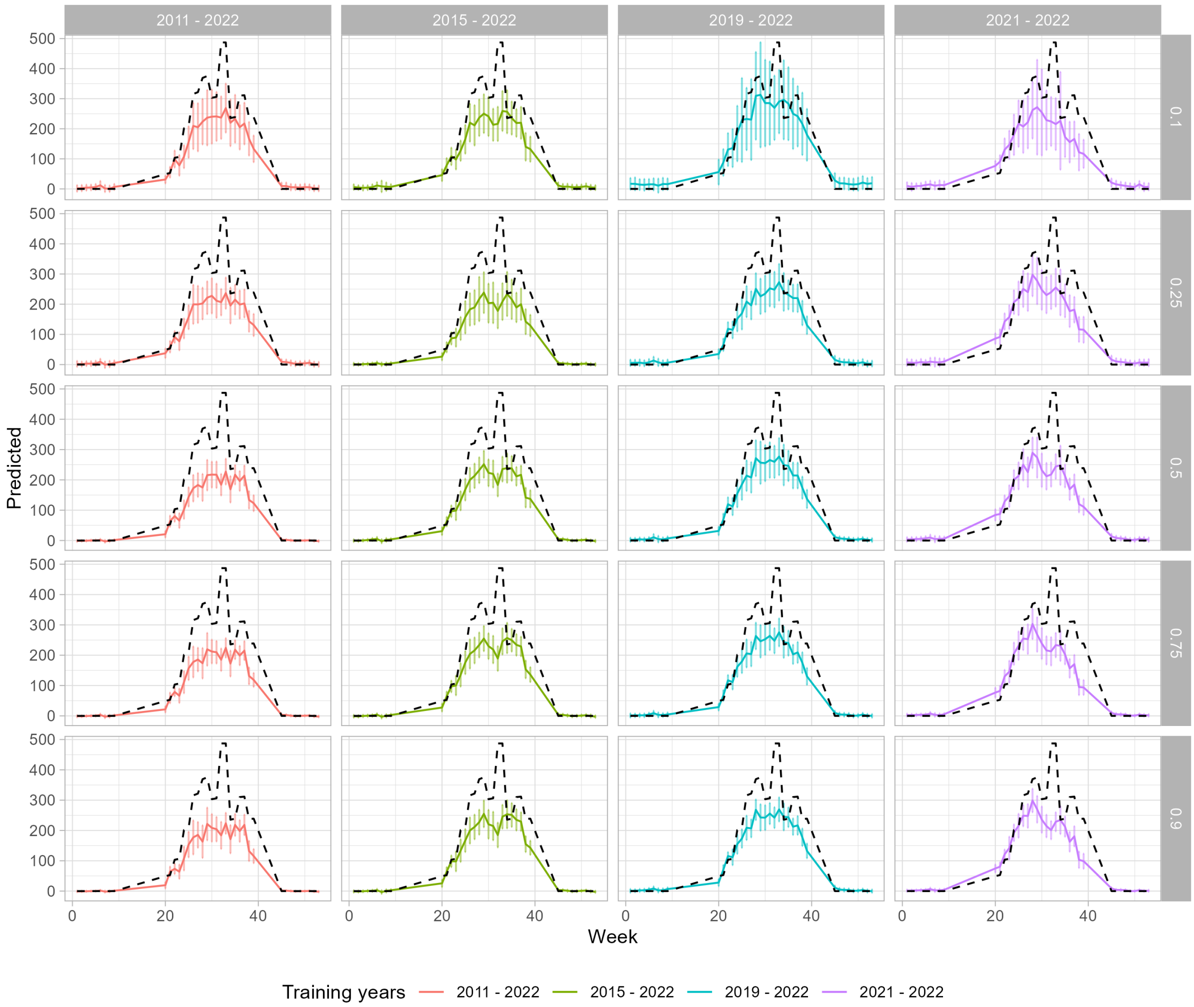


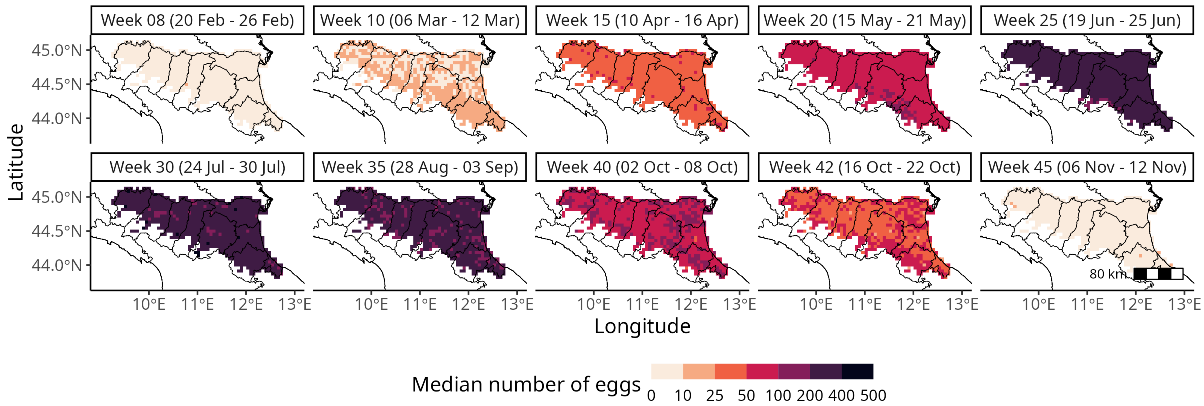
Figure 5: Mean predicted (coloured lines) and mean observed (dashed lines) *Ae. albopictus* egg abundance for the temporal validation (year 2023) across four training periods (2011-2022, 2015-2022, 2019-2022, and 2021-2022) and five data fractions (0.10, 0.25, 0.50, 0.75, and 0.90).

3.4 Prediction maps

Spatial predictions for 2021 and 2022 were used to check if the predictions aligned with expected seasonal trends (Figure S8). However, it is important to note that these years overlap with the training years, meaning the model's predictions are based on data it was partially exposed to during training.

The prediction maps for 2023 were first generated using the best-performing model based on metrics of the spatial validation, which is composed by the unused SLs in training (Figure 6a). The model successfully captured the general trend of increasing egg abundance from spring to autumn, with predictions aligning with observed seasonal patterns in *Ae. albopictus* activity. However, using the model trained with the longest period and the largest fraction, a notable drop in egg abundance was predicted for mid-May 2023 (Figure 6b).

(a)



(b)

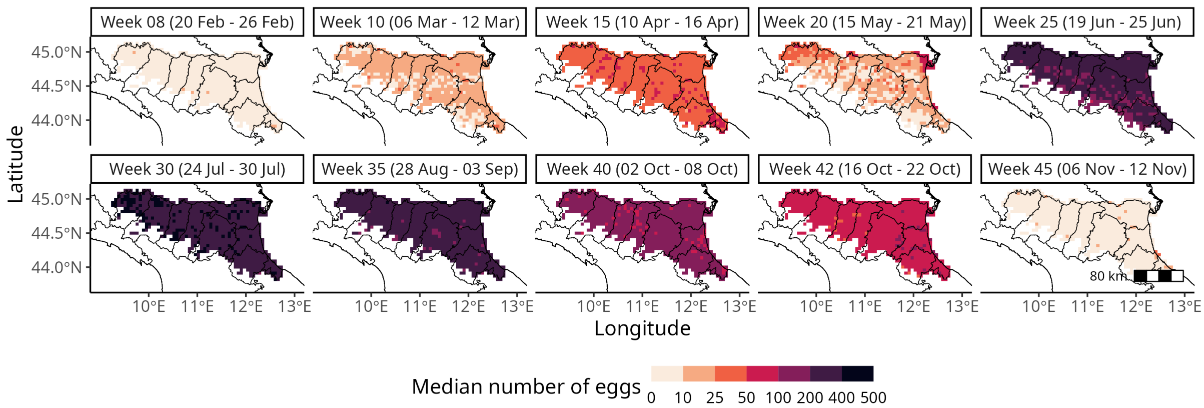


Figure 6: Prediction map showing the distribution and abundance of *Ae. albopictus* eggs over 10 weeks in 2023. The model used to develop image (a) was trained using data from 2021-2022 and 0.75 of the SLs, while for (b) training was done on years 2011-2022 and 0.90 of the SLs.

4 Discussion

This study investigated the development of a passive surveillance system for *Ae. albopictus* in Emilia-Romagna, aiming to define optimal temporal and spatial data requirements and to produce short- and medium-term forecasts of *Ae. albopictus* egg abundance. Accurate predictions of disease vector distribution and abundance trends are essential to guide decision-making and enable effective and timely control measures. Additionally, these predictions are crucial for addressing the nuisance caused by invasive mosquito species, which can significantly impact the quality of life in affected areas. These efforts align with the United Nations Sustainable Development Goals 3 and 13, which focus on ending vector-borne disease epidemics and enhancing early warning systems for global health risks (UN General Assembly 2015). Although earlier studies have explored the distribution and abundance of *Ae. albopictus* using environmental variables and various modelling techniques, both mechanistic and correlative, they have typically focused on a global or continental scale. Moreover, they did not explicitly address the feasibility of producing forecasts within an operational surveillance context, but rather they sought to understand general trends and species-environment relationships. This study aims to bridge that gap by integrating spatial and temporal scaling analyses with predictive modelling into a coherent passive surveillance system, tailored to inform vector control efforts in a timely and regionally specific manner.

The findings presented here have both economic and public health implications. From an economic perspective, the study evaluates the trade-offs between spatial sampling density and model accuracy, potentially informing cost-effective surveillance strategies. From a public health standpoint, the model provides practical insights for vector surveillance and control, offering an alternative to species distribution models (SDMs) by predicting actual mosquito abundance rather than habitat suitability. Unlike suitability models, abundance forecasts can better reflect the expected mosquito pressure in specific locations and time windows. Therefore, while previous studies have predominantly employed SDMs to study the population dynamics of *Ae. albopictus*, our findings suggest that modelling abundance directly, despite its higher data demands and sensitivity to environmental noise, provides a more concrete and actionable metric for vector control planning. For instance, global-scale studies by Kraemer et al. (2015) and Kraemer et al. (2019) adopted a data-driven approach using Boosted Regression Trees (BRTs) to model habitat suitability for Aedes mosquitoes. These studies emphasised mapping global distributions and predicting long-term trends under future climate and urbanisation scenarios. While powerful for assessing global risk and guiding international public health responses, these models focus on presence–absence and suitability, rather than abundance, and are not designed for local or short-term forecasting.

Compared to these earlier works, our model departed from both physiologically explicit and habitat suitability paradigms by directly predicting species abundance at a regional spatial scale and a dynamic temporal scale. Moreover, our approach was largely data-driven and does not require parametrisation of species physiology. A study by Carrieri et al. (2023) applied a Bayesian framework to assess the weather-dependent seasonal trends of *Ae. albopictus* populations, emphasising the role of meteorological variables in shaping egg density patterns. Their work provided valuable insights into the influence of weather and highlights seasonal drivers, however, their outputs focused on relative trends (for instance, expected increase or decrease in egg density) rather than producing direct numerical forecasts. Our study advanced this by offering quantitative abundance predictions, expressed as estimated egg counts per ovitrap per pixel per week, thus enabling more operationally relevant interpretations for mosquito control planning. Finally, our study went beyond correlational modelling by conducting systematic sensitivity analyses on both the temporal and spatial dimensions of input data. This helped assess the robustness of predictions under various data availability scenarios, a consideration largely absent from previous works. In doing so, we provided a more adaptable and scalable framework for regional surveillance systems, capable of balancing forecasting accuracy with practical constraints such as limited data or computational resources.

Our ML model showed improved accuracy with more sampling locations, peaking at 90% coverage (70 ± 1 out of 79 SLs). However, models trained on 50–75% of SLs (38 - $\sim$58 out of 79 SLs) performed comparably, making them viable options when computational or logistical constraints limit data availability. ANOVA confirmed that model performance improved with greater spatial coverage, though intermediate sampling levels performed with comparable accuracy, suggesting a plateau effect beyond a certain threshold.

Maintaining adequate spatial coverage remained critical, as models trained on only 10% of SLs (7 out of 79 SLs) exhibited statistically significant performance degradation compared to those trained on 90% ($p = 0.0041$). Thus, while reducing SLs can be feasible within a certain range, overly limited spatial distribution compromises accuracy. A balance between efficiency and performance was achieved with SL fractions between 50% and 75%, offering flexibility for future applications under resource constraints.

The observed performance degradation could be due to two primary factors: (1) the overfitting of complex models when trained on datasets with limited data, where the model may learn spurious patterns that do not generalise well to unseen data, and (2) a reduction in spatial variability within the dataset. When the spatial coverage is constrained, the model is exposed to a narrower range of environmental conditions, potentially failing to capture the full spectrum of spatial heterogeneity that is critical for making accurate predictions (Randin et al. 2006; Ramampiandra et al. 2023). As a result, the model may have struggled to generalise to regions with unobserved or under-represented conditions, leading to decreased predictive accuracy.

We also expected that models trained with longer historical data periods would show increasingly better prediction accuracy (Goodfellow 2016). However, our results suggested that the model trained on the least number of years exhibited the highest performance metrics during the testing and validation phases. This outcome may be explained by the variance-bias trade-off, where models trained on smaller datasets had lower variability in the data, which reduced variance and overfitting but may have limited the model's ability to capture extreme events or outliers (Bishop et al. 2006; Hastie 2009; Boehmke et al. 2019). Essentially, with fewer years of data, the model was exposed to a narrower range of variability in environmental conditions, making it easier for the model to generalise with a low statistical error for the temporally adjacent data. This could have resulted in a lower prediction error also because the model was less likely to overfit to outlier conditions present in a more extensive temporal dataset (Boehmke et al. 2019; Ramampiandra et al. 2023). Nevertheless, the trade-off depends on environmental stability. In dynamic systems, a longer training period may be necessary to capture relevant patterns and ensure robustness across different scenarios. The balance between bias reduction and generalisation should therefore be assessed in context, particularly for species affected by fluctuating environmental conditions. At the same time, the reduced variability of a limited dataset also means that the model has less information during the training phase and therefore could be less generalised, making it less capable of capturing extreme or rare events outside its training distribution (Boehmke et al. 2019; Ramampiandra et al. 2023), which could explain why the model trained on two years of data failed to predict the decline in abundance in May 2023.

In contrast, the model trained on the most extensive dataset, which included 12 years of data and a more comprehensive spatial distribution of data (a 0.90 fraction of SLs, 70±1 SLs), successfully predicted the lower abundance of mosquitoes in May 2023, which coincided with severe flooding in the eastern part of the region that could have affected reproductive and mortality rates (Harrington 1995; Alto et al. 2001; Medici et al. 2011; Dieng et al. 2012; Carrieri et al. 2023) of *Ae. albopictus*. Indeed, the floods possibly disrupted the tiger mosquito's larval habitats (Carrieri et al. 2011). Specifically, the heavy rains inundated the area, flushing out immature mosquitoes, while subsequent mud accumulation clogged breeding sites, such as manholes (Arrighi et al. 2023; Koenraadt et al. 2008; Roiz et al. 2015; Tran et al. 2013). This population reduction was observed exclusively in municipalities within the southeastern part of the region (Arrighi et al. 2023).

Overall, our model successfully predicted the seasonal timing of mosquito egg abundance, even though they underestimated the peak magnitudes during the summer months (Figure 5). Accurate prediction of seasonal timing remains the core objective of our modeling framework, given its critical importance for anticipating vector activity and guiding public health interventions. Nevertheless, the underestimation of peak abundance may reflect limitations in the model's ability to fully capture population dynamics during periods of high mosquito activity. A factor contributing to this behaviour of the model could be a bias toward the observed mean of the training dataset, which could have lead to the smoothing of extreme values, which is a well-documented tendency in machine learning literature (Zhang et al. 2012; Nguyen et al. 2015; Song 2015; Hooker et al. 2018; Ghosal et al. 2020). This bias can be evident in ensemble methods, particularly those that rely on averaging across multiple models, such as bagging approaches (e.g. Random Forests). This averaging effect tends to shrink the prediction range, resulting in a narrower spread of values compared to the actual variability in the response variable (Meinshausen et al. 2006; Zhang et al. 2012; Frame et al. 2022). Consequently, lower values are often overestimated, whereas higher values, such as peaks in abundance, are underestimated. In the case of stacking, this effect can be primarily observed if the meta-learner assigns a dominant weight to models prone to smoothing extreme values, such as tree-based ensembles like Random Forests - exactly what happened in this study. However, if the highest-weighted model within the ensemble is one that better captures extreme values, such as quantile regression models (Meinshausen et al. 2006), simple neural networks or deep learning-based models - this effect may be less pronounced or absent. While such alternative base models might potentially mitigate this bias by better capturing extreme values, their influence in this specific context remains unexplored due to computational constraints. Future research could systematically evaluate the role of different base learners in stacking, testing whether models optimised for capturing extreme values improve predictions of peak abundance. Additionally, hybrid modelling approaches that integrate process-based models with machine learning could provide an alternative way to better represent population dynamics, particularly under conditions of high variability (Reichstein et al. 2019; Madzokere et al. 2020; Kraft et al. 2021; Steele et al. 2024; Acuña Espinoza et al. 2025).

While this study provides valuable insights into the application of machine learning models for predicting the spread and abundance of *Ae. albopictus* in Emilia-Romagna, some limitations indicate that further research and computational advancements could enhance the accuracy of the results. We observed that generally model predictions align well with observed seasonal patterns in egg abundance, with peaks occurring in the mid-summer weeks. However, 2023 exhibits some differences: observed egg counts fluctuated in ways not fully captured by predictions, which may be attributed to atypical environmental responses. Specifically, the observed mosquito egg abundance in 2023 seems less correlated with temperature and precipitation (Figure S6) compared to previous years (Figure S6), suggesting that possibly external factors beyond the selected covariates or unusual climatic events could have influenced mosquito dynamics.

Another possible source of variability is the impact of vector control measures on the abundance of collected eggs. Pest control agencies are working to reduce the population of the species and minimise the nuisance caused by bites to the public (Ravasi et al. 2021). Unfortunately, this is an uncontrollable factor, as we lack access to detailed information about the timing and location of pest control treatments conducted in the area and period of interest. Although regional authorities adhere to standard guidelines available in technical documents on www.zanzaratigreonline.it, the number of anti-larval treatment cycles varies across municipalities. Furthermore, the products used for vector control were changed in 2017 due to the emergence of resistance in *Culex pipiens* (Grigoraki et al. 2017), which may have influenced the effectiveness of the treatments and, consequently, the variability in egg abundance observed in the dataset.

One of the main practical challenges of this study was determining the appropriate methodology to prevent data leakage between the training and validation sets during the hyperparameter tuning process with 10-fold cross-validation. This issue has been highlighted as potentially problematic in several machine learning studies in the ecological field, particularly when working with highly structured spatial and temporal data (Roberts et al. 2017; Schratz et al. 2019; Kapoor et al. 2023). In this study, we opted to use consistent hyperparameters across all models, which were tuned using 10-fold cross-validation on the training set. This approach was chosen to maintain uniformity in model configuration while maximising generalisation across different data subsets. However, we acknowledge that using complex models on datasets with low volume, limited temporal coverage, and small fractions of data might have increased the risk of overfitting. While tuning each model separately for different partitions could theoretically improve local performance, it would also introduce a higher risk of overfitting due to reduced sample sizes in individual subsets. Future work could explore alternative tuning strategies, particularly for cases where larger datasets or more extensive temporal coverage allow for partition-specific hyperparameter optimisation.

Regarding the spatial distribution of predicted egg counts, the models occasionally estimated high values in areas predominantly characterised by humid rural environments and even in higher mountainous regions. However, we cannot verify the accuracy of these predictions, as ovitraps are typically placed in urban areas at relatively low elevations. For this reason, we chose to mask mountainous areas above 600 m, where no observations are available to validate the predictions. We are also exploring the use proxy variables that capture aspects of microclimatic conditions that benefit *Ae. albopictus*, which thrive in shaded and humid environments. For instance, the leaf area index (LAI) is widely recognised as a reliable proxy for microclimate (Hardwick et al. 2015; De Frenne et al. 2019; Zellweger et al. 2019). LAI measures the amount of leaf surface area relative to the ground area, providing an indicator of canopy cover. Studies have consistently shown a strong correlation between dense canopy cover and moderated microclimatic conditions, such as reduced temperature variability (Scheffers et al. 2014; John et al. 2024), increased humidity (Chen et al. 1999), and decreased solar radiation reaching the substrate (Lieffers et al. 1999; Drever et al. 2003). Additionally, since data collection occurs only between late May and early October, incorporating data from winter monitoring could significantly enhance model performance. Future research could explore adding seasonal adjustments or variables to better capture seasonal abundance peaks, potentially incorporating mechanistic models to address mosquito life cycle shifts (for example, see Madzokere et al. (2020)).

Under ongoing development, a passive surveillance system is being designed to operationalise these predictive models into a user-accessible platform. This system will integrate ovitrap monitoring data with environmental covariates to provide near real-time tracking of *Ae. albopictus* population dynamics and short-term forecasts with an approximate lead time of two weeks. The platform Open-Earth-Monitor will enable the visualisation of historical trends, spatial distributions, and weekly fluctuations in egg abundance, offering an automated and scalable framework for continuous vector monitoring. By streamlining data processing and forecast generation, this tool will enhance the capacity of public health authorities to implement timely and evidence-based mosquito control strategies. Once fully operational, it is expected to improve risk assessment and resource allocation in Emilia-Romagna, with potential applications in other regions facing similar vector-borne disease challenges. Currently, our model has already been implemented in collaboration with the Emilia-Romagna Region and is available as a user-facing tool on the official regional mosquito monitoring portal - www.zanzaratigreonline.it. This platform has been developed to support public health practitioners in planning and prioritising vector control efforts and provides maps of *Ae. albopictus* egg abundance based on the best model in this study.

5 Conclusion

Extensive ovitrap data and associated environmental covariates have allowed the development of models capable of forecasting mosquito population dynamics with significant implications for public health management. Our findings indicate that models trained on extensive historical and spatial data captured broader environmental variability, which was particularly useful under unusual conditions. Moreover, it is clear that models that were trained on a higher fraction of sampling locations consistently produced more accurate predictions, emphasising the value of comprehensive spatial coverage of the monitoring.

The results help enhance mosquito surveillance and control strategies through the operational application of the developed predictive models in initiatives intending to reduce the risk of mosquito-borne diseases in both Emilia-Romagna and other regions facing similar challenges. Indeed, accurate, short-term forecasts of *Ae. albopictus* populations can guide targeted interventions, helping public health authorities allocate resources more efficiently, particularly in high-risk urban areas. A passive surveillance system is currently being developed to integrate ovitrap data with environmental factors, providing near real-time tracking and short-term forecasts of *Ae. albopictus* populations, aiming to enhance vector monitoring and support evidence-based mosquito control in Emilia-Romagna and beyond.

Data Availability

All analyses were performed in R 4.3 (R Core Team 2024). The code and ovitrap data used throughout the study are available in a GitHub repository at www.github.com/margoblaha/StackedER.

Acknowledgements

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Supplementary Material

Table S1: Akaike Information Criterion (AIC) for model selection, where *K* is the number of parameters, *AICc* is the corrected Akaike Information Criterion, *DeltaAICc* is the difference from the best model (competitive if less than 2), *AICcWt* is the probability the model is the best, *CumWt* is the cumulative weight of models and *LL* is the log-likelihood.

Model	K	AICc	DeltaAICc	AICcWt	CumWt	LL
two-way	9	40939.34	0.00	0.63	0.63	-20460.65
interaction	21	40940.40	1.07	0.37	1.00	-20449.08
one-way (fraction of SLs)	6	40964.01	24.67	0.00	1.00	-20475.99
one-way (training years)	5	41025.77	86.44	0.00	1.00	-20507.88

Table S2: Relative RMSE (%) with standard errors (±) for different training years and sampling fractions in the spatial validation. All values are interpreted as a percent of the observed range.

	2021 - 2022	2019 - 2022	2015 - 2022	2011 - 2022	mean
0.10	20.25 ± 0.66	24.34 ± 0.79	21.51 ± 0.57	22.91 ± 0.66	22.25 ± 0.34
0.25	18.43 ± 0.64	18.84 ± 0.56	20.51 ± 0.64	20.46 ± 0.58	19.56 ± 0.30
0.50	18.58 ± 0.74	18.32 ± 0.69	19.02 ± 0.74	19.85 ± 0.72	18.95 ± 0.36
0.75	16.72 ± 0.93	17.69 ± 0.95	19.18 ± 0.92	18.23 ± 1.05	17.97 ± 0.48
0.90	18.75 ± 1.54	17.22 ± 1.60	17.52 ± 1.35	17.49 ± 1.26	17.75 ± 0.72
mean	18.96 ± 0.36	20.54 ± 0.39	20.31 ± 0.33	20.88 ± 0.35	

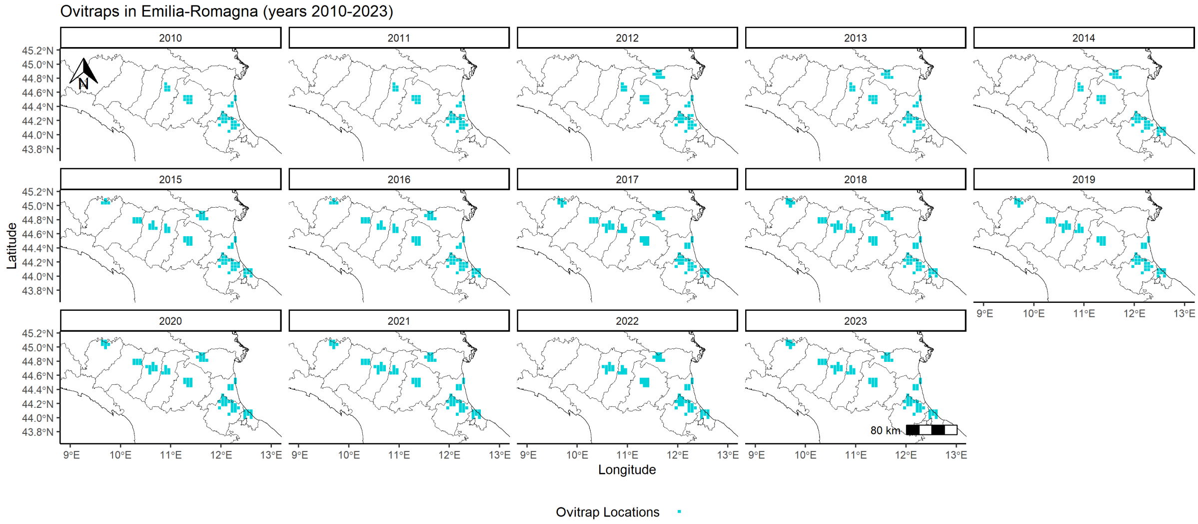


Figure S1: Ovitrap locations for each of the 14 years of sampling.

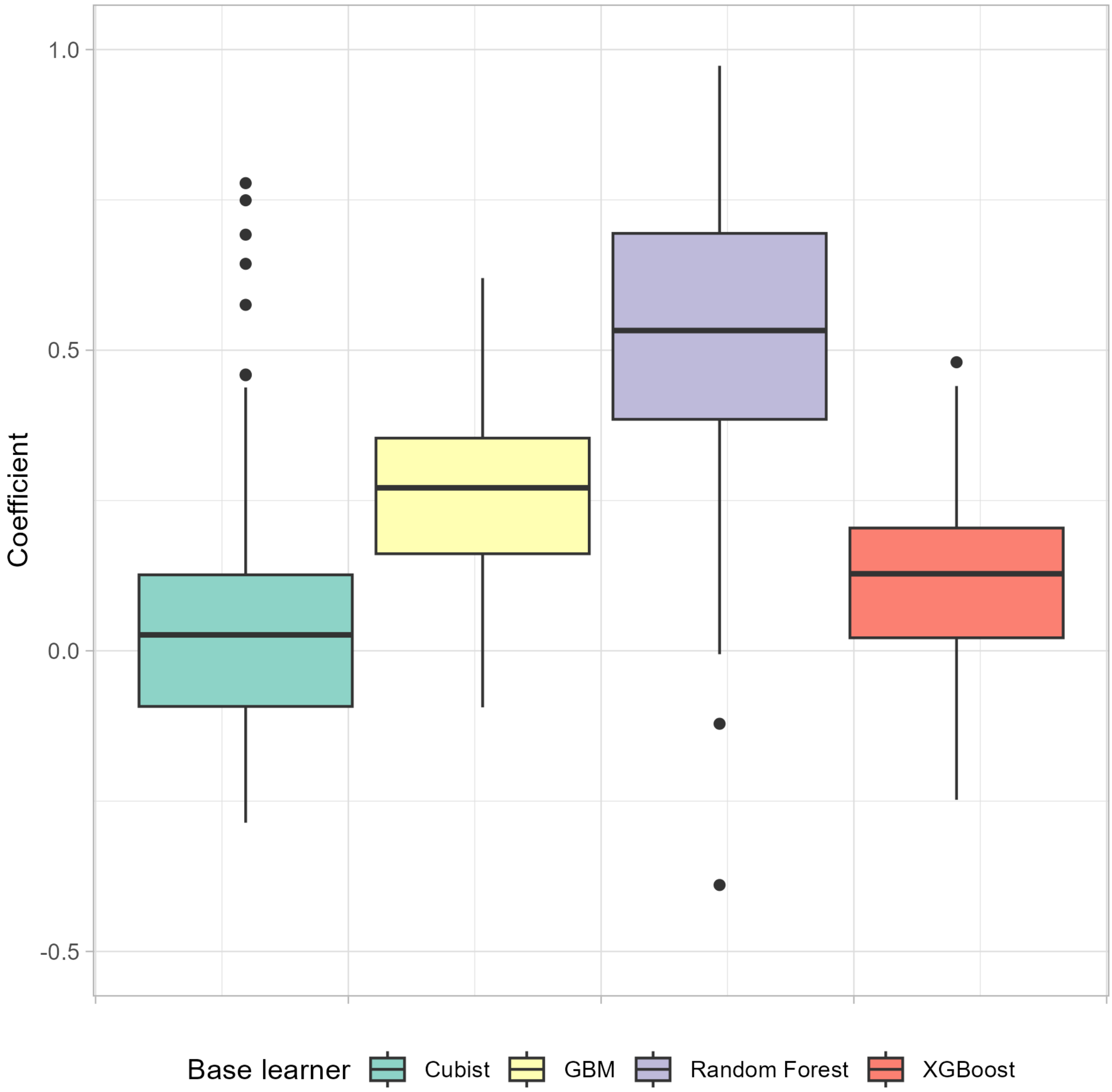


Figure S2: Boxplots of the weights assigned to base learners in the stacked model.

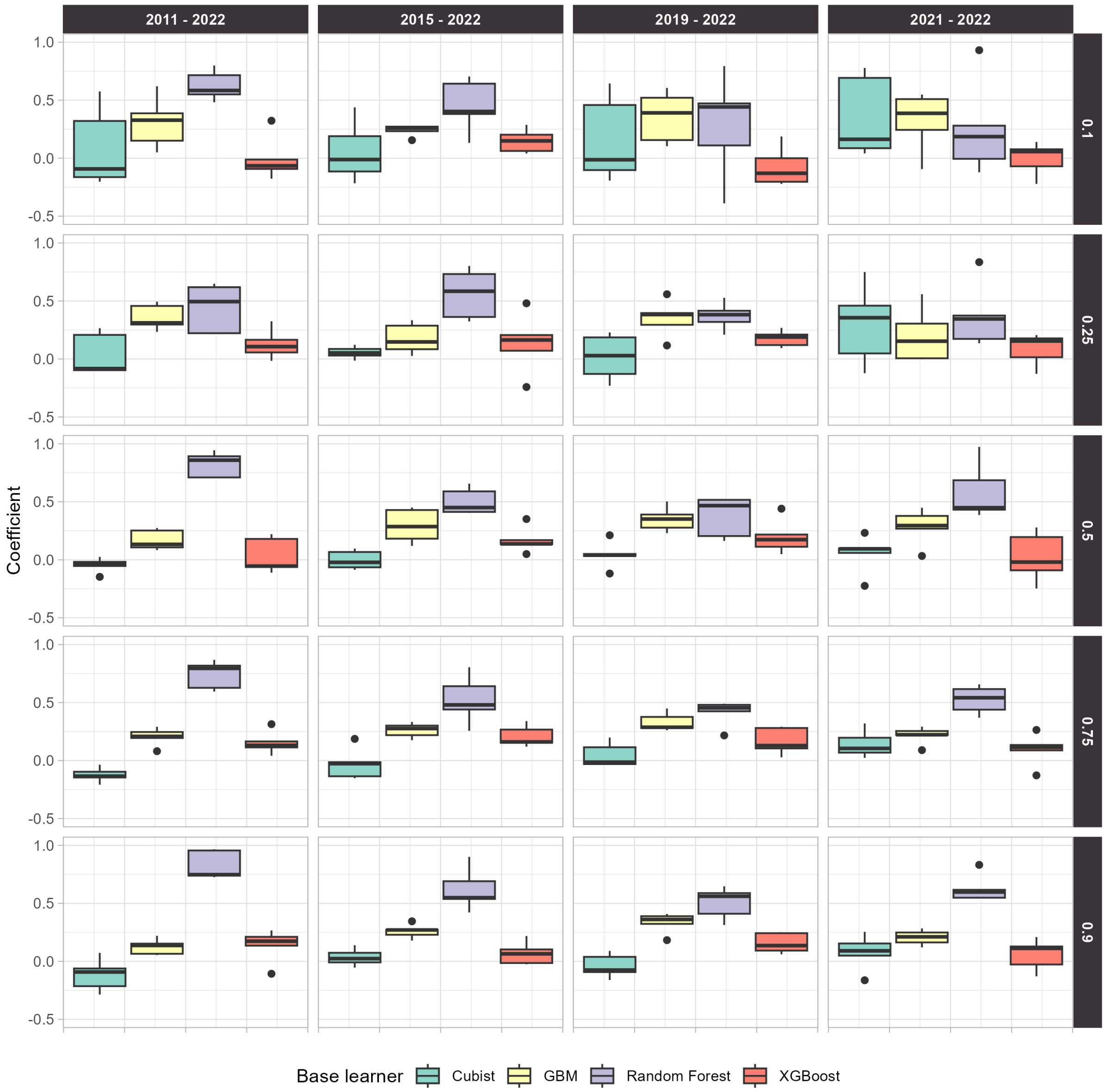


Figure S3: Boxplots of the weights assigned to base learners in the stacked model, grouped by training years and fractions. Each boxplot represents the distribution of weights for a specific base learner (Cubist, GBM, Random Forest, XGBoost) across multiple models. The individual panels show the effect of different training data periods and fraction of sampling locations on the assigned weights.

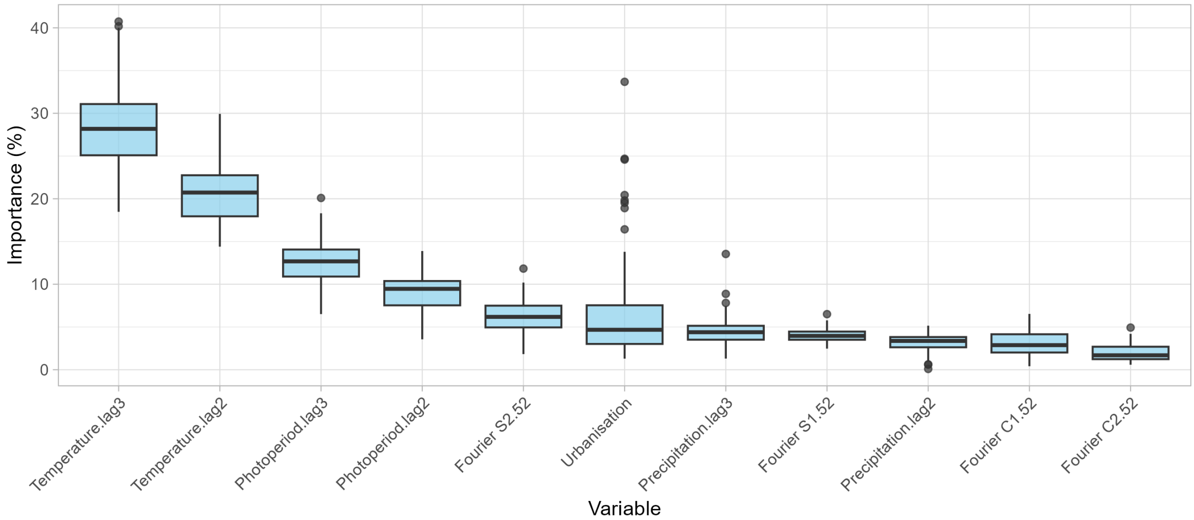


Figure S4: Distribution of variable importance percentages across all models for 11 predictor variables. Each boxplot represents the variability in importance for a specific variable, aggregated over 100 stacked models.

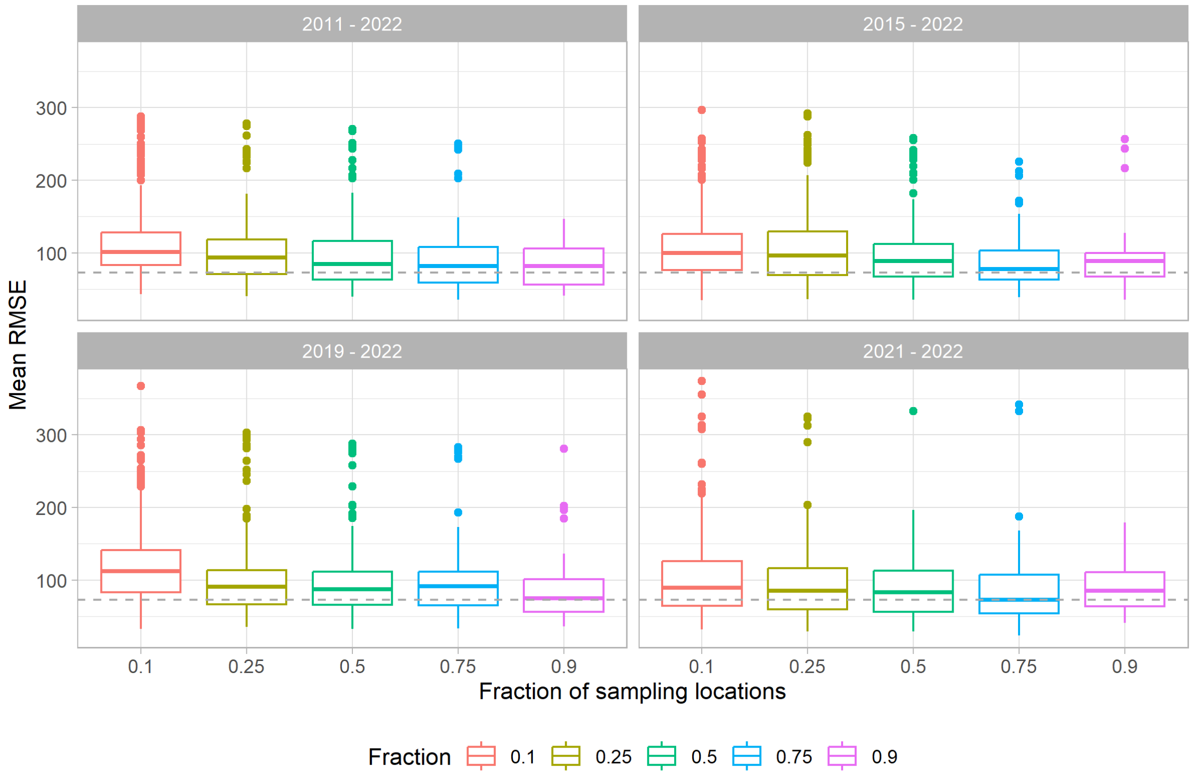


Figure S5: Boxplots illustrating the effect of the fraction of SLs on the mean RMSE for different training year sets (2011-2022, 2015-2022, 2019-2022, and 2021-2022) on the temporal validation set. Each colour represents a different fraction of SLs used in the model training. As the fraction increases, RMSE tends to decrease, indicating better model performance with more spatial coverage.

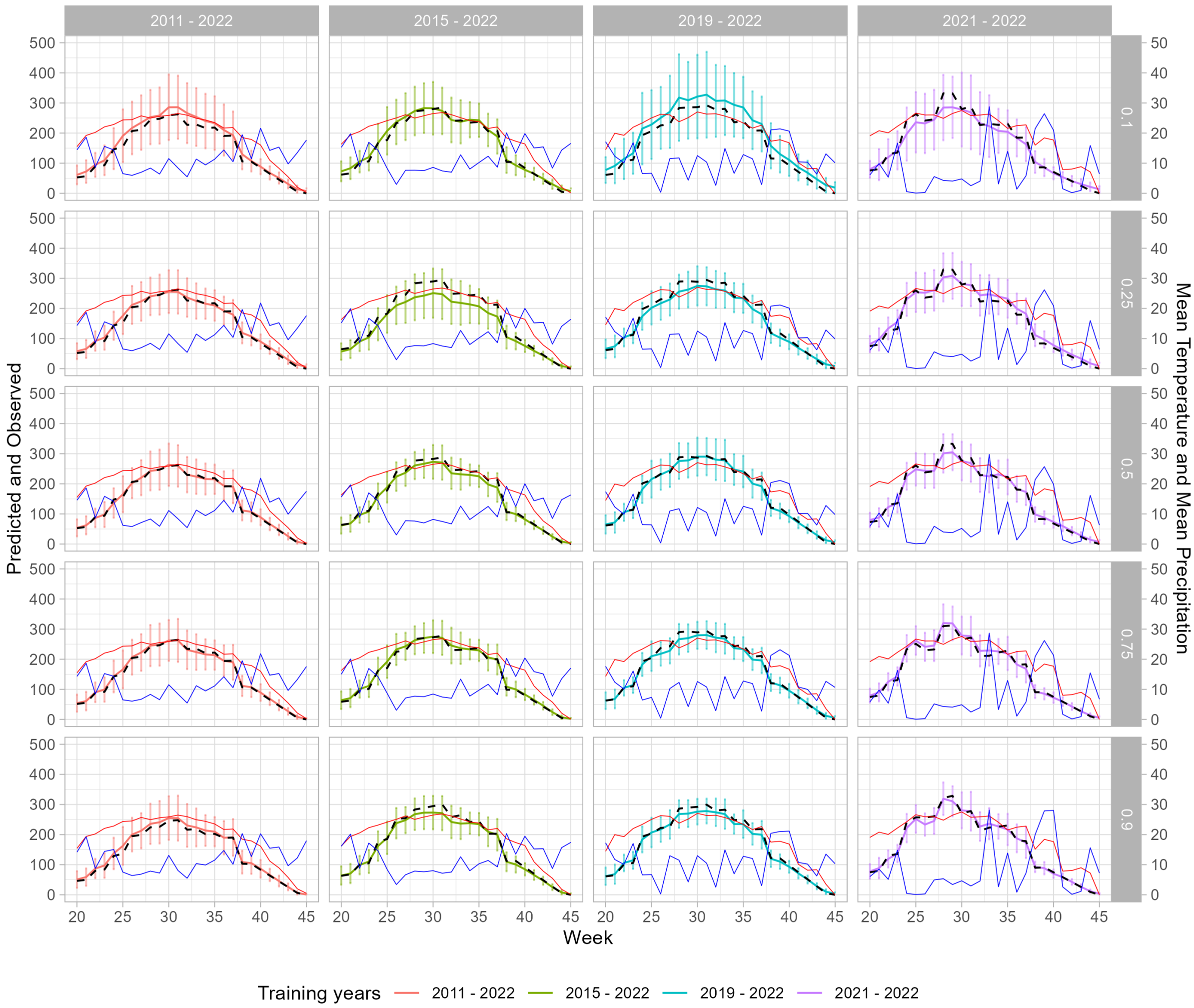


Figure S6: Mean predicted (coloured lines) and mean observed (dashed lines) *Ae. albopictus* egg abundance for weeks 20-45 compared with mean weekly temperature and precipitation (red and blue lines, respectively) for the spatial and temporal validation set across four training periods (2011-2022, 2015-2022, 2019-2022, and 2021-2022) and five data fractions (0.10, 0.25, 0.50, 0.75, and 0.90).

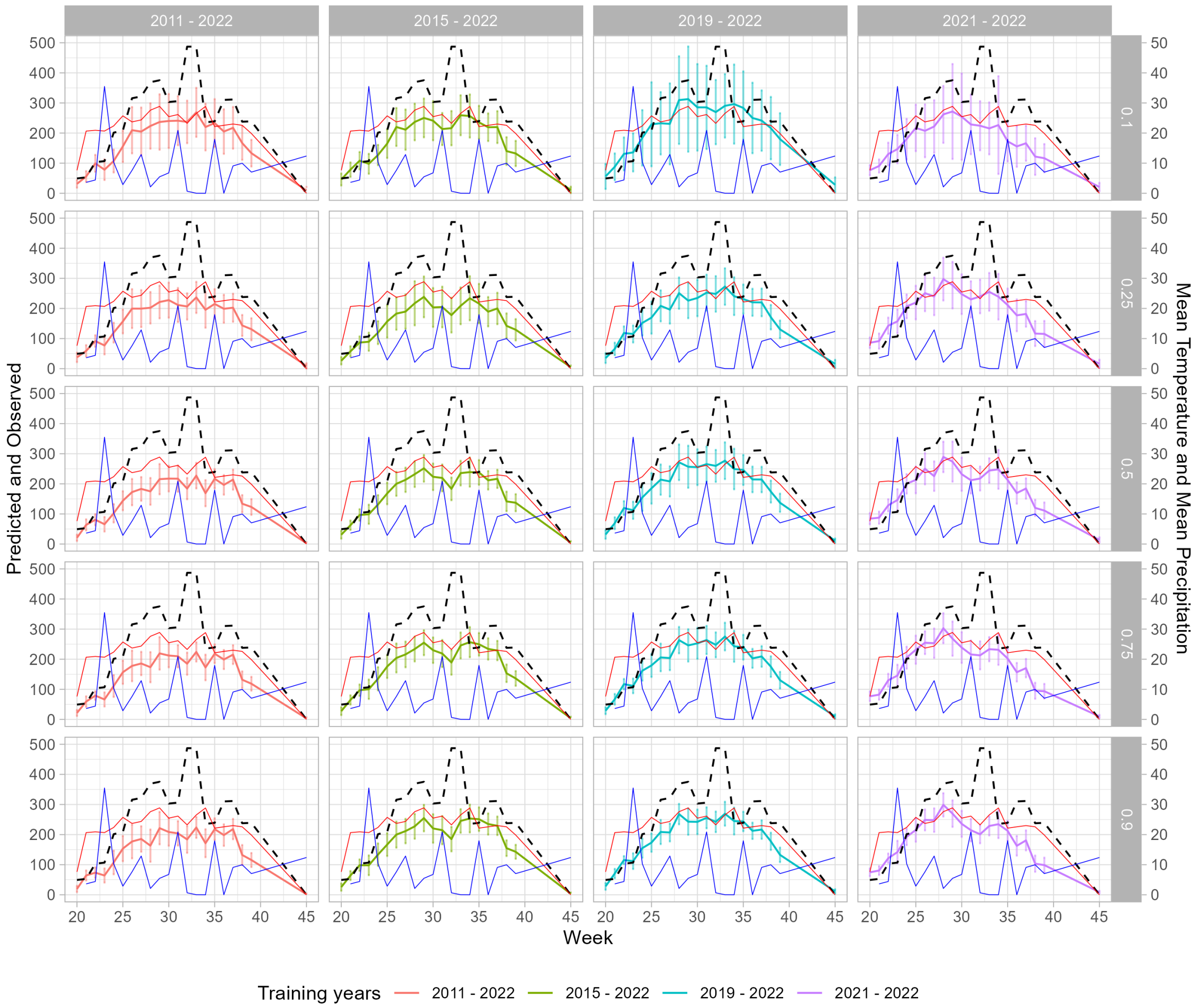
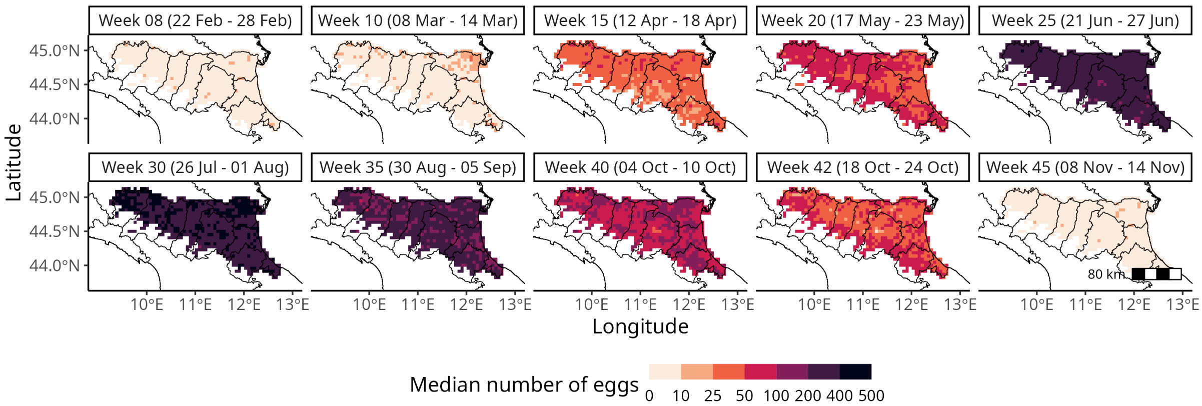


Figure S7: Mean predicted (coloured lines) and mean observed (dashed lines) *Ae. albopictus* egg abundance for weeks 20-45 compared with mean weekly temperature and precipitation (red and blue lines, respectively) for the temporal and spatial validation set across four training periods (2011-2022, 2015-2022, 2019-2022, and 2021-2022) and five data fractions (0.10, 0.25, 0.50, 0.75, and 0.90).

(a)



(b)

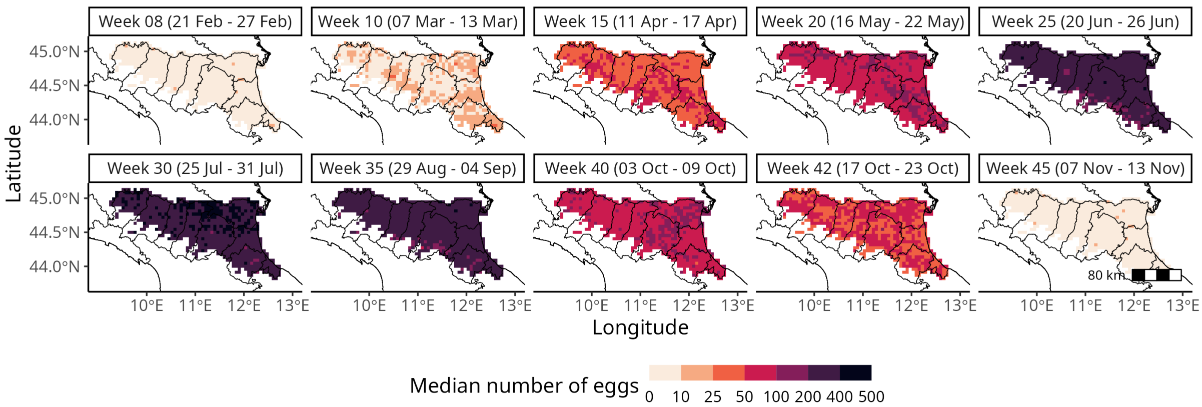


Figure S8: Prediction map showing the distribution and abundance of *Ae. albopictus* eggs over 10 weeks (a) in 2021 and (b) in 2022. The model implemented was trained using data from 2011-2022 and 90% of the SLs.

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