WildMon

PROJECT REPORT

Ecoacoustic Biodiversity Monitoring in Forest Gardens in Homa Bay and Migori, Kenya

In partnership with: Catona Climate,

Trees for the Future (TREES)

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Executive Summary

WildMon, Catona Climate, and Trees for the Future have partnered on a passive acoustic monitoring project within the Forest Garden program in Homa Bay and Migori, Kenya. This initiative seeks to evaluate how the establishment of agroforestry parcels, known as Forest Gardens, influences local biodiversity. By combining acoustic species detection with soundscape analysis, the study provides valuable insights into wildlife presence and distribution, and the ecological impact of Forest Gardens on regional biodiversity patterns.

In 2024 we identified 148 species across 112 sites, bringing the two-year survey totals to **157 species and 120 sites**, including 151 birds, 5 amphibians, and 1 insect. This marks a 23% increase in the number of species and a 67% increase in sites with data compared to the 128 species and 67 sites in 2023, reflecting an expansion in the area monitored and the growing diversity detected through our ongoing work.

Among the most widely distributed species were the common bulbul, village weaver, and white-browed robin-chat. In contrast, the croaking cisticola, northern white-faced owl, scaly-throated honeyguide, and white-headed woodhoopoe were not detected in 2024. None of the species detected are endemic or invasive in Kenya. The grey crowned crane was the only species found that is currently listed as threatened on the IUCN RedList.

Acoustic Space Use (ASU) varied significantly across sites and frequency ranges, highlighting the influence of environmental and site-specific factors. NDVI consistently emerged as the strongest predictor, with **greener areas supporting higher ASU** across all frequencies, while elevation negatively impacted ASU, particularly at higher frequencies associated with insect activity. Notably, **years since enrollment in the Forest Garden Program (FGP) significantly influenced low- and mid-frequency ASU**, reflecting shifts in soundscape composition linked to program participation. Soundscape composition also shifted notably with years of enrollment in the FGP, with distinct differences between conventional agriculture sites and those participating in the program for longer periods.

NDVI and elevation also emerged as key predictors of species occurrence, with NDVI positively associated with higher occupancy rates and elevation exerting a negative influence. **Time since enrollment in the Forest Garden Program significantly boosted species occupancy probabilities**, with sites enrolled for 4 years showing the strongest effects. Furthermore, the 2024 survey recorded higher occupancy rates compared to 2023, indicating a positive trend likely driven by habitat improvements, including vegetation restoration efforts under the FGP.

Estimated species richness was significantly higher at Forest Garden Program sites compared to conventional agriculture sites, with richness increasing with years of FGP enrollment. The greatest gains were observed among species associated with vertically stratified vegetation, such as woodlands and forests, with **woodland species richness increasing by 55% and forest species by 50%**.

These findings highlight the critical role of Forest Gardens in enhancing biodiversity metrics such as ASU, species occupancy, and species richness western Kenya.

Methods

Data Collection

For the second consecutive year, we implemented passive acoustic monitoring (PAM) in Homa Bay and Migori Counties in the Lake Victoria region in Kenya from May 28 to July 08, 2024 (Figure 1). This period of PAM aligns with the region's rainy season, characterized by peak activity for vocally active species such as birds, frogs, and insects. Importantly, the 2024 PAM period mirrors that of 2023, enabling direct comparisons of results between years.

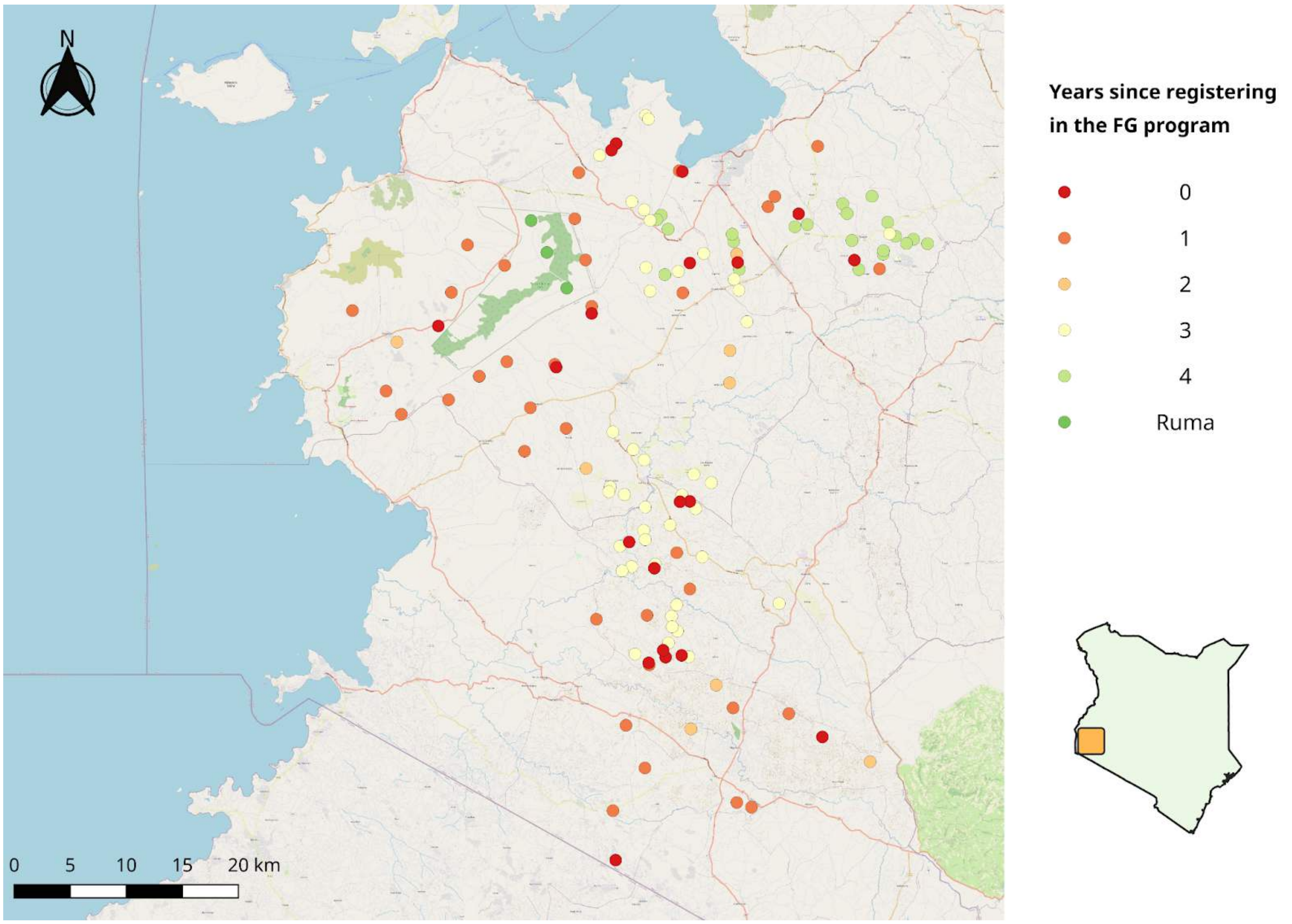
Notably, the 2024 PAM effort presented an opportunity for expansion over 2023 sampling, with a planned increase of 30 new Forest Garden (FG) sites in Migori, 20 conventional agriculture sites split evenly between Migori and Homa Bay, and 20 natural habitat sites in Ruma National Park and other forest patches in the region, effectively doubling the number of locations from the previous year.

Sites were selected to represent a range of time since farms entered into the Forest Garden (FG) program (0-4 years), while also capturing variation in elevation, proximity to protected areas and water bodies, and enabling comparisons with nearby control sites (conventional agriculture) and reference sites (natural habitat). Unfortunately, 11 sites from 2024 had to be excluded from the ecological analyses due to various data limitations. Seven sites from 2023 lacked recordings in 2024 (FG-032397, FG-013923, FG-013974, FG-015179, FG-061560, FG-063670, and FG-050524), while site FG-050564 contained fewer than 15 recordings, likely due to deployment or upload issues.

Additionally, only three reference sites were deployed, resulting in the exclusion of the Ruma National Park sites (Ruma1, Ruma2, and Ruma3) from ecological modeling due to their small sample size, which could have introduced high variance or uncertainty into the analyses.

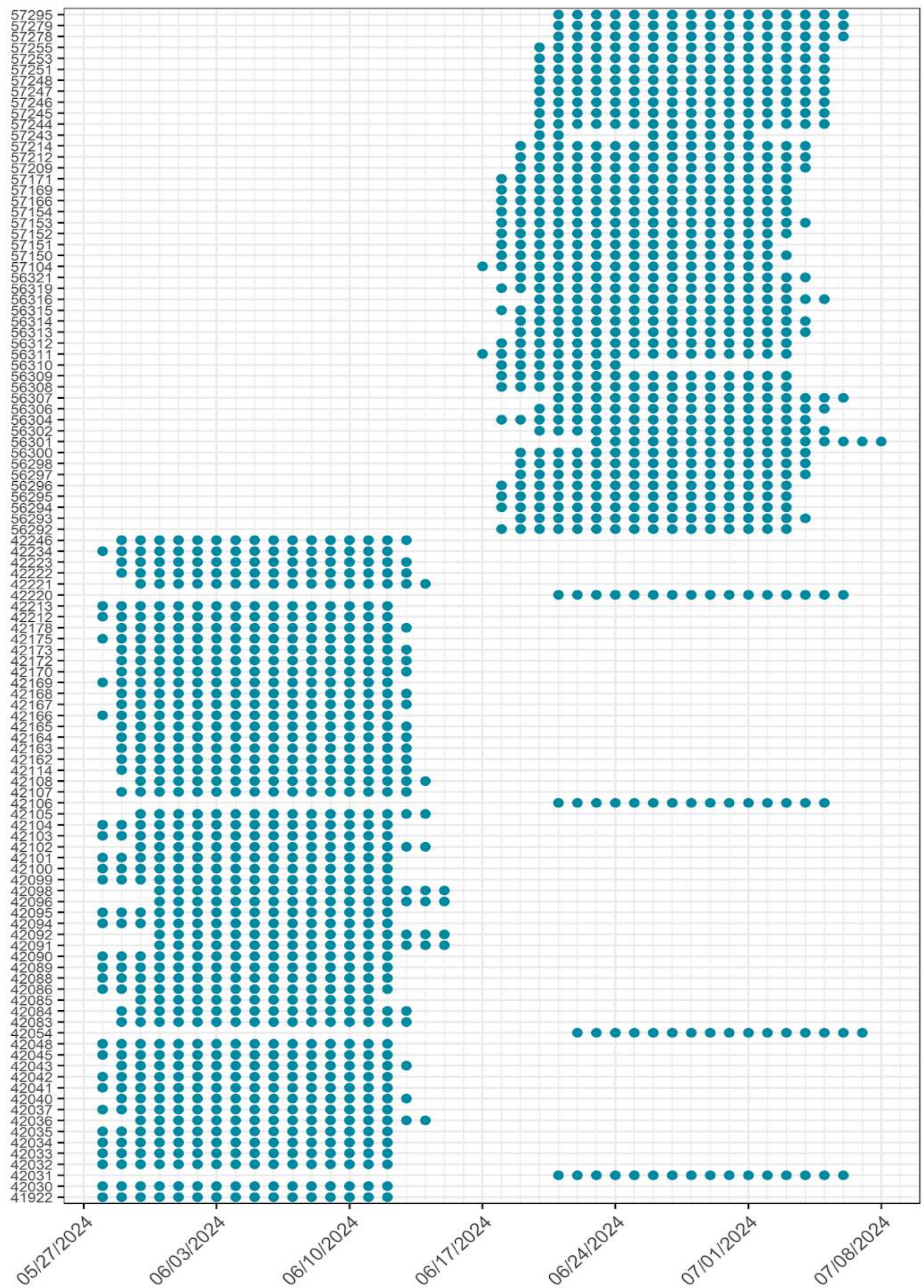
The total number of sites included in this round of ecological analyses came to 116–of which 60 were sampled in both years, 49 were added in 2024, and 7 had data from only 2023, as mentioned above.

Figure 1. Map of the area of interest (AOI) for the 2024 survey. Sampling sites are represented by colored circles indicating the years since enrollment in the Forest Gardens (FG) program.



TREES field staff used Song Meter Micro recorders set to collect a one-minute audio clip every five minutes (48kHz sample rate), resulting in 288 recordings per site per day. Recorders collected data at each site for an average of 16 days in 2024 (range: 8-19, Figure 2). This resulted in a total of 484,808 one-minute recordings, which were subsequently uploaded to the Arbimon platform and WildMon Biodiversity Analytical Platform for acoustic analysis.

Figure 2. Recording periods at 109 sites sampled during the 2024 survey. Each dot represents a recording day. The first recording day was May 28 and the last was July 08, 2024.



Environmental Variables

To better understand how environmental variables influence species distribution and occurrence, we extracted landscape-scale remote sensing (GIS) layers for our ecological models. We selected these environmental variables based on their public accessibility and potential to explain biodiversity patterns based on previous literature (Appendix A).

Some environmental variables tend to be collinear with each other, which can cause problems in ecological models. Therefore, we excluded highly correlated variables within the same models to prevent these issues. After assessing the multicollinearity of the variables and analyzing their value distribution across the sample sites, we retained the following variables for ecological models:

- **Canopy height:** Canopy height data from 2020, derived from GLAD
- **NDVI:** Normalized Difference Vegetation Index calculated using the Planet monthly reflectance basemap. The mean NDVI for June 2023 corresponds to the 2023 sampling period, while the mean NDVI for June 2024 corresponds to the 2024 monitoring period (Planet)
- **Elevation:** Global elevation data at 30m resolution, obtained from Earth Explorer (STRM DEM)
- **Dist to water:** Distance from any water source, calculated using a 9-class land cover dataset (Impact Observatory)
- **Bio15:** Precipitation Seasonality (%; Coefficient of Variation). This metric measures the variability in precipitation, highlighting areas with distinct wet and dry seasons (Worldclim)
- **Survey year:** A categorical variable indicating whether PAM occurred in 2023 or 2024.
- **Years_reg:** The number of years since the site was registered in the Forest Garden (FG) program

To incorporate these variables in our model, we used ArcGIS Pro to create a 200-meter radius buffer around each site (12.57-hectare total area; this corresponds to the estimated detection distance of the recorder across species' calls). This buffer allows us to capture the site-specific micro-environment to better understand how environmental variables influence species detection and occurrence. By using this approach, we can systematically and uniformly incorporate relevant environmental data into ecological analyses at a landscape-scale, and effectively assess these variable's influence on species distribution and occurrence.

Soundscape Analyses

A soundscape encompasses all sounds from a specific location and time, including biophony (sounds from living organisms), geophony (natural sounds like rain), and anthrophony (human-made sounds; Pijanowski et al., 2011). Soundscape analyses serve as a valuable tool to assess spatial and temporal variations of acoustic patterns, unveiling patterns in the community of acoustically active species. Soundscape analyses can also provide insights into how environmental factors, such as land cover and restoration, influence local biodiversity.

We used two soundscape analyses: composition and Acoustic Space Use (ASU). Soundscape composition focuses on the recurrence of acoustic energy in particular time-frequency bins across recording days within a site, as a means to understand the acoustic community of a site.

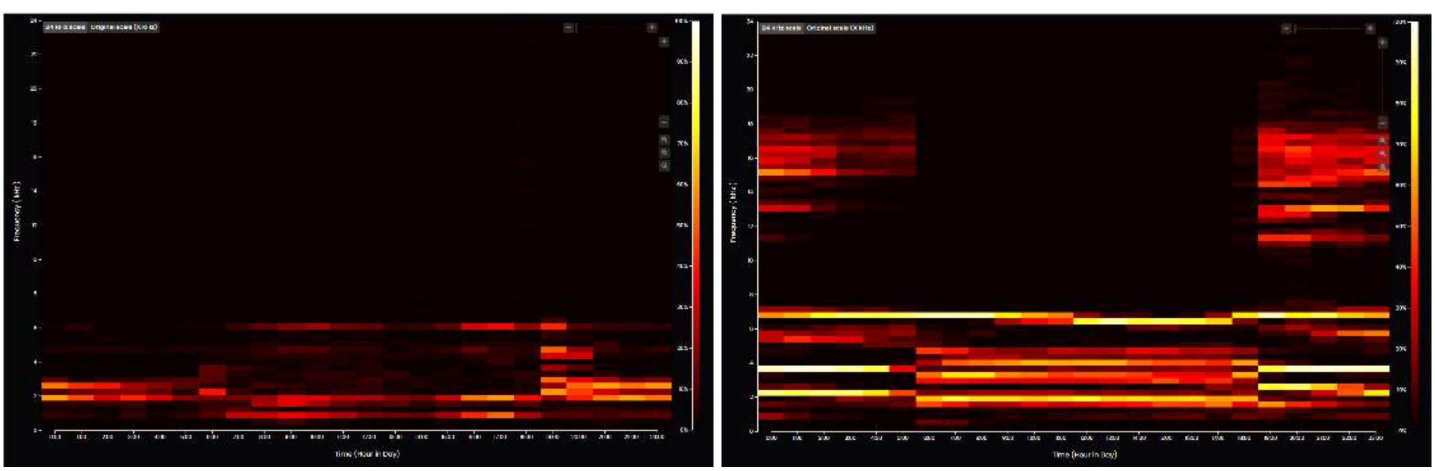
On the other hand, ASU aims to provide a proxy for species richness by averaging the proportion of time-frequency bins occupied across recording days per site. ASU quantifies how much the soundscape from each location is used over time. Species-rich sites, particularly those with many insects, tend to generate more saturated soundscapes with a higher ASU (Aide et al., 2017; Campos-Cerqueira et al., 2019; Ramesh et al., 2023). Both approaches can be valuable for understanding biodiversity patterns and ecological dynamics.

Soundscape Composition

We compared soundscape composition among the 108 sites surveyed in 2024 and tested whether any environmental variables influenced composition. The sampling site FG-026443 was not able to be included in soundscape analysis because recordings only recorded to 22 kHz rather than 24 kHz, which did not allow for comparison. We used Arbimon's soundscape tool to summarize acoustic activity per site; this tool aggregates the amount of acoustic activity at each frequency and hour-of-day period, across all sampling days at that site (Figure 3).

To summarize the variability and composition of acoustic activity in these soundscape maps we employed an ordination technique called non-metric multidimensional scaling (NMDS). NMDS is a dimensionality reduction method that creates a visual representation of objects (in this case, study sites) based on their similarities of a certain variable (here, soundscapes; Figure 3). The resulting NMDS components were then used in further analyses to assess their relationship to environmental variables using linear models. We used a suite of follow-up tests (PERMANOVA, beta-dispersion) to confirm the robustness of our model results.

Figure 3. Soundscape view showing acoustic activity throughout the day in two sites in 2024. The left panel represents MC06, a control site characterized by conventional agriculture, while the right panel shows FG-024428, which has been part of the FG program for three years. The color gradient represents soundscape saturation within each time-frequency bin, ranging from no activity (black) to low activity (red) and high activity (bright yellow).



Acoustic Space Use

We compared soundscape composition among the 108 sites and tested whether any environmental variables influenced composition. We summarized acoustic activity per site; aggregating the amount of acoustic activity at each frequency and hour-of-day period, across all sampling days at that site (Figure 3).

To calculate each site's ASU, we divided each site's recordings into 1,656 time/frequency bins (24 hours x 69 frequency bins) and calculated the percentage of bins 'used' out of the 1,656 total. We considered a time/frequency bin 'used' if a sound with an amplitude >0.05 was detected.

We categorized soundscapes into three distinct frequency ranges:

- **<2 kHz:** low-frequency sounds typical of human noise/machinery, geophony (wind) and some animals
- **2-8 kHz:** mid-frequency sounds typical of terrestrial vertebrates (e.g., birds, amphibians, primates)
- **>8 kHz:** high-frequency sounds typical of insects (e.g., crickets, cicadas)

We conducted our analyses across the full frequency spectrum (0–24 kHz) and within the distinct frequency bins, allowing for a more nuanced understanding of how different taxonomic groups or sound classes respond to environmental factors. Since species can vary in their sensitivity to these factors, analyzing ASU across specific frequency bands provides valuable insights into these patterns.

We then used general linear models with automated model selection and averaging to identify the environmental variables that most influenced Acoustic Space Use (ASU) across all frequencies and within each of the three frequency subsets. Additionally, we examined the relationship between ASU and species richness at each site to evaluate whether ASU could serve as a proxy for the number of bird species in a site. Statistical significance for all soundscape analyses was set at $p < 0.05$.

Species Identification Pipeline

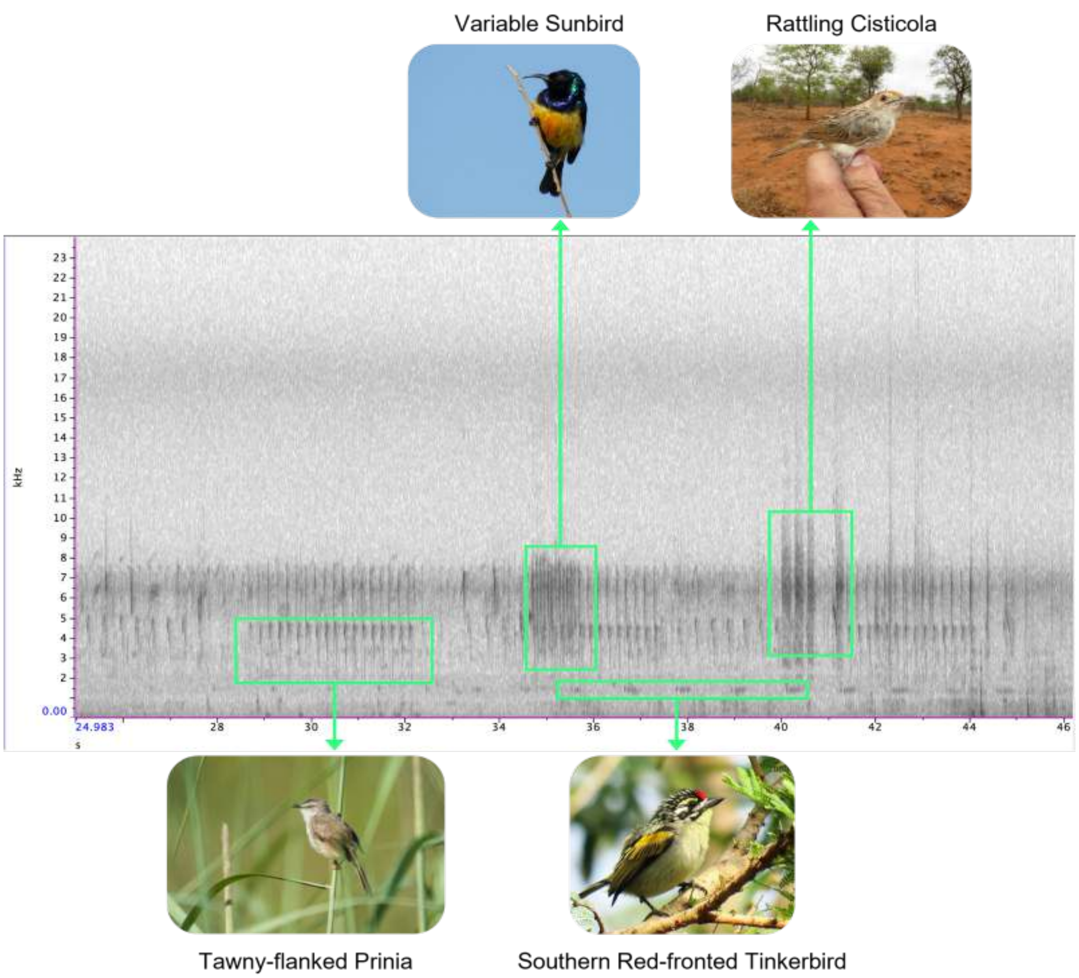
For species identification, we implemented a new pipeline that integrates AI-driven sound recognition, template matching, and expert validation. This approach maximizes detection accuracy and produces a comprehensive species inventory, as detailed below.

The pipeline involves a multi-step process to identify and validate species present in the recordings. First, we generate an initial list of potential species for the area. For this we create a polygon with a radius of 10 to 30 km around the sampling points to define a spatial search area. Within this polygon, the algorithm uses the Global Biodiversity Information Facility (GBIF) database to search for any species groups that can typically be detected by sound, including birds, mammals, frogs, crickets/grasshoppers, and cicadas. This list serves as a starting point and is manually verified to ensure its accuracy.

Once the species list is finalized, it is processed through the BirdNET model, an AI-based sound recognition tool trained on an extensive library of animal vocalizations and human sounds (e.g. chainsaw). The BirdNET model analyzes the audio recordings from our sampling points, matching detected calls and songs to species from the list. The output provides a detailed report of potential matches, which we manually validate to confirm the presence of each species. This step helps us generate a refined list of species identified in the recordings.

To enhance the detection process, we also create a set of acoustic templates based on the species not identified by the BirdNET model, but that were present in the initial list of potential species in the area. This procedure extends detections to species missed by the BirdNET model and is especially important for identifying amphibian, mammal, and insect species not yet included in the model. Using these templates, we run an additional method, based on Template Matching (TM) to detect these missing species. Our Template Matching tool allows us to select an example of a species' call or song (shown as a green box in Figure 4), which acts as the "template". These templates are carefully reviewed to ensure they represent high-quality, species-specific vocalizations. The tool then scans through recordings to automatically detect similar sounds that match the selected template (Figure 5).

Figure 4. Annotated spectrogram with species' calls from a 1-minute recording.

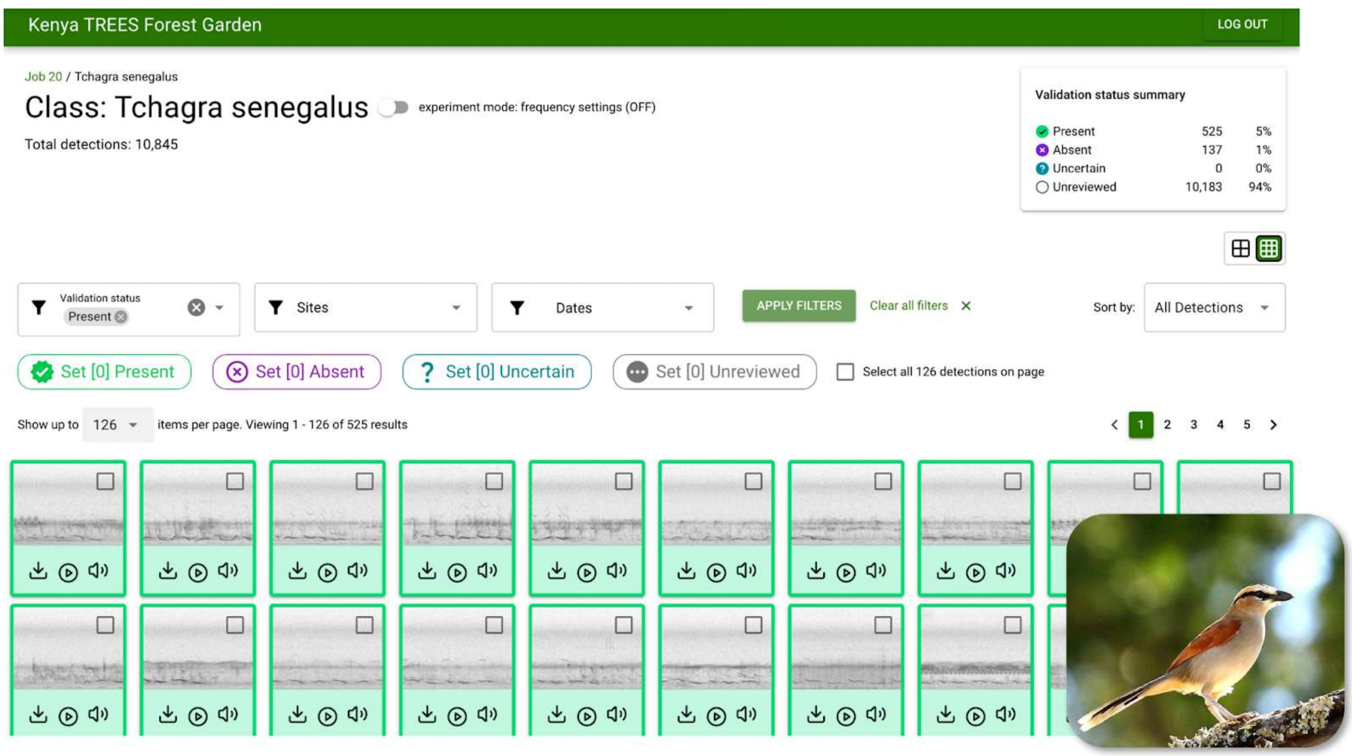


Finally, for species of particular interest to the project that were not detected through BirdNET, we conduct targeted searches using platforms such as Xeno-canto to find audio recordings of these species. These recordings are used to create external acoustic templates in Raven, a specialized tool for analyzing sound. These external templates are then used in TM, and the results are manually validated to further expand the list of identified species.

This iterative pipeline ensures a comprehensive inventory of species, combining the power of AI sound recognition, database queries, and expert manual validation to maximize detection accuracy and completeness.

The BirdNET model and Template Matching results were validated using two distinct filtering approaches. The first, *Best per Location per Day*, identifies the detection with the highest possible score for each site and each day, ensuring that all species data used in analyses are verified. The second approach, *All Detections*, aims to increase the number of recorded presences, particularly for species with few detections, using the first filter to achieve a sufficient sample size to effectively train an AI model.

Figure 5. Template Matching visualization page from the WildMon Biodiversity Analytical Platform.



Species Identification - AI Model

We used the validated species detections from TM and the previously trained model as presence-absence data to train a new Convolutional Neural Network (CNN) model. Details of the AI model's training, evaluation, and workflow are provided in Appendix B.

The training dataset included 136 species (classes), up from 104 species in the previous iteration. The final model achieved strong performance on the test set, with a Weighted Average Precision (wAP) score of 0.94 or higher for most classes (Appendix C).

Species Classification - Ecological traits

Species classification into habitats and ecological guilds was performed using the AVONET dataset, which provides comprehensive morphological, ecological, and geographical data specifically for avian species. As AVONET does not encompass data for non-avian taxa, biological groups such as mammals and amphibians were assigned a classification of 'NA' for both guild and habitat traits (Appendix D).

Ecological Analyses - Occupancy Models

Occupancy modeling is a powerful method that can be used to predict the probability that a species "occupies" sites while accounting for imperfect detection. Further, occupancy modeling enables us to integrate environmental variables to assess how these influence species presence and distribution (Dorazio & Royle, 2005; Doser et al., 2022).

We developed multi-species occupancy models (MSOM) for 132 species using validated acoustic detections from 2023 and 2024, combined with the previously described environmental variables. Notably, the number of species incorporated into the MSOM increased from 95 to 132, representing a 39% expansion in the number of species analyzed. While this reflects a significant improvement in species coverage, three species analyzed in 2023 — emerald-spotted wood-dove, blue-spotted wood-dove, and brubru — were not included in the 2024 analyses. These species possess distinctive song characteristics, such as extended song durations, which posed challenges for precise identification using the first iteration of our pipeline. Additionally, for brubru, discrepancies in the classification of vocalizations from the 2023 dataset were identified, prompting its exclusion from ecological analyses in 2024 to maintain consistency and accuracy. All issues with identification work for these species have been resolved since ecological analyses were completed, and data for each will be available for the 2025 analyses.

Our focus on the 132 species included in the MSOM stems from species presence during the first year of passive acoustic monitoring, the ecological traits they possess that enhance understanding of broader biodiversity patterns, and the availability of reliable call templates for species identification. Importantly, all species included in the MSOM underwent manual detection validation for both the 2023 and 2024 monitoring periods. Newly incorporated species for 2024 had any 2023 data reviewed and revalidated to ensure standardization and enable meaningful year-to-year comparisons.

Further information on all acoustic and ecological analyses, including support tables, candidate models, and figures, is available in the supplementary files.

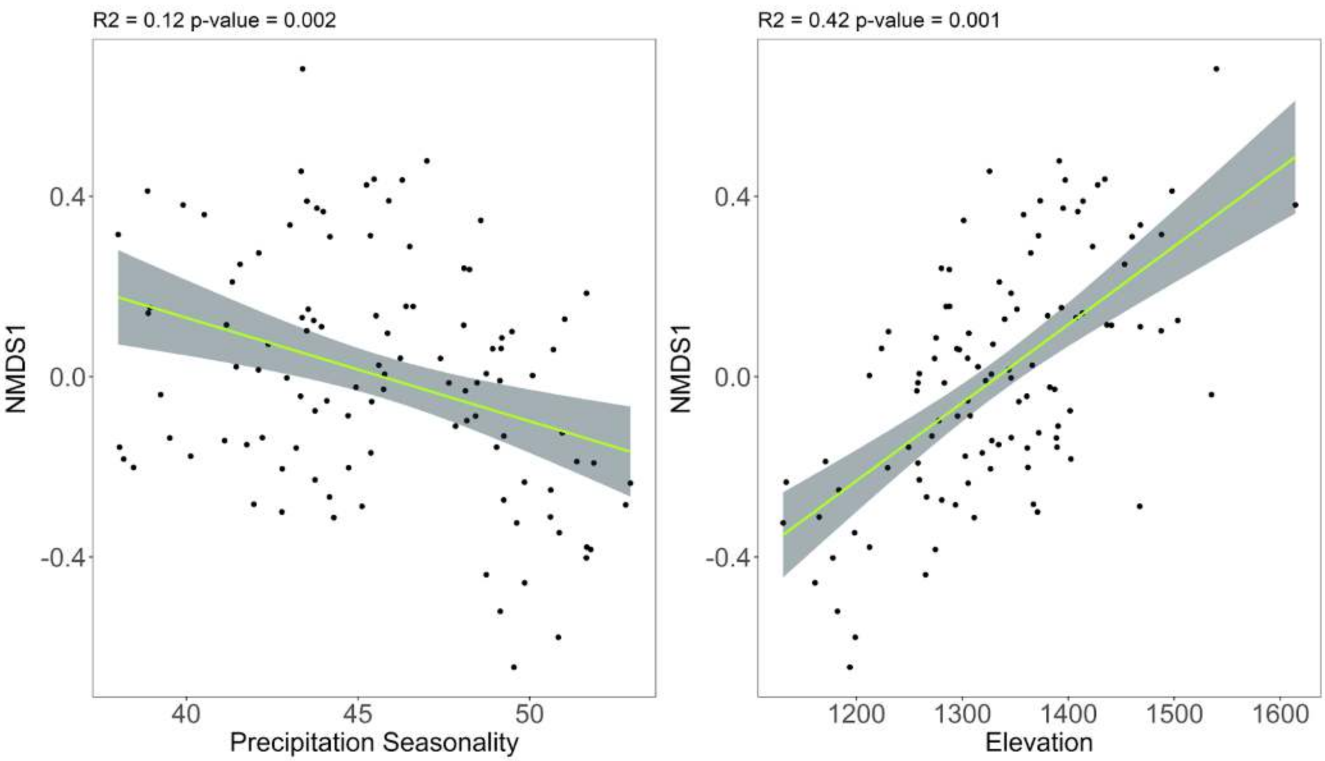
Red-fronted tinkerbird (*Pogoniulus pusillus*)

Results

Soundscape Composition

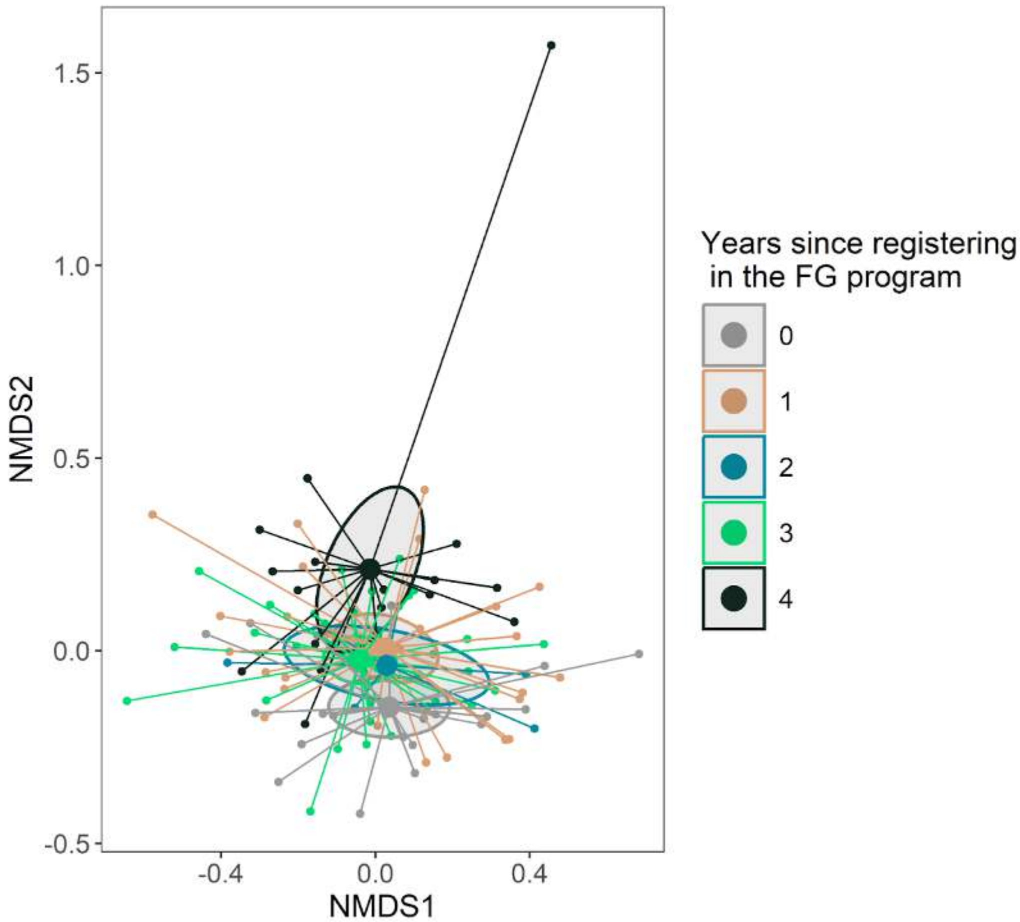
The NMDS analysis captured a substantial portion of the original dissimilarity, with a non-metric fit R^2 of 0.968 and a stress value of 0.18, indicating a robust representation of the data in reduced dimensions. Among the variables tested, precipitation seasonality (Bio15) and elevation were identified as significant factors influencing changes in soundscape composition across the sampling sites (Figure 6; supplementary files). In contrast, canopy height, the NDVI (vegetative greenness), and distance from water did not exhibit a significant impact on soundscape composition.

Figure 6. Variation in soundscape composition (NMDS1) across precipitation seasonality (left panel) and elevation (right panel) gradients, based on data from 108 sampling sites surveyed in 2024.



Furthermore, our NMDS ordination results and Envfit analysis revealed significant differences in soundscape composition among site groups categorized by years since enrollment in the FGP. The biplot of the first two NMDS dimensions indicates that the groups are primarily separated along the second ordination axis. Typical agriculture sites (not enrolled in the FGP) are positioned at one extreme, while sites with four years of FGP participation occupy the opposite end of the axis (Figure 7). Sites with 1 to 3 years of FGP enrollment fall between these two extremes and exhibit greater overlap in soundscape composition, suggesting a less distinct separation among these intermediate groups (Figure 7).

Figure 7. NMDS ordination plot illustrating variation in soundscape composition across 108 sampling sites surveyed in 2024, grouped by years since enrollment in the Forest Gardens program.



To statistically validate these differences, a Permutational Multivariate Analysis of Variance (PERMANOVA) confirmed significant variation in soundscape composition among the site groups ($F = 1.61$, $R^2 = 0.059$, $p = 0.002$). Post-hoc pairwise comparisons revealed that the most pronounced difference occurred between sites with no FGP enrollment and those enrolled for four years, while intermediate groups (1 to 3 years of FGP enrollment) displayed less distinct differences, aligning with the patterns observed in the NMDS biplot. Multivariate homogeneity of group dispersion, assessed using Betadisper, indicated no significant differences in variance among groups ($F = 1.82$, $p = 0.13$), suggesting that the observed differences in soundscape composition are not driven by differences in within-group variability but rather by shifts in composition between groups.

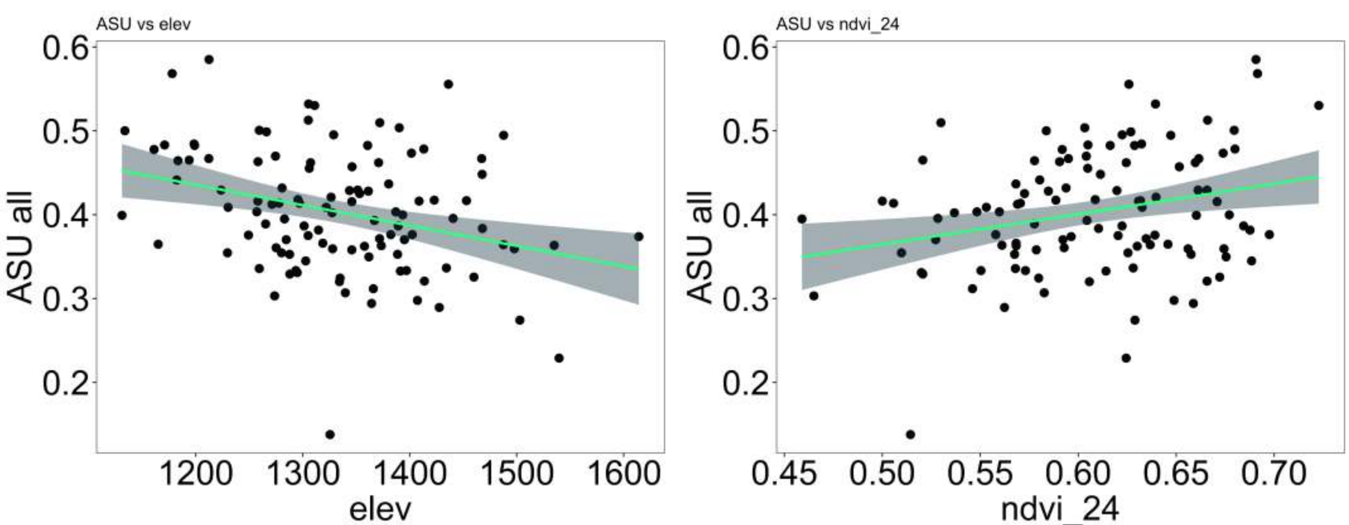
Acoustic Space Use (ASU)

Our results revealed considerable variation in Acoustic Space Use (ASU) across sites, ranging from 14% to 59%, with a mean of 40.3% (SD = 7.3%). Notably, the use of acoustic space in 2024 was slightly lower and less variable compared to the 2023 acoustic monitoring results (ASU-2023: mean 44.7%, range: 30.5%–86.5%).

Our analysis of ASU across all frequencies (from 0 to 24 kHz) revealed significant variation influenced by environmental factors and site characteristics. The top-ranked model explaining ASU variation included years since enrollment in the Forest Gardens program, elevation, NDVI, and distance to water as explanatory variables (AICc = -274.34, weight = 94.7%; Appendix E). Among these, only elevation and NDVI were statistically significant predictors (Figure 8).

Elevation had a negative influence on ASU, with a relatively small effect size (Estimate = -0.000277, SE = 0.000069, $p < 0.001$; Figure 8), indicating that ASU decreased slightly at higher elevations. Conversely, NDVI had a positive and much stronger effect (Estimate = 0.43, SE = 0.13, $p < 0.01$; Figure 8), suggesting that areas with greener vegetation exhibited substantially higher acoustic space use. While other variables, including years since enrollment and distance to water, were included in the model, their effects were not statistically significant. These findings underscore the role of vegetation cover and elevation in shaping soundscape characteristics, with greener, low-elevation areas supporting greater acoustic space use.

Figure 8. Variation in Acoustic Space Use (ASU) across elevation (left panel) and NDVI (right panel) gradients.



The analysis of Acoustic Space Use revealed notable differences in environmental and site-specific drivers across low, medium, and high-frequency soundscapes. While the all-frequencies model highlighted elevation and NDVI as significant predictors of ASU, frequency-specific models provide additional insights into the factors shaping acoustic space use across the soundscape spectrum.

Low-frequency ASU, often associated with human and geophonic noises (e.g., rain, wind) as well as the vocalizations of certain species such as doves, pigeons, and large terrestrial mammals, was best explained by years since enrollment in the FGP, distance to water, and precipitation seasonality (Bio15; Appendix F). Significant effects were observed for precipitation seasonality (Estimate = -0.0075, p = 0.0075) and sites enrolled in the FGP for four years (Estimate = -0.068, p = 0.0451), indicating that areas with lower variability in precipitation and those participating in the program for longer periods exhibited reduced use of the acoustic space in low frequencies.

Mid-frequency ASU, typical of terrestrial vertebrates (i.e. birds and frogs), was best explained by years since enrollment, elevation, NDVI, and distance to water (Appendix G). NDVI had a significant positive effect (Estimate = 0.80, $p < 0.001$), highlighting the importance of vegetation cover, while elevation showed a negative effect (Estimate = -0.00019, p = 0.046), indicating reduced ASU at higher altitudes.

High-frequency ASU, dominated by insect sounds, was best explained by years since enrollment, elevation, NDVI, and distance to water (Appendix H). Elevation exhibited a negative effect with a relatively small effect size (Estimate = -0.00037, $p < 0.001$), reflecting lower insect activity at higher elevations, while NDVI had a marginally positive effect (Estimate = 0.29, p = 0.074).

Across all frequency ranges, NDVI consistently emerged as an important predictor, underscoring the role of vegetative cover in shaping acoustic activity. Elevation also consistently showed a negative effect, with the most pronounced impact in high-frequency sounds, likely due to elevation-driven changes in microclimate affecting insect activity.

Species Identification

We identified a total of 157 species, including 152 birds, five amphibians, and one insect (the African mole cricket) across 2 years of acoustic monitoring. Notably, this represents a 23% increase in the number of species identified compared to the 128 recorded during the 2023 acoustic monitoring alone. None of the identified species are classified as endemic or invasive to Kenya (Appendix D) according to the Global Invasive Species database and BirdLife.

Among the identified species, the grey crowned crane is listed as Endangered on the IUCN Red List (Appendix D). Notably, the number of detections of grey crowned crane increased remarkably from 11 to 91, and the proportion of occupied sites rose from 0.05 to 0.20 between 2023 and 2024. Although it is difficult to distinguish whether these changes are due to population fluctuations or improvements in habitat quality, the data are promising and suggest that the region's landscape may be becoming a more suitable habitat for this species, which is of significant conservation concern. Forest Gardens accounted for 65% of sites where the crane was detected (15 of 23), with conventional agriculture sites (n = 7) and reference sites (n = 1) representing 30% and 4% respectively.

The bird species analyzed in this project exhibited diverse dietary categories, with invertivores (invertebrate eaters) comprising 54% of the species studied (Figure 9a). Following this, the most common dietary groups were granivores, frugivores (fruit eaters), and omnivores (Figure 9, left).

Among the 126 bird species included in the models, 39 (31%) are woodland specialists, primarily inhabiting medium-stature tree-dominated habitats such as Acacia woodlands, riparian woodlands, and forest edges (Figure 9, right). These were followed by species specializing in scrublands (35), grasslands (18), and forests (17). Notably, 12 species were associated with wetlands, likely reflecting the influence and proximity of Lake Victoria to the sampling areas.

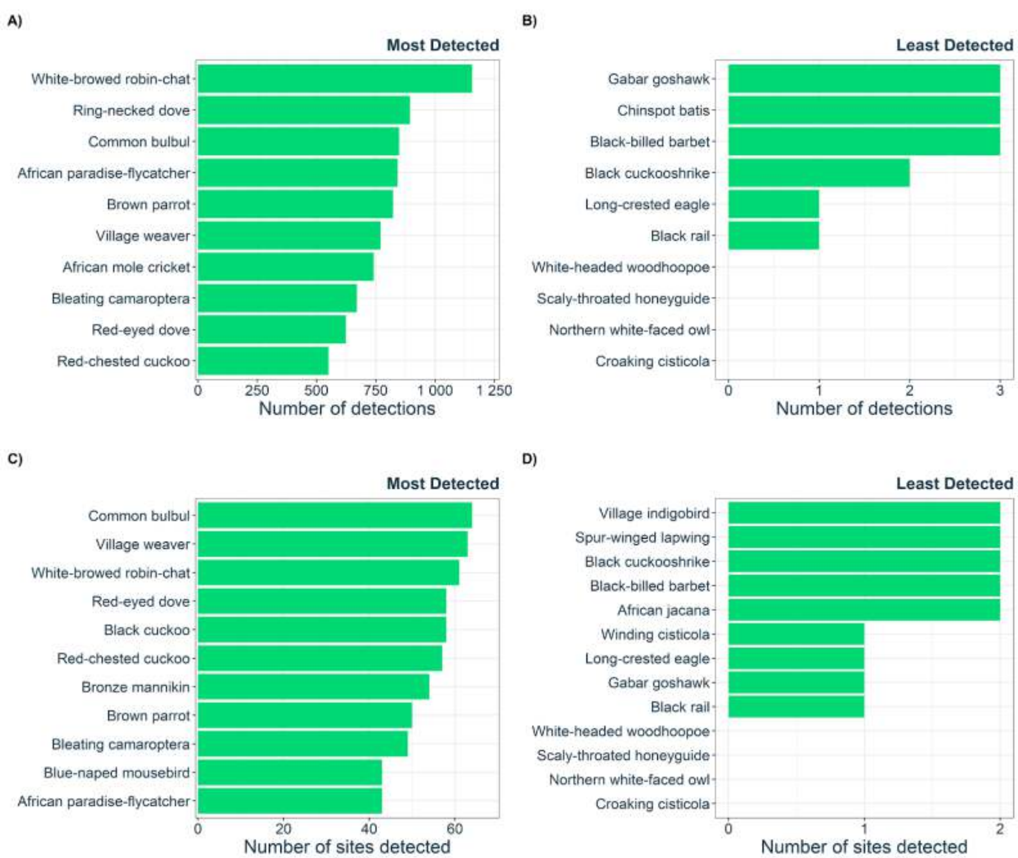
The diversity of bird species in these habitat groups reflects the dominance of land use and cover in Homa Bay and Migori counties. Agricultural land, which makes up >58% of Homa Bay and >70% of Migori, has likely shaped the prevalence of shrubland and grassland specialists, as these habitats are often associated with cultivated or degraded landscapes (Onyango et al. 2021). The scarcity of forest specialists aligns with the extremely low forest cover (<0.6%) in both counties, highlighting the limited availability of intact forest habitats. Meanwhile, the relatively high proportion of wetland-associated species emphasizes the ecological importance of Lake Victoria and its surrounding wetlands, which act as vital refuges for biodiversity. Overall, these results underscore the need to conserve a mosaic of habitat types, particularly wetlands, and woodland and forest fragments, to sustain avian diversity in this highly modified landscape.

Figure 9. Treemap bird species plot, showing the diet preference (left) and habitat preference (right) of species detected.

In the 2024 acoustic survey, the white-browed robin-chat was the most detected species, with over 1,110 detections. This high detection rate can be attributed to its widespread distribution and relatively low habitat specificity. The white-browed robin-chat primarily inhabits riverine forests with discontinuous canopies and dense thickets but is also recorded in drier areas following rainfall in Kenya. Additionally, while vocal activity is typically highest during the rainy seasons in East Africa, the species is known for having a loud song that can last for several minutes and for breeding and maintaining vocal activity year-round in regions surrounding Lake Victoria, where the survey was conducted.

Following the white-browed robin-chat, the ring-necked dove, common bulbul, African paradise-flycatcher, brown parrot, and village weaver each registered more than 750 detections (Figure 10A). Notably, three of these species—the common bulbul, village weaver, and white-browed robin-chat—were the most widely distributed, occurring in more than half of the sampling sites (Figure 10C). In general, the high detection rates of these species can be attributed to their commonality, abundance, and adaptability to diverse habitats. Species such as the African paradise-flycatcher and common bulbul are well-suited to wooded or bushy environments and are frequently found near human settlements, orchards, and gardens. Similarly, the ring-necked dove and village weaver thrive in savannas, cultivated areas, and rural landscapes, aligning closely with the Forest Garden program's approach. In particular, village weavers live in breeding colonies where they build their nests in trees close to houses and home gardens. Together, their habitat preferences and ecological flexibility make them highly compatible with the mosaic of natural and managed environments in the study area. The brown parrot, which inhabits a wide range of open woodland and riparian habitats, is also a common breeding resident. However, it warrants attention as it is listed in Appendix II of CITES, highlighting the need for controlled trade to mitigate potential threats to its persistence.

Figure 10. Multiplot showing most and least detected species across all sites in 2024.



Four species detected in the 2023 acoustic survey—white-headed woodhoopoe, scaly-throated honeyguide, northern white-faced owl, and croaking cisticola—were not detected in 2024. Black rail, gabar goshawk, long-crested eagle, and winding cisticola were detected in only 1 site each in 2024 (Figure 10B, D). These species were relatively rare in the 2023 samples, occurring at only one or a few sites with very few detections. Their absence in 2024 could be attributed to their general scarcity in Kenya, as is the case for the scaly-throated honeyguide.

Occupancy Models - Species Detectability

Overall, the top-ranked MSOM demonstrated good model convergence, with all community-level parameters showing satisfactory values for the Gelman-Rubin diagnostic (R-hat) and effective sample size (ESS). However, a few species-level parameters had R-hat values exceeding 1.1 and ESS below 450, indicating inadequate mixing of the MCMC chains. Consequently, the results for these species should be interpreted with caution (supplementary materials).

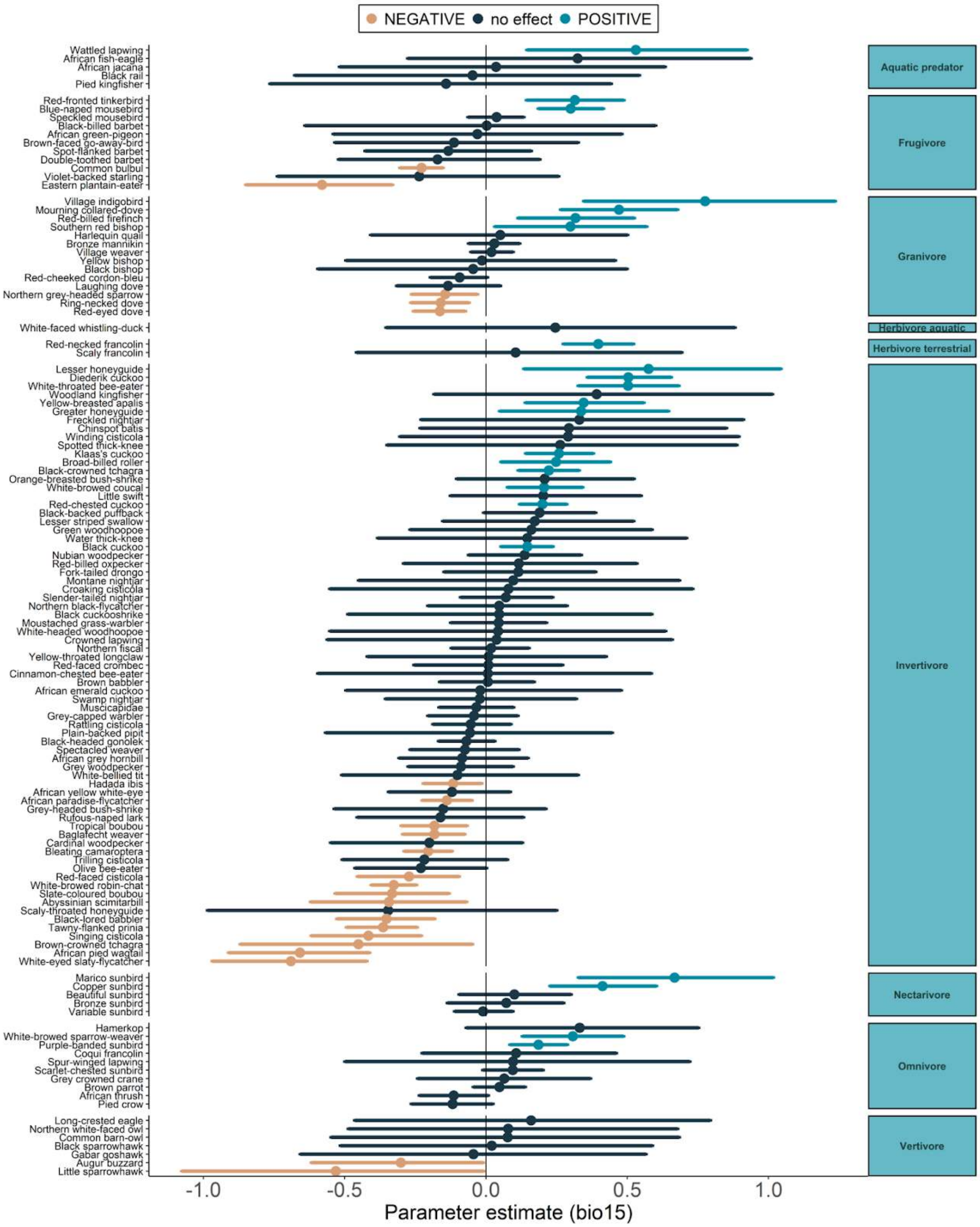
Detection probabilities varied widely, with lows of 0.037 in 2023 and 0.024 in 2024, and highs of 0.666 in 2023 and 0.706 in 2024 (mean: 0.229 in 2023; 0.246 in 2024). The best MSOM indicated that detection probability was primarily influenced by survey year and precipitation seasonality (i.e. the two variables used for detection). However, these factors were not significant predictors at the community level, suggesting that, on average, detection probability across all species did not vary significantly between survey years or along the precipitation seasonality gradient.

At the species level, both survey year and precipitation seasonality (supplementary materials; Figure 11) significantly influenced detection probabilities for several species, though no clear pattern emerged within trophic guilds. Twenty-two bird species (Figure 11) and 2 amphibians (supplementary materials) responded negatively to precipitation seasonality, suggesting greater vocal activity in areas with low precipitation variability, i.e., regions with more uniform rainfall throughout the year, as seen in frugivores like the eastern plantain-eater and common bulbul. Areas with lower precipitation variability and higher annual rainfall were moderately correlated, a pattern that may explain the increased detectability of amphibians in these regions. The combination of stable precipitation and abundant rainfall likely aligns with the breeding behaviors of amphibians, creating favorable conditions for their activity and detectability.

Conversely, 23 species showed a positive response to precipitation seasonality, indicating greater detectability in environments with more pronounced rainfall variability. Examples include the nectarivorous Marico sunbird and copper sunbird.

Source: Trees for the Future on Twitter

Figure 11. Species-level detection probability of birds in relation to the precipitation seasonality, with 95% credible intervals shown as horizontal bars. Species exhibiting a significant negative relationship are displayed on the left (red), while those with significant positive relationships are on the right (blue). Species with non-significant responses, where the 95% credible interval overlaps zero, are shown in black.



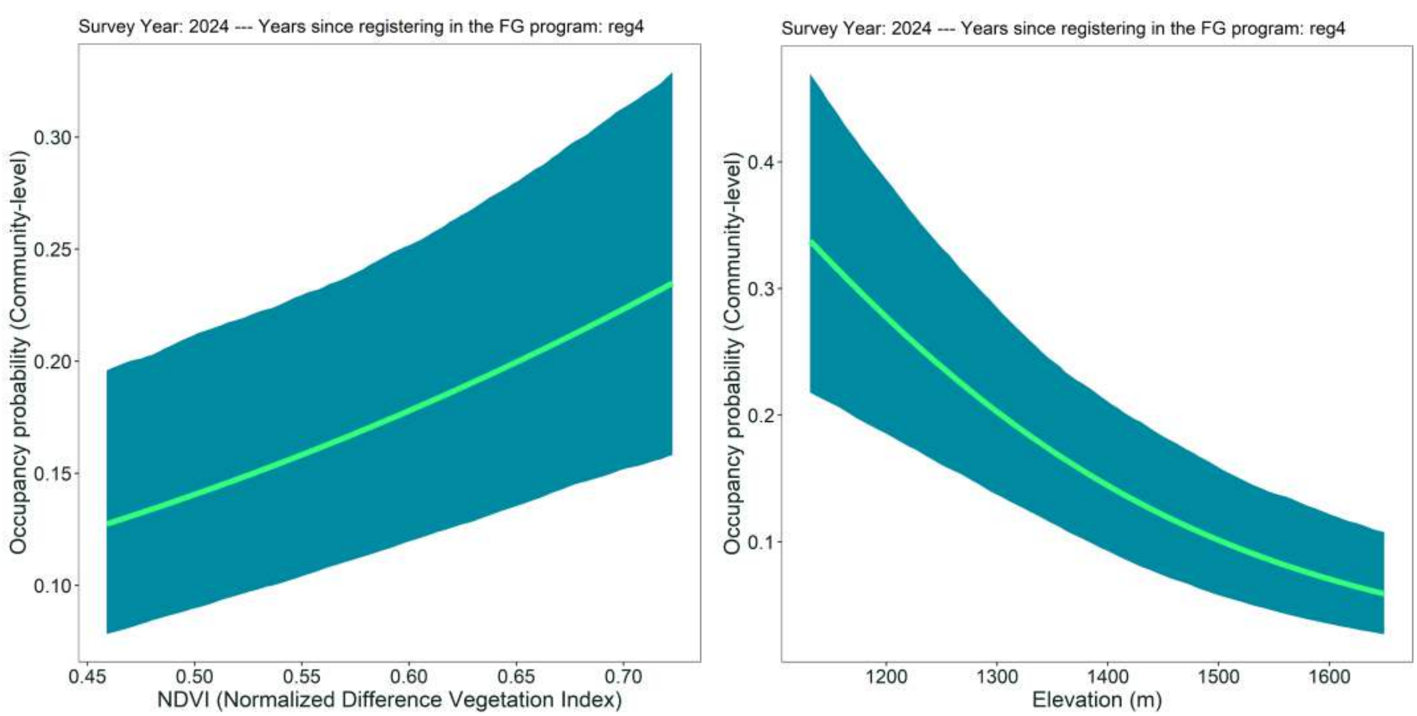
Occupancy Models - Species Occupancy

The best-performing MSOM was a multi-species spatial occupancy model that accounted for residual spatial autocorrelation in species occurrence. This model included survey year, NDVI, elevation, distance to closest water, and years since registering in the FGP as explanatory variables. While precipitation seasonality and canopy height were left out of the best model.

At the community level, we found that NDVI had a significant and positive effect, while elevation had a significant and negative effect on occupancy (Figure 12). This means that on average across all species in the community, it is more-likely for a species to be present at low elevations and higher vegetation greenness.

Time since site initiation in the FGP had a positive and significant influence on occupancy probabilities compared to conventional agriculture or sites just starting in the FGP (0 years). Sites that had been in the FGP for 4 years showed the largest average effect (mean = 0.501, SD = 0.116), followed by those in the program for 3 years (mean = 0.391, SD = 0.079). Sites in the FGP for 1 and 2 years also exhibited significantly higher occupancy compared to conventional agriculture, with mean estimates of 0.301 (SD = 0.085) and 0.288 (SD = 0.094), respectively. The similar mean values for 1 and 2 years since initiation suggest comparable occupancy probabilities for these timeframes

Figure 12. Community-level occupancy probability relationships with NDVI (left panel) and elevation (right panel) in the 2024 survey for sites enrolled for 4 years in the Forest Garden program, showing 95% credible intervals (shaded areas).



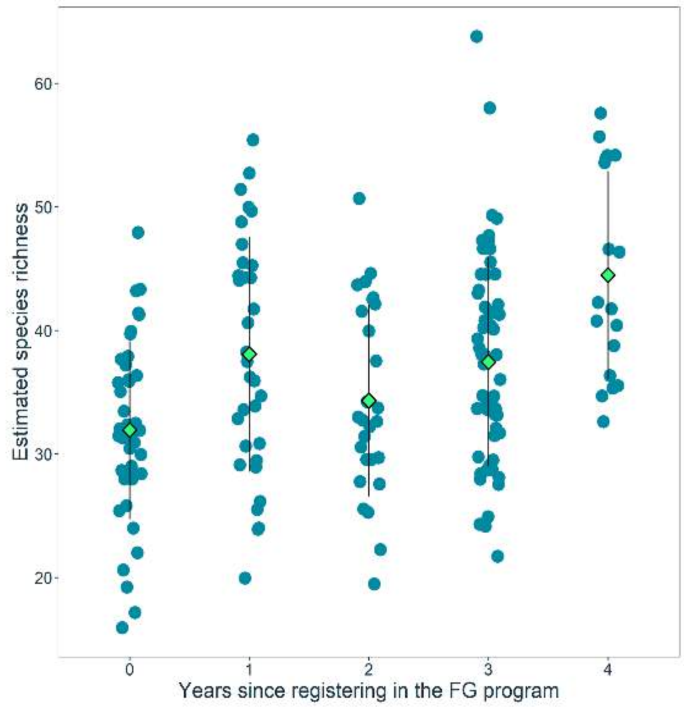
Notably, the 2024 acoustic survey revealed significantly higher occupancy rates (mean = 0.534, SD = 0.113) compared to the 2023 survey. While two years of sampling limit the ability to disentangle whether this increase reflects natural fluctuations in species occurrence, the findings strongly suggest a positive trend linked to habitat improvement. This hypothesis is supported by the observed positive and significant effects of vegetation cover (as indicated by NDVI) and the duration of site participation in the Forest Garden program on occupancy rates. The FGP's efforts to restore vegetation and enhance habitat quality likely contributed to creating more favorable conditions and refuges for species, which may explain the higher occupancy levels observed in 2024.

Occupancy Models - Predicted Species Richness

We used the MSOM Z matrix to estimate mean species richness per site and the average richness for groups based on years since enrolling in the Forest Garden program (Figure 13).

Sites not enrolled in the FGP had an average species richness of 31.9 (SD = 7.24), which was consistently lower than the richness observed at FGP sites. For instance, sites enrolled in the FGP for three years had an average estimated richness of 37.5 species, reflecting a 17.5% increase compared to non-FGP sites. Sites participating for four years showed an even greater increase, with an average estimated richness of 44.5 species, representing a 39.5% improvement.

Figure 13. Mean estimated species richness at each site (dark green circles) based on the multispecies model's Z matrix. The overall mean for years since registering in the Forest Garden program is represented by light green diamonds, with credible intervals shown as vertical bars.

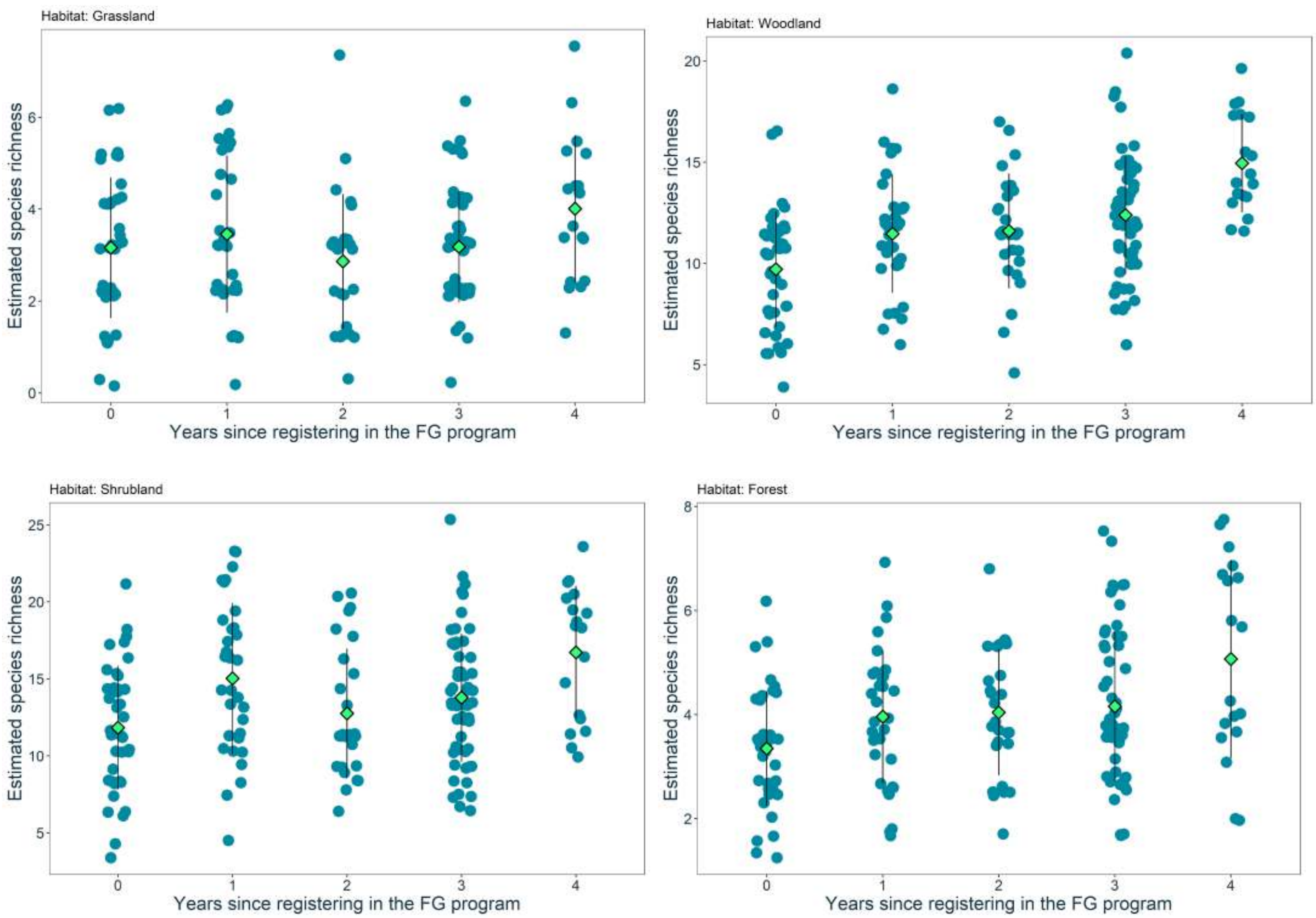


We used the AVONET bird species habitat classification to explore possible patterns within groups that may be hidden when using the richness of all species present. For this investigation, we considered the groups with the largest number of recorded birds, which were Woodland (39 species), Shrubland (35), Grassland (18), and Forest (17).

The richness plots indicate that bird species richness tends to increase more significantly in localities participating in the FGP for 4 years compared to those that do not participate, particularly for species associated with habitats characterized by more complex and vertically stratified vegetation, such as woodlands and forests. In contrast, species linked to habitats with less stratified vegetation, such as shrublands and grasslands, show more modest increases (Figure 14).

For woodland-associated species, estimated richness increased by 55%, from an average of 9.7 in conventional agriculture localities to 15 in 4-year FGP locations. Similarly, forest-associated species exhibited a 50% increase, from an average of 3.4 to 5.1. Shrubland-associated species had a 42% increase in richness, from 11.8 to 16.7. However, grassland-associated species exhibited the smallest change, with richness increasing by only 27%, from 3.2 to 4, which is in line with expectations given the transition away from the open, less structurally diverse habitats that the FGP seeks to restore.

Figure 14. Mean estimated species richness at each site (dark green circles) based on the multispecies model's Z matrix. The overall mean for years since registering in the Forest Garden program is represented by light green diamonds, with credibility intervals shown as vertical bars for each group year.



Conclusions

Current Limitations and Future Recommendation

While this project has yielded important ecological insights, there were some limitations which we present here, along with recommendations that would help to improve future sampling and analysis.

Although we employed a multi-species spatial occupancy model that accounts for potential correlations in species occupancy, the close proximity of some control sites (conventional agriculture, not participating in the FGP) to FGP sites may have reduced the observed differences in patterns between the two. Species benefiting from improved habitat quality in FGP sites may spill over into nearby control sites, potentially confounding estimates of the program's impacts. To address this, future studies should prioritize selecting control sites that are geographically distant from FGP sites. This spatial separation would help reduce spillover effects and allow for a clearer distinction in biodiversity patterns attributable to the program. Despite this limitation, the existing control sites still offer opportunity for comparison over time in areas outside of the FGP.

For the passive acoustic monitoring in 2024, sites in Ruma National Park were included as a reference for a more preserved area, serving as a gold standard for habitat in the region. These sites were excluded from the ecological models, however, due to the limited number of sampling units available (only three sites). Including such a small sample size in the models would have introduced excessive variability and reduced the reliability of parameter estimates, potentially compromising the inference power of the analyses. While these three sites were not included in the ecological modeling, they were retained in the acoustic analyses, where their outputs can be qualitatively explored through the project's WildMon Biodiversity Analytical Platform and interactive Dashboard.

Key Takeaways

1) Diverse Species Detection: Our passive acoustic monitoring across 120 sites in Kenya identified 157 species across two years, including the Endangered grey crowned crane (IUCN Red List). This highlights the region's critical conservation value. The 2024 survey **revealed a remarkable 23%** increase in species detected compared to 2023, highlighting the improved sampling effort and the broader scope of our acoustic monitoring to provide a more comprehensive view of the region's rich biodiversity.

2) Species Detection Rates The white-browed robin-chat, ring-necked dove, common bulbul, African paradise-flycatcher, brown parrot, and village weaver were among the most frequently detected bird species. Rarer species in the data included the woodhoopoe, scaly-throated honeyguide, northern white-faced owl, and croaking cisticola, which were not detected in 2024; long-crested eagle and black rail had one detection each. This variation highlights the diverse community across different areas of the study region.

3) The retrained CNN model was developed to classify 136 species, an increase of 32 classes compared to the previous version. The final model demonstrated strong performance on the test set, achieving a Weighted Average Precision (wAP) score of 0.94 or higher for most classes. Additionally, the average False Positive Rate across classes was low, at 0.02. The AI model developed in this project can be used to efficiently detect species in new datasets including during the upcoming 2025 acoustic survey. This will facilitate long-term monitoring in western Kenya to assess patterns and trends over time.

4) NDVI consistently emerged as a key predictor of acoustic space use (ASU), highlighting the critical role of vegetation greenness and density in shaping acoustic activity across all frequency ranges. In contrast, elevation showed a consistent negative effect, with lower elevations supporting more saturated acoustic environments. Overall, locations characterized by dense vegetation and low elevation exhibited the highest ASU, emphasizing the ecological importance of these habitats for maintaining soundscape richness.

5) We found clear evidence that increasing vegetation greenness and density (represented by NDVI) as well as the time since a site entered the Forest Garden program has improved species occupancy and supported a greater number of species. This boost in species numbers was most pronounced in species associated with more complex and vertically stratified vegetation types.

Source: Trees for the Future on Twitter

PROJECT REPORT

Ecoacoustic Biodiversity Monitoring in Forest Garden Project in Homa Bay and Migori, Kenya