Assessing the Relationship Between Weather Conditions and Acoustic Activity of Insects and Fauna Using Noise Monitoring

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ABSTRACT

This paper investigates the relationship between weather conditions and environmental noise generated by fauna and insects at a site in Queensland, Australia, characterised by dense vegetation and proximity to a significant water source. Twelve months of continuous environmental noise monitoring (April 2025 to March 2026) were analysed to examine how temperature, humidity, rainfall and wind are associated with diel and seasonal acoustic activity across species. Audio recordings were processed with an Artificial Intelligence (AI) based tool programmed for audio recognition to identify vertebrate fauna and insect callers; detections were aggregated by hour and month alongside meteorological variables and noise descriptors. Spearman correlations were computed at hour of day resolution per month and pooled annually across all twelve months. Nineteen vertebrate and insect taxa were detected, and three independent acoustic guilds were identified: a temperature-driven daytime cicada chorus, a wind- and rain-tolerant bird dawn chorus, and a humidity-loving nocturnal owl and frog signal. Anthropogenic noise was negligible. The study demonstrates the value of long-term passive acoustic monitoring combined with the AI audio recognition tool for characterising species activity and environmental noise patterns in ecologically sensitive environments.

1. INTRODUCTION

Passive acoustic monitoring (PAM) has emerged as a non-invasive method for long-duration recording of environmental background noise, enabling species temporal activity patterns to be characterised across the measured period without disrupting the fauna under observation [1,2]. Environmental soundscapes captured through PAM integrate contributions from biological sources, including birds, insects, and amphibians, as well as geophysical and anthropogenic sounds, providing a continuous record of ecosystem acoustic dynamics.

When combined with artificial intelligence (AI) tools capable of automated species identification from audio recordings, PAM provides a scalable framework for biodiversity assessment that reduces the need for intensive manual survey effort [3].

Acoustic activity in wildlife communities is strongly modulated by environmental conditions. Temperature, humidity, and rainfall have been identified as key drivers of calling behaviour across birds, insects, and amphibians, shaping both seasonal and diel patterns of acoustic output [4,5].

In parallel, noise levels recorded in natural environments reflect not only biological activity but also anthropogenic influences, which can mask wildlife vocalisations, reduce communication distances, and alter species behaviour [6,7]. Understanding the relative contribution of each source to the overall

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noise environment is therefore important for interpreting soundscape variation and assessing potential impacts on fauna. Standard noise metrics such as the equivalent continuous sound level (LAeq) and statistical background level (LA90) provide useful descriptors of energetic and residual sound levels, while source-specific interpretation requires species or source classification.

This study was conducted at a site in Queensland, Australia, characterised by dense riparian vegetation and a permanent water source, conditions that support fauna diversity and acoustic complexity. Using one year of continuous noise monitoring combined with AI-based analysis of audio recording, this paper examines how climatic variables relate to acoustic activity across the detected species assemblage and evaluates the relative contributions of biological and anthropogenic sources to the observed noise environment across seasons [8,9].

2. STUDY AREA AND METHODOLOGY

This section describes the study site, the equipment and data-processing chain, and the statistical approach used to relate species detections to environmental variables.

2.1. Site description

Monitoring was carried out within a densely vegetated subtropical riparian corridor in the south- east area of Queensland, Australia. The site is characterised by tall eucalypt and rainforest fringe vegetation and proximity to a significant water source with limited continuous human presence and only intermittent vehicle access.

2.2. Acoustic monitoring

Continuous environmental noise monitoring was carried out between April 2025 and March 2026 (twelve months). Audio recordings and noise measurements were stored at fifteen-minute resolution. For each fifteen-minute period, the equivalent continuous A-weighted sound pressure level (LAeq) and the 90th percentile background level (LA90) were computed. Hour-of-day averages were obtained by pooling all fifteen-minute records falling in the same hour-of-day across each month, using an energy-correct mean for LAeq and LA90 as given by Equation 1 [7, 8]:

$$L_h = 10 \cdot \log_{10} [(1/N) \cdot \Sigma\, 10^{(L_i/10)}] \quad (1)$$

where Li are the fifteen-minute SPL values and N is the number of valid samples. The diel acoustic 'gap' was defined as LAeq − LA90 and is interpreted as a proxy for the dynamic range of the soundscape — higher values indicate more transient acoustic events superimposed on the residual background.

2.3. AI audio recognizer - species identification

Audio recordings were processed using the KNM Analysis ProAI developed by InstraLabs, which is a recognizer trained on a global library of bird, frog and insect vocalisations. The used recognizer applies two complementary models (*beats-general* and *perch-species*) to identify the vocalising species present in the recordings. Detections were filtered with a confidence threshold of ≥ 0.85 to reduce false-positive rates. Detections were aggregated to hour-of-day for each month. Where two models reported overlapping detections within the same time window, only the highest-confidence label was retained. The resulting per-month species count represents an effective lower bound, since rare species may not exceed the detection threshold.

2.4. Meteorological data

Temperature (mean, minimum and maximum, in °C), relative humidity (%), rainfall (mm/h) and wind speed (m/s) were recorded at fifteen-minute resolution from a weather station located near the acoustic logger. Hour-of-day aggregations used arithmetic means for temperature, humidity and wind, and arithmetic sums for rainfall.

2.5. Statistical analysis

Spearman rank correlation coefficients (r) were computed between hourly detection counts for each species and hourly climate and noise variables. Per-month analyses used the 24-hourly values within

each calendar month (n = 24). Annual pooled correlations were computed across all 12 months (n = 24 × 12 = 288). Statistical significance was reported at $p < 0.05$ (*), $p < 0.01$ (**) and $p < 0.001$ (***). Correlations with (r) ≥ 0.6 were classified as strong, 0.4–0.6 as moderate, 0.2–0.4 as weak and < 0.2 as negligible. Vehicle and chainsaw detections were retained as a separate anthropogenic group, distinct from the fauna categories (Bird, Insect, Amphibian, Mammal and Fowl).

3. RESULTS

3.1. Annual soundscape and weather summary

Across the twelve months of monitoring, monthly LAeq ranged from 36.6 to 54.0 dB, and monthly LA90 from 31.6 to 50.4 dB. Monthly mean temperature ranged from 12.8 to 23.1 °C, with cumulative monthly rainfall ranging from 0.6 to 164.2 mm. The complete monitoring period yielded 7,888 fauna detections distributed across nineteen distinct vertebrate and insect taxa (per-month species counts: 7 to 15). Anthropogenic noise events were rare: only a handful of vehicle and chainsaw detections were captured over the year, indicating that the soundscape was dominated by biophonic and geophonic sources. A summary of these metrics, disaggregated by austral season, is given in Table 1.

Table 1: Summary of acoustic, climatic and biological metrics for the full year and disaggregated by austral season.

Metric	Annual	Autumn	Winter	Spring	Summer
Mean LAeq (dB)	44.2	41.2	39.1	45.1	51.4
Mean LA90 (dB)	37.8	34.6	32.7	38.1	45.6
Mean temp (°C)	18.9	19.1	13.1	20.7	22.7
Total rainfall (mm)	705	302	291	90	22
Total detections	7,888	3,627	2,191	1,091	979
Max species/month	15	15	15	11	8

3.2. Monthly diel patterns

Figures 1 to 12 show the diel structure of the soundscape, weather and species detections for each of the twelve calendar months. Each figure is organised in three panels sharing a common 24-hour on X axis: (top) LAeq and LA90 with the noise gap shaded; (middle) hourly mean temperature and relative humidity; and (bottom) stacked fauna detections coloured by species. Period-of-day bands (Night, Dawn, Morning, Afternoon, Evening) are shown as background tints to aid interpretation.

Several recurring features are visible across months. First, the dawn chorus produces a sharp rise in LAeq between 05:00 and 08:00 in nearly all months, driven by a small number of dominant bird taxa (notably Pied Butcherbird, Pardalotus rubricatus and Psophodes occidentalis). Second, the evening peak around 17:00 to 18:00 is consistently elevated in LAeq and is partly attributable to insect activity in the warmer months. Third, temperature and humidity show the expected anti-phase diurnal cycle, with humidity minima coinciding with early-afternoon temperature maxima. Detection counts vary by one to two orders of magnitude between months, primarily driven by the seasonality of cicada and insect activity.

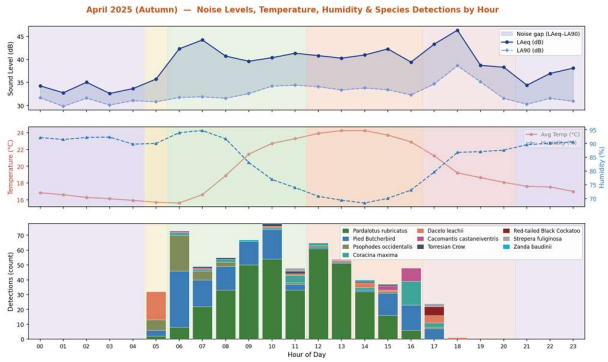

Figure 1: April 2025 (Autumn). Monthly LAeq 38.9 dB; LA90 32.5 dB; 671 fauna detections across 10 species.

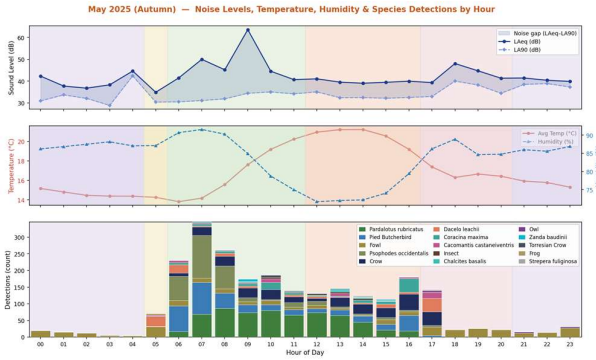

Figure 2: May 2025 (Autumn). Monthly LAeq 42.3 dB; LA90 34.2 dB; 2,451 fauna detections across 15 species.

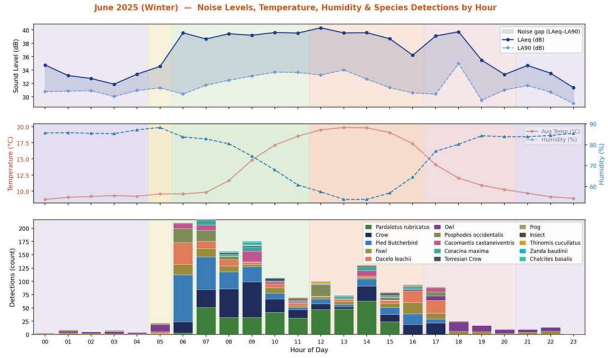

Figure 3: June 2025 (Winter). Monthly LAeq 36.6 dB; LA90 31.6 dB; 1,633 fauna detections across 15 species.

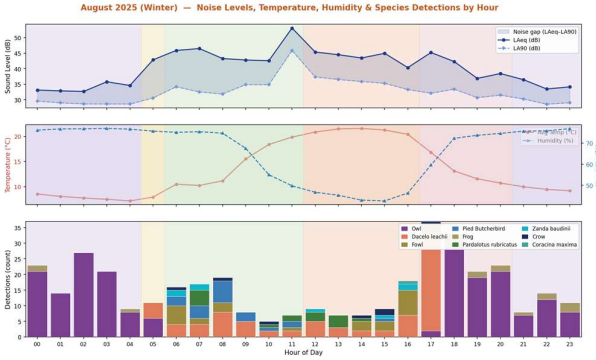

Figure 5: August 2025 (Winter). Monthly LAeq 40.5 dB; LA90 32.6 dB; 374 fauna detections across 9 species.

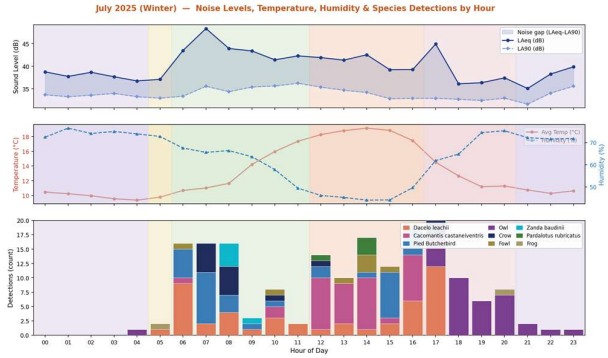

Figure 4: July 2025 (Winter). Monthly LAeq 40.1 dB; LA90 33.9 dB; 184 fauna detections across 9 species.

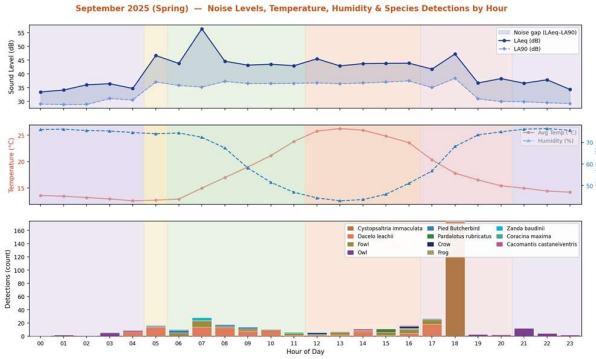

Figure 6: September 2025 (Spring). Monthly LAeq 41.2 dB; LA90 33.7 dB; 398 fauna detections across 11 species.

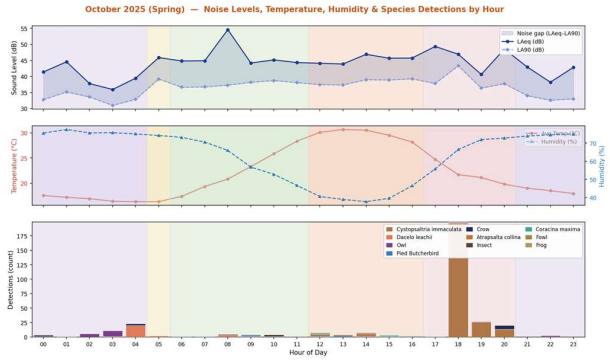

Figure 7: October 2025 (Spring). Monthly LAeq 44.1 dB; LA90 36.5 dB; 341 fauna detections across 10 species.

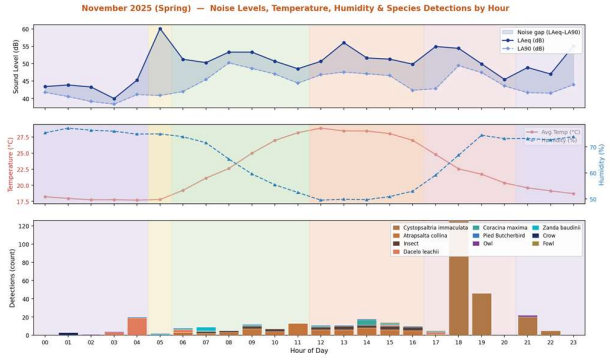

Figure 8: November 2025 (Spring). Monthly LAeq 49.9 dB; LA90 44.2 dB; 352 fauna detections across 10 species.

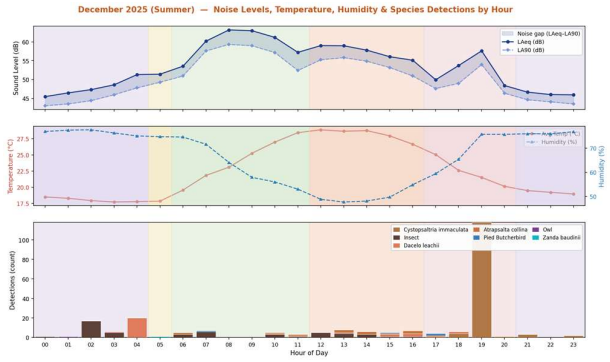

Figure 9: December 2025 (Summer). Monthly LAeq 53.5 dB; LA90 50.4 dB; 231 fauna detections across 7 species.

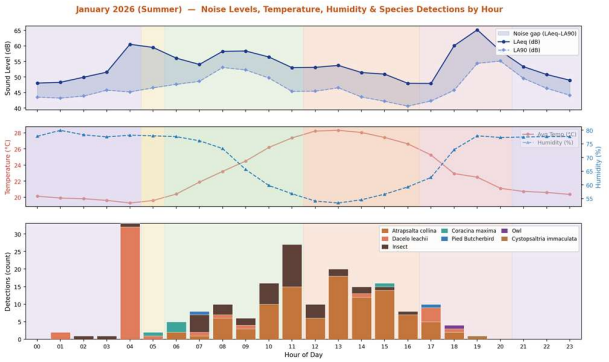

Figure 10: January 2026 (Summer). Monthly LAeq 54.0 dB; LA90 46.7 dB; 195 fauna detections across 7 species.

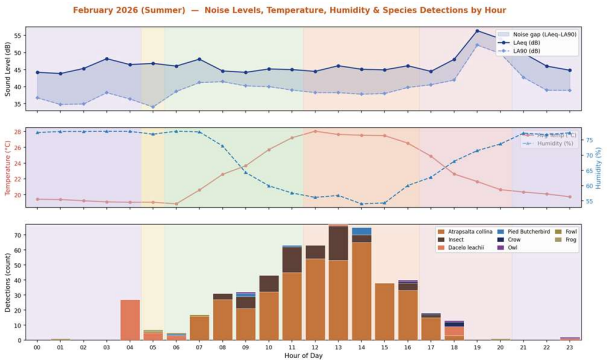

Figure 11: February 2026 (Summer). Monthly LAeq 46.6 dB; LA90 39.7 dB; 553 fauna detections across 8 species.

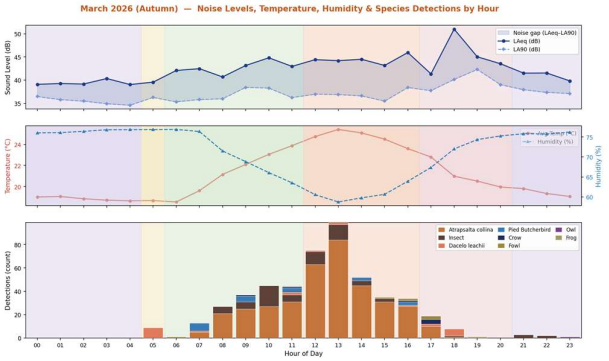

Figure 12: March 2026 (Autumn). Monthly LAeq 42.4 dB; LA90 37.1 dB; 505 fauna detections across 8 species.

3.3. Seasonal diel patterns

Pooling months into the four austral seasons reveals strong contrasts in the dominant acoustic guilds. Figures 13 to 16 show the seasonal composites: per-hour energy-mean LAeq and LA90 (top), mean temperature and humidity (middle), and the typical hourly detection counts for the seven most frequently detected species in each season (bottom).

3.3.1. Autumn

(April–May 2025 and March 2026) is dominated by the bird dawn chorus (Pied Butcherbird, Pardalotus rubricatus, Psophodes occidentalis), with cicada Atrapsalta collina contributing to mid-afternoon detections. Temperatures average in the high teens with high relative humidity (~85%).

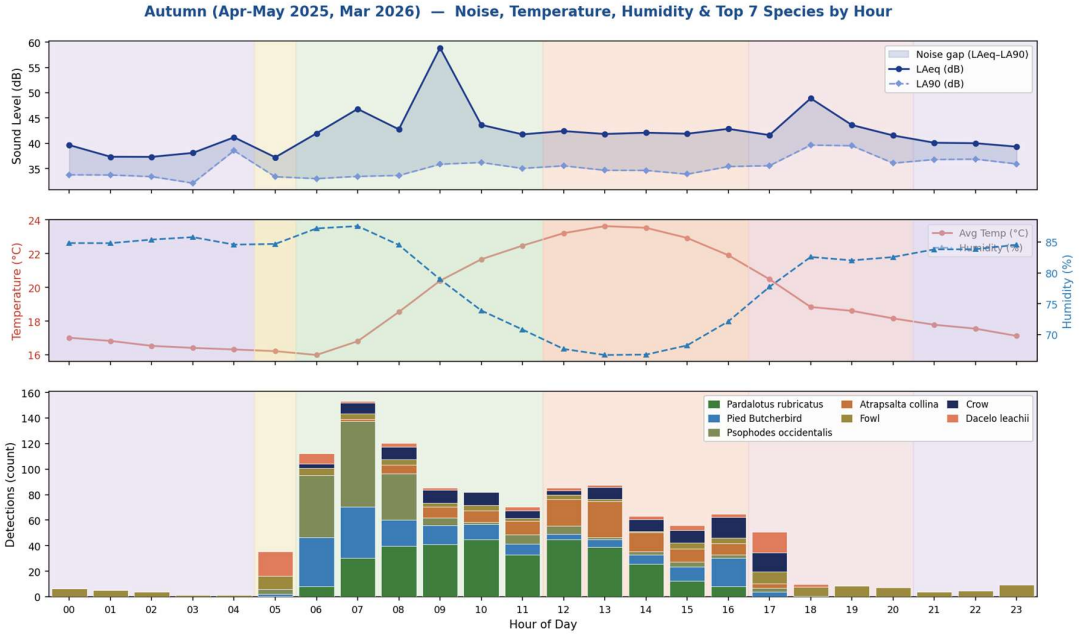

Figure 13: Seasonal diel patterns — noise, climate and key species (Autumn).

3.3.2. Winter

(June–August 2025) is the coolest season (daytime peak about 20 °C). Insect callers are largely absent. The diel signal is dominated by birds — particularly Pardalotus rubricatus, Pied Butcherbird and Crow — and Owl detections rise during the night hours. Total fauna detections in winter are intermediate between the autumn maximum and the summer minimum, but per-month species richness remains high (up to 15 species/month), comparable to autumn.

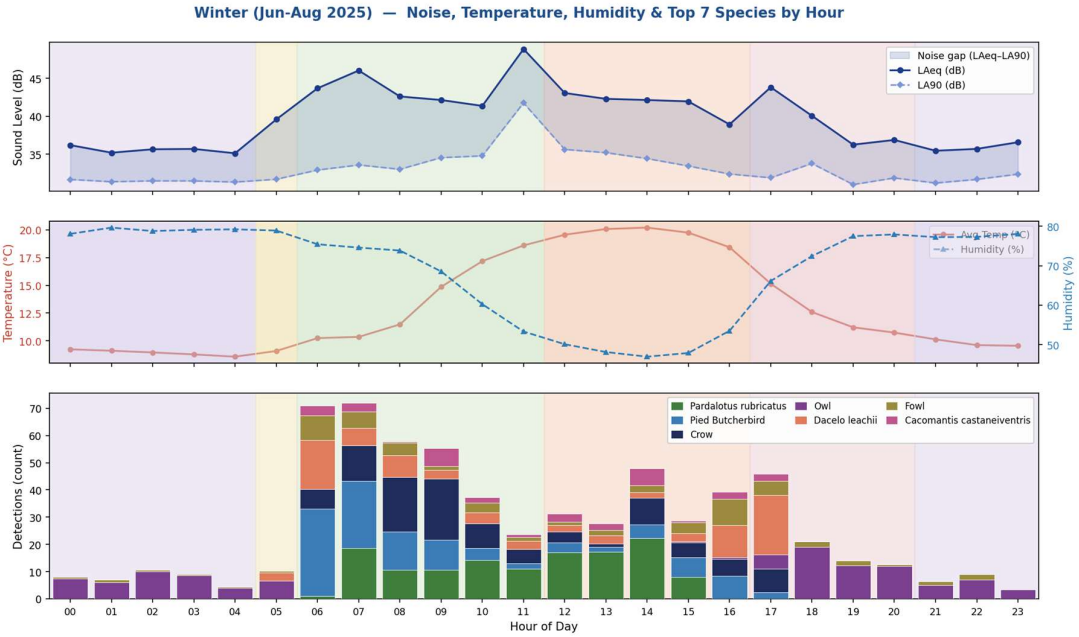

Figure 14: Seasonal diel patterns — noise, climate and key species (Winter).

3.3.3. Spring

(September–November 2025) marks the emergence of the cicada chorus. Cystopsaltria immaculata and Atrapsalta collina dominate daytime detections, and the LAeq dynamic range broadens markedly during warm afternoons. Bird detections persist but are increasingly masked by the insect band.

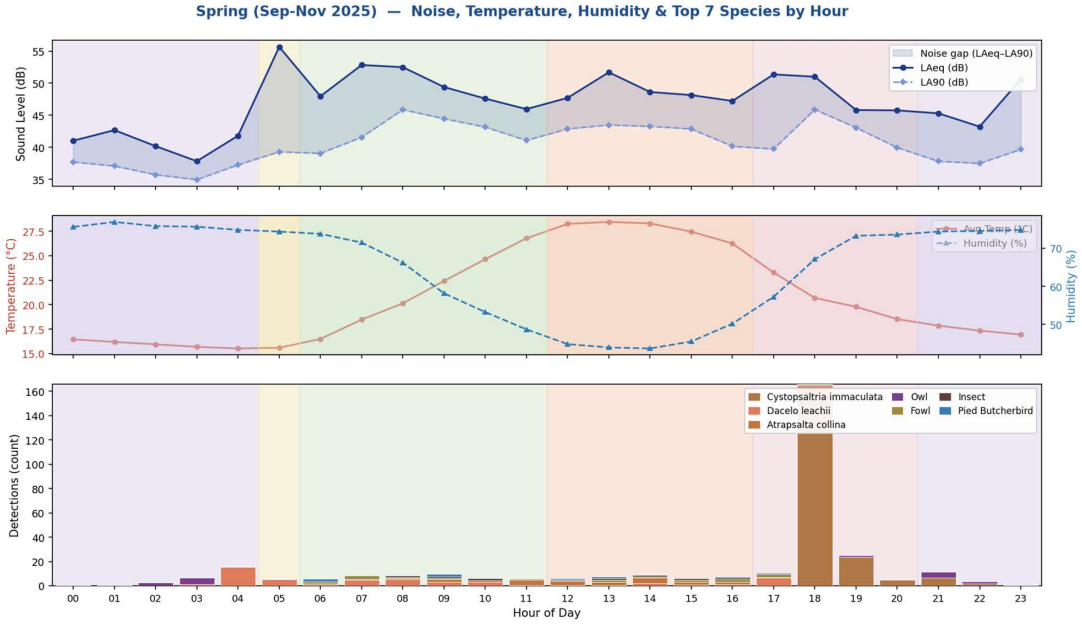

Figure 15: Seasonal diel patterns — noise, climate and key species (Spring).

3.3.4. Summer

(December 2025–February 2026) is the loudest season but, paradoxically, the season with the fewest discrete detections and the lowest per-month species richness. Cicada and generic insect detections form a near-continuous daytime band that elevates LAeq while masking individual bird vocalisations and reducing the number of discrete detections counted by the recogniser. Night soundscapes include Owl and frog detections. Summer thus represents a soundscape that is acoustically intense but biologically concentrated in a small number of dominant insect taxa.

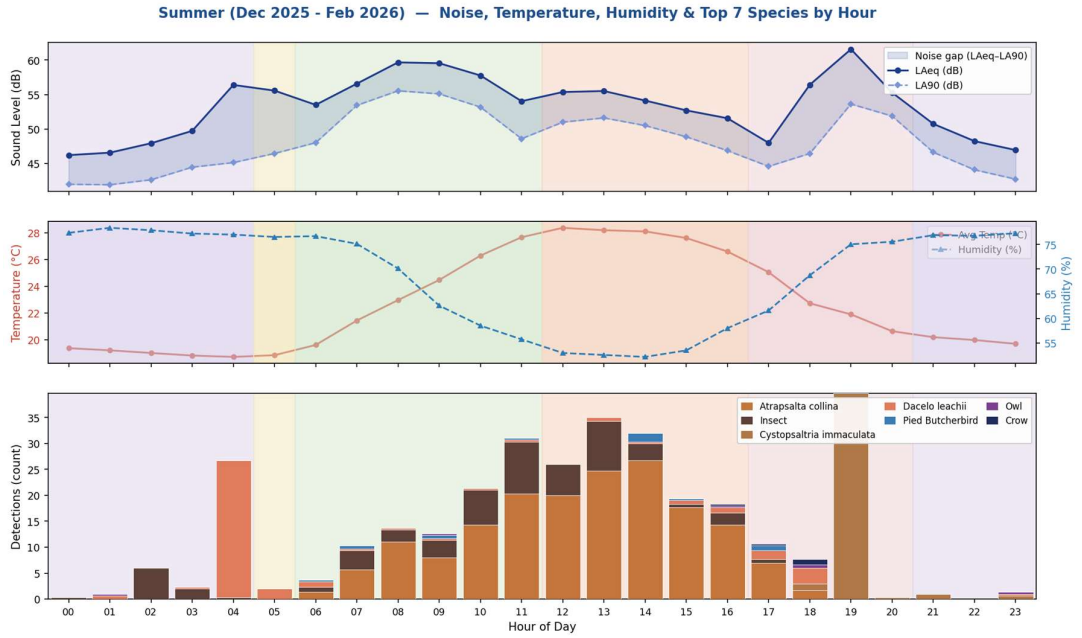

Figure 16: Seasonal diel patterns — noise, climate and key species (Summer).

3.4. Annual species–environment correlations

Spearman rank correlations between hourly species detections and the five environmental variables (LAeq, temperature, humidity, rainfall, wind) were computed on the pooled annual dataset (n = 288 hour-of-day observations = 24 hours × 12 months) and are summarised in Figure 17. The colour scale is divergent: dark green denotes strong positive associations ($r \geq +0.6$), dark red denotes strong negative associations ($r \leq -0.6$); intermediate shades represent moderate correlations.

Annual Spearman Correlations between Species Detections and Environmental Variables

(Pooled across 12 months, n = 288, LAeq energy-corrected)

Species		LAeq	Temp	Humidity	Rain	Wind
Cacomantis castaneiventris	(Bird)	-0.15 *	-0.12 *	+0.02	+0.31 ***	+0.28 ***
Chalcites basalis	(Bird)	-0.05	-0.01	+0.03	+0.27 ***	+0.28 ***
Coracina maxima	(Bird)	-0.01	+0.12 *	-0.04	+0.36 ***	+0.26 ***
Crow	(Bird)	-0.09	-0.07	-0.07	+0.34 ***	+0.28 ***
Dacelo leachii	(Bird)	+0.07	-0.01	-0.21 ***	+0.21 ***	+0.25 ***
Owl	(Bird)	**-0.51** ***	**-0.53** ***	+0.26 ***	+0.01	-0.31 ***
Pardalotus rubricatus	(Bird)	-0.12 *	+0.04	-0.05	+0.38 ***	+0.39 ***
Pied Butcherbird	(Bird)	-0.01	+0.08	-0.15 **	+0.38 ***	**+0.41** ***
Psophodes occidentalis	(Bird)	-0.17 **	-0.09	+0.20 ***	**+0.41** ***	+0.31 ***
Red-tailed Black Cockatoo	(Bird)	-0.00	+0.04	+0.07	+0.10	-0.02
Strepera fuliginosa	(Bird)	-0.10	+0.09	+0.04	+0.19 **	+0.20 ***
Thinornis cucullatus	(Bird)	-0.09	-0.07	-0.02	+0.19 **	+0.08
Torresian Crow	(Bird)	-0.12 *	+0.01	+0.04	+0.35 ***	+0.26 ***
Zanda baudinii	(Bird)	+0.05	-0.06	-0.02	+0.21 ***	+0.21 ***
Atrapsalta collina	(Insect)	**+0.41** ***	**+0.62** ***	**-0.44** ***	-0.18 **	+0.22 ***
Cystopsaltria immaculata	(Insect)	+0.21 ***	+0.10	-0.01	+0.02	-0.21 ***
Insect	(Insect)	+0.31 ***	**+0.51** ***	-0.35 ***	-0.05	+0.31 ***
Frog	(Amphibian)	-0.31 ***	-0.36 ***	+0.24 ***	+0.03	-0.19 **
Fowl	(Fowl)	-0.22 ***	-0.25 ***	+0.13 *	+0.37 ***	+0.33 ***
Chainsaw	(Anthropogenic)	+0.03	-0.05	+0.09	+0.08	+0.10
Vehicle	(Anthropogenic)	-0.06	+0.02	+0.05	+0.07	+0.14 *

* p<0.05 ** p<0.01 *** p<0.001 n=288 hourly obs (pooled all months, energy-corrected LAeq)

r ≥ +0.6 strong + | r +0.4 to +0.6 | r +0.2 to +0.4 | |r|<0.2 none | r −0.2 to −0.4 | r −0.4 to −0.6 | r ≤ −0.6 strong −

Figure 17: Annual Spearman correlations between species detections and environmental variables, pooled across all twelve months (n = 288, energy-corrected LAeq). Significance: * p<0.05, ** p<0.01, *** p<0.001.

Three independent correlation patterns emerge from the table. First, the cicada Atrapsalta collina shows a strong, highly significant positive association with temperature (r = +0.62, p<0.001) and LAeq (r = +0.41, p<0.001), and a strong negative association with humidity (r = −0.44, p<0.001). The generic insect category shows the same signature at a slightly lower magnitude (r = +0.51 with temperature). Second, almost all bird taxa show positive correlations with rainfall and wind — for example, Pied Butcherbird (r = +0.38 rain, +0.41 wind, both p<0.001), Pardalotus rubricatus (+0.38, +0.39), Psophodes occidentalis (+0.41 rain, p<0.001) and Crow (+0.34, +0.28). This pattern indicates that bird vocal activity persists through windy and even rainy periods, which is consistent with the dawn-chorus structure visible in the monthly figures. Third, Owl detections show a distinctive nocturnal signature, with strong negative correlations against LAeq (r = −0.51), temperature (r = −0.53) and wind (r = −0.31), and a positive association with humidity (r = +0.26). Frog detections

follow a similar humidity-loving / temperature-avoiding pattern ($r = -0.31$ vs LAeq, $+0.24$ vs humidity).

Anthropogenic events were too sparse to support robust annual correlations: the pooled correlations for vehicle and chainsaw all fall in the weak / non-significant range ($|r| \leq 0.14$), confirming that anthropogenic noise neither drives nor is driven by weather conditions in this dataset, and that it does not act as a confounder for the fauna correlations reported above.

4. DISCUSSION

This section interprets the diel and seasonal patterns reported above, identifies three independent acoustic guilds, and discusses methodological limitations and the role of anthropogenic noise.

4.1. Three independent acoustic guilds

The annual correlation matrix reveals that the site of study supports at least three ecologically distinct acoustic guilds, each responding to different sets of environmental drivers: (1) The insect-temperature guild, such as Atrapsalta collina and the generic insect class show strong positive correlations with temperature (up to $r = +0.62$) and weak to moderate correlations with LAeq, and negative correlations with humidity; activity concentrates in spring and summer afternoons. (2) The bird wind/rain-tolerant dawn-and-day guild, with Pied Butcherbird, Pardalotus rubricatus, Psophodes occidentalis, Crow and Cacomantis castaneiventris that shows consistent positive correlations with rainfall and wind speed, peak detections at dawn, and only weak (often non-significant) associations with temperature; this guild represents the strongest biophonic signal in autumn and winter, declining markedly in summer. (3) The nocturnal humidity-loving guild, Owl and Frog are strongly negatively correlated with temperature and LAeq, and positively associated with humidity; activity is most prominent in winter and summer nights and is largely independent of the daytime insect and bird soundscape.

These three guilds are largely independent: their preferred environmental conditions occur at different hours of the day and seasons of the year, which means that the broadband LAeq metric alone is a poor proxy for biological activity. Species-resolved AI detection is therefore essential: a single LAeq curve cannot distinguish a hot afternoon dominated by cicada chorusing from a windy morning dominated by birds, even when both produce similar broadband levels.

4.2. The LAeq–LA90 gap as a biological indicator

The diurnal evolution of the LAeq–LA90 gap (visible as the shaded region in the top panel of every monthly figure) is consistently widest at dawn and during late afternoon, and narrowest at night. This pattern reflects the transient nature of bioacoustic events: discrete calls raise the energetic mean (LAeq) above the residual background (LA90), and the gap therefore tracks the intensity of the dawn chorus and the daytime cicada chorus. Quiet, steady night-time soundscapes show very small gaps (typically 2–3 dB), even when owl and frog calls are present, because those calls are temporally sparse. As an indicator, the gap is best read alongside species-resolved detections rather than in isolation.

4.3. Limitations

The AI recognition tool operates on a global training distribution and under-detect rare or geographically restricted Australian taxa and, conversely, to assign vocalizations to phylogenetically close but geographically inappropriate sister species. The per-month species count of 7 to 15 is therefore a lower bound on local diversity, and the per-species labels in this dataset must be interpreted with caution.

Specifically, several species labels reported by the AI recognition tool are biogeographically implausible for south-eastern Queensland and almost certainly represent sister-species substitutions. Some examples include Strepera fuliginosa (Black Currawong), endemic to Tasmania and almost certainly Strepera graculina (Pied Currawong) at this site; Psophodes occidentalis (Chiming Wedgebill), an arid-zone species of inland Western Australia and almost certainly Psophodes

olivaceus (Eastern Whipbird) here; Zanda baudinii (Baudin's Black Cockatoo), endemic to south-western Western Australia and most consistent with Zada funerea (Yellow-tailed Black Cockatoo).

This taxonomic uncertainty does not invalidate the diel and seasonal results presented in Section 3, because the three acoustic assemblages identified in Section 4.1 are defined by ecological response (diel timing and correlations with temperature, humidity, rainfall and wind), not by species identity. The dawn-chorus signature, for example, is preserved whether the responsible currawong is correctly labelled as S. graculina or incorrectly as S. fuliginosa, because both congeners share the same broad diel and meteorological niche. Similarly, the temperature-driven daytime cicada chorus is robust to uncertainty at the species level, because all candidate Australian Cicadidae are temperature-dependent. Finally, the study covers a single site and a single year and therefore should not be extrapolated to other riparian environments without further validation.

4.4. Anthropogenic influence

The twelve-month dataset captured only a small number of vehicle and chainsaw detections. Vehicle and chainsaw annual correlations with weather were weak and largely non-significant, indicating that anthropogenic activity neither covaries with weather conditions nor materially biases the fauna correlations reported above. This confirms the suitability of the site as a low-disturbance reference location for ongoing acoustic monitoring.

5. CONCLUSIONS

Twelve months of continuous acoustic and meteorological monitoring at a subtropical riparian site in Queensland have produced a coherent, species-resolved picture of the local soundscape. Combining hourly LAeq and LA90 descriptors with AI audio recognition (KNM Analysis Pro AI by Instralabs) and pooled Spearman correlations (n = 288) revealed three independent acoustic guilds: a temperature-driven daytime cicada chorus, a wind- and rain-tolerant bird dawn chorus, and a humidity-loving nocturnal owl/frog guild. Anthropogenic noise was negligible. The methodology is reproducible at low incremental cost and provides a baseline against which future change in this ecologically sensitive habitat can be measured. The approach is recommended for routine biodiversity monitoring of subtropical riparian sites in Australia, especially where direct observational survey is constrained by access, vegetation density, or diel/seasonal logistics.

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