

Detecting potential declines in a threatened dung beetle with N- mixtured models: *Eurysternus impressicollis* Castelnau 1840 in north-western Venezuela

José R. Ferrer-Paris [first autor]

University of New South Wales - Kensington Campus: University of New South Wales

CECILIA MARIA (✉ lozanoceci@gmail.com)

Secretaria do Meio Ambiente do Estado de Mato Grosso <https://orcid.org/0000-0003-0215-6335>

Arlene Cardozo

Laboratorio de ecologia espacial

Ada Sánchez-Mercado

PROVITA

Research Article

Keywords: detectability, pitfall traps, Maracaibo province, threatened species, catch per unit effort

Posted Date: June 22nd, 2023

DOI: <https://doi.org/10.21203/rs.3.rs-3026733/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Abstract

Implementation of conservation planning and management strategies for threatened dung beetle species have been hampered by lack of reliable information about temporal and spatial patterns in abundance. Distinguishing “real” patterns responding to ecological processes, from “artifacts” created by sampling limitations, is not a simple task. Pitfall trap data from NeoMaps standardized surveys (2006 and 2009) were combined with environmental variables from remote sensors, and used N-mixture models to evaluate how observed changes in detection and abundance of *Eurysternus impressicollis*, a Vulnerable dung beetle species in northwestern Venezuela, could be attributable to differences in sampling effort or changing conditions in habitat across time. Minor temporal changes in detectability had a positive relationship with sampling effort, but a negative relationship with evapotranspiration. Sampling effort was enough to detect the species where it was present, so lack of detection in other transects are likely to represent true absences. Temporal change in abundance was explained by vegetation condition and temperature so, the low abundance recorded in 2009 were not a sampling artifact, but were likely to reflect multi-year fluctuations in environmental conditions. Also, the model allowed to explain landscape variation in abundance, being more abundant in localities with denser, more humid forest. This approach could be widely applied to pitfall data from other dung beetle monitoring programs across the world to inform conservation status assessment and guide future studies on the distribution and ecology of dung beetle threatened species.

Introduction

The modern day biodiversity crisis is most often portrayed in terms of vertebrate and plants, yet it is overwhelmingly a loss of invertebrate life (Hallmann et al. 2017). Particularly, invertebrate species with restricted range, or dependency to specific habitats or vegetation types facing a high risk of transformation (Dunn 2005).

Invertebrates groups species like dung beetles (Coleoptera: Scarabaeidae: Scarabaeinae) have been extensively used to characterize, and to monitor changes in habitat due their sensitivity to alterations in habitat structure and quality (Gardner et al. 2008; Nichols et al. 2008). Thus, research in tropical dung beetles has focused in understanding how community composition responds to habitat changes (Davis and Scholtz 2001; Scheffler 2005; Spector et al. 2008) while species level ecological studies are much less frequent (Ferrer-Paris et al. 2016). Beside their usefulness as indicators, Scarabaeidae species, including dung beetles, are of conservation concern themselves. Of the 6,837 Scarabaeinae species (Schoolmeesters 2023), only 300 have conservation status assessments (IUCN 2021). Equally worrying as the 20% of species currently threatened (from Critically Endangered to Vulnerable IUCN categories), is the overwhelming 40% of species classified as Data Deficient. Ecosystems modifications is the main threat faced by dung beetle species (IUCN 2021), and most of them are known to be extremely range restricted, or are often limited to areas of high forest biomass subject to logging or charcoal production (Spector 2006).

Implementation of conservation planning and management strategies for threatened dung beetle species have been hampered by lack of reliable information about patterns in occurrence and abundance across time and landscape (Koch et al. 2000). However, distinguishing “real” patterns responding to ecological process, from “artifacts” created by sampling limitations, is not a simple task (Bates et al. 2015; Dénes et al. 2015a). Temporal pattern in detectability could be affected by factors related with sampling strategies like, low effectiveness of sampling methods, insufficient sampling effort or modifications in sampling methods. In those cases, lack of detection, does not necessarily means a true absence (Kéry and Schmidt 2008). On the other hand, lack of detection as well as, temporal and landscape patterns in abundance, could be explained by ecological processes, like presence of historical barriers, displacement by more competitive and widespread species, or low tolerance to anthropogenic disturbance (Joseph et al. 2009).

Multiple approaches have been developed to estimate the true number of individuals in a population from field samples. For example, using removal sampling which requires the systematic capture and removal of individuals (Brown and Matthews 2016), the population size can be estimated on the basis of the decline in catch size during sequential capture sessions. The repeated catch size in a given site are then used to jointly estimate the detectability of individuals and population size based on N-mixture models. N-mixture models accounts for the simultaneous estimation of detection rates and abundance, and allow modelling the confounding effect of sampling effort and ecological variables (Royle 2004). Despite the fact that removal sampling (pitfall traps) is the most common sampling method for dung beetles, we are not aware of any application of the N-mixture models to estimate abundance of tropical Scarabaeinae.

Here, pitfall trap data from standardized surveys for a threatened dung beetle species, were combined with environmental variables from remote sensors, and multinomial-Poisson mixture models (Kéry and Royle 2016) to evaluate how much of observed changes in detection and abundance of this species could be attributable to differences in sampling effort or differences in habitat conditions across time. This study focuses on *Eurysternus impressicollis* Castelnau 1840, which inhabits dry forests in northern South America, and is classified as Vulnerable in Venezuela, due to its restricted distribution and habitat lost (Rodríguez et al. 2015). This species is endemic to the Maracaibo biogeographical province, *sensu* Morrone et al. (2022; see also Rubio & Lobo 2010), with most records from Colombian (Génier 2009), and recent reports from a couple of localities in the Sierra de Perijá in western Venezuela (Lozano 2010; Ferrer-Paris et al. 2013; Figure 1). Here, pitfall-trap data from a national dung beetle sampling program (NeoMaps; Ferrer-Paris et al. 2013) in Rosario de Perijá in 2006 and 2009 were analyzed to estimate abundance and detectability of *E. impressicollis* using a removal-design. Here the hypothesis that temporal changes in detectability is affected by factors related with the sampling effort and environmental condition during the period of sampling was tested, while changes in abundance is better explained by vegetation and climatic conditions affecting the life cycle and population dynamic of the species.

Materials And Methods

Field sampling

NeoMaps proposes a cost-effective, systematic monitoring program for the assessment of biodiversity in Venezuela (Rodríguez and Sharpe 2002). Sampling regions were selected across the country according to a stratified sampling design, and within each region, a 40-km road route was identified in order to account for the largest possible gradient in environmental variation. Sampling sites were located along these 'gradsects' and spaced ca. 5 – 7 km apart to minimize spatial autocorrelation (Ferrer-Paris et al. 2013).

The Rosario de Perijá gradsect (code NM05) is located in Zulia state in northwestern Venezuela (Figure 1), covering an elevation gradient from 81 – 229 m. Across the gradsect, segments of dry forest were present at both extremes, which represents remaining natural vegetation, while in the middle part of the gradsect, mosaic of forest patches, isolated trees and pastures were the most dominant vegetation type. Minimum monthly temperature vary between 6.9 – 23.4 °C, while maximum monthly temperature vary between 17.9 – 33.4 °C. Annual precipitation are between 1,228 – 2,151 mm, being September through November the period with maximum precipitation, and January to March the driest.

Dung beetle sampling protocol was calibrated between 2005 and 2006, and surveys were performed in August 2006 and September 2009. Different sampling protocols were used in each year. In 2006 seven groups (G01 – G07) containing seven to nine traps were placed, totaling 60 dung baited traps. Samples were taken once daily during four consecutive days (i.e. four visits). In 2009, five groups of 14 traps were placed, totaling 70 baited traps: 25 with dung, and 45 were baited with carrion. Three groups matched locations already sampled in 2006 (G02, G04 and G06) while two groups represent new locations (G08 and G09). In this case, samples were taken once daily for three consecutive days (i.e. three visits). Carrion baits were not considered in the analysis because they are not effective for sampling the two *Eurysternus* species expected in the area, thus total effective sampling effort in 2006 was 5,258.52 trap * hours, while in 2009 it was only 1,842.12 trap * hours. With this effort, only two species of *Eurysternus* were collected during the 2006 and 2009 surveys. *E. impressicollis* and *E. mexicanus*, Harold 1869. This last species was the more abundant and widespread *Eurysternus* species across NeoMap surveys, detected in 17 of 31 gradsect, being more abundant in El Manteco (NM22; 346 individuals), Anacoco (NM93; 97 ind.), Coromoto (NM55; 102 ind.) and Rosario de Perijá (NM05; 79 ind.). *E. impressicollis*, on the other hand was only detected in Rosario de Perijá (NM05; 145 ind.).

Abundance estimation

Hierarchical models handle variation in the observed data as a result of explicit "observation" and "state process" components (Kery and Dorazio 2008). Detection error is incorporated in the observation component, while the state process component incorporates the underlying ecological process (i.e. abundance or occupancy; Dénes et al. 2015b). Assuming abundance varies among sites, one can expect local variation in the site-level detection probability (p) because sites with higher abundance yield more 'net' detections and *vice versa*. In the N-mixture model, counts at site i are defined as the number of individuals of a given species detected in the repeated j samples (i.e. the observation process), and are

assumed to follow a binomial distribution with number of trials equal to j and probability p_i , which in turn depends on the unknown abundance N_i (i.e. the underlying state process), modeled as a random variable with a Poisson distribution. The method generates parameter estimates of the abundance distribution across sites (λ) that allow evaluation of temporal changes or geographic comparisons. Measurable variables that are thought to influence detection at the site level and abundance were added to the model as covariates using a link function. The model assumes that the population sampled is closed during the sampling period with respect to mortality, recruitment and movement. It also assumes that detections at a site are independent, and that all individuals recorded at a given site, and time have the same detection probability (Dénes et al. 2015b).

Here, each trap was considered a site ($i = 1, \dots, \hat{i}$) for the purpose of modelling, assuming that intertrap distance within a group (>50m) was enough to avoid autocorrelation (Ferrer-Paris et al. 2013), but data from each group of traps was aggregated in order to summarize results. Each site was independently surveyed on j sampling occasions (i.e. visits), For each site i and sampling occasion j , the total observed count, was recorded, giving a matrix of observed point counts, denoted $\{n_{ij}\}$. A latent Poisson distribution was assumed for species abundance at each site, and a multinomial distribution for the observation state or detection process.

Covariates for p were sampling effort (E) and evotranspiration (ETs) during sampling period. Sampling effort for each visit j was measured as the number of hours between visits ($E_{mean} = 22.28 \pm 2.58$ hours per visit in 2006, and $E_{mean} = 25.94 \pm 3.73$ hours per visit in 2009). In order to get representative data on climatic condition at the time of the survey, the location and date of each observations were matched with point estimates of Evapotranspiration (ETs; MOD16A2, version 6, 1 km resolution; Running et al. 2017) derived from the Moderate Resolution Radio Spectrometer (MODIS) sensors in Terra-Satellites (Funk et al. 2015).

Five covariates were tested as explanatory variables of abundance. The representative value of each covariates for the year prior to the sampling time (approx. August 2005 – August 2006) was calculated: 1) the total annual precipitation (PREC; CHIRPS database, (Funk et al. 2015)); and 2) the total accumulated Evapotranspiration (ET; MOD16A2, version 5, 1 km resolution; Running et al. 2017) as proxies of water balance; 3) the average of day and night Land Surface Temperature (LST; MOD11A2, version 5, 1 km spatial resolution) as a measure of local temperature (Wan et al. 2015); 4) the Enhanced Vegetation Index (EVI; MOD13Q1, version 5, 250 m; Huete et al. 2002), and 5) the mean Leaf Area Index (LAI; MOD15A2 version 5, 1km; (Myneni et al. 2015; Yang et al. 2006) as proxies of vegetation condition. Variables were standardized before analysis to zero mean and unit standard deviation.

For both species a multinomial-Poisson mixture model was fitted using package unmarked in R (Royle et al. 2006; Fiske and Chandler 2011) using the built-in removal multinomial cell probability function. The models were fitted using data from 2006 surveys only. For *E. impresicollis*, models were fitted using data from 60 sites corresponding to gradsect NM05 where the species was detected. For *E. mexicanus*, models were fitted with data from 384 sites, which include 17 NeoMaps gradsects surveyed in 2006 where the

species was detected at least once. The model included a linear combination of ET, LAI, EVI, LST and PREC as covariates of abundance, for *E. impressicollis* the model considered sampling effort and ETs as covariates of detection probability, while for *E. mexicanus* only sampling effort as covariate of detection probability was included (Table 1). Alternative models with different variable combinations were tested, but were discarded due to poorer fit (higher value of Akaike Information Criterion), overfitting of parameters (extreme estimates or standard errors), and/or poor predictive performance (higher bias in parametric bootstrapping tests with data for 2006 and 2009; Royle 2004). For both species the selected model explained more than half of the residual deviance when compared with a null model with sampling effort as covariate of detection probability and group of traps as covariate of abundance (Royle 2004).

Then, fitted models for each species were used to estimate posterior distribution of abundance conditioned on observed sampling effort in the localities sampled in 2006 and 2009 using empirical Bayes methods (Kery and Dorazio 2008). In order to rule out the effect of different sampling locations and effort between years, we also predicted temporal patterns in expected (unconditional) abundance in the group of 60 traps sampled in 2006 using time series of the covariates between 2004 and 2010.

Results

For *E. impressicollis* variables related with vegetation conditions (EVI and LAI) and temperature (LST) were the most important to explain the observed abundance which was higher in forested and hottest localities (Table 1). As expected, detectability of *E. impressicollis* had a positive relationship with sampling effort, but a negative relationship with evotranspiration (Table 1).

Abundance of *E. mexicanus* had a negative association with vegetation conditions (LAI) and precipitation (PREC), and a positive association with evotranspiration (ET) (Table 1). Sampling effort had a positive but not significant effect on detectability of *E. mexicanus* (Table 1).

The estimated posterior distribution of the latent abundance suggests significant differences in overall abundances between species during 2006: Estimated abundance and 95% CI was 265 (192 – 395) for *E. impressicollis* and 88 (79 – 158) for *E. mexicanus*. This can be largely attributed to differences in the first group of traps (Figure 2). *E. impressicollis* was significantly more abundant in G01 at the extreme north of the gradsect, while both species had similar high abundances in G07 at the extreme south of the gradsect. Both species were predicted to be absent or have low abundances in the intermediate groups of traps.

The prediction for the localities sampled in 2009 suggest lower abundance with similar levels of variations across group of traps, but observed differences between species are not significant: 35 (31 – 35) for *E. impressicollis* and 41 (20 – 64) for *E. mexicanus* (Figure 2).

The differences between years is congruent with predicted fluctuations in abundance based on time series of the covariates. For example, precipitation showed a regular pattern between 2004 to 2006, but high precipitation in 2007 was followed by extended dry seasons in 2008 and 2009 (Figures 3a), and

resulted in longer seasons with low values of the Leaf Area Index (Figure 3b). The fitted model predicts a sharp decline in the abundance of *E. impressicollis* in 2008 with a slow recovery afterward (Figure 3c), but *E. mexicanus* show less extreme fluctuations throughout this period (Figure 3d).

Discussion

Variability in sampling methods, including variation in sampling design and effort might affect the ability to detect target species, confounding the perceived patterns of species presence across the landscape. NeoMaps sampling methods, as in other biodiversity monitoring schemes, have been repeatedly tested and modified to improve their effectiveness in estimating richness and abundance patterns (Ferrer-Paris et al. 2013). These modification however, hamper the direct comparison of count data from different years and localities. The approach used here solved these limitations and allowed to: 1) discriminate between the confounding effect of variability in detection across a wide range of survey conditions, 2) get reliable abundance estimates for two *Eurysternus* species, and 3) describe the local pattern in abundance as response to climatic and environmental factors.

Variability in detection

Fitted models support the hypothesis that temporal changes in the detectability of *E. impressicollis* respond to sampling effort and environmental conditions during sampling (Camero-Rubio and Lobo 2012), the high estimates of detectability reported here, suggest that NeoMaps sampling effort in 2006 and 2009 was enough to detect this species where it was present, and thus lack of detection in other transects are likely to represent true absences or very low abundances. Environmental conditions were assumed to be related to species activity during the surveys. The relationship of daily activity pattern with ground temperature and time of day have been studied for species of the tribe Eucraniini, and different responses seems to be associated to the thermal tolerance of each species (Giménez-Gómez et al. 2017). Studies on eco-physiology for *Eurysternus* species are needed in order to correctly interpret the observed relationship between evapotranspiration and detectability for *E. impressicollis*, but the predicted accumulated probability of detection was high enough to guarantee an effective sampling with the NeoMaps sampling protocol in 2006 and 2009.

Although records from literature and collections have suggested that *E. impressicollis* could have a wider ecological niche and extensive potential distribution in northern Venezuela (Camero-Rubio and Lobo 2012), the lack of detection in other NeoMaps gradsects are likely to represent true absences or very low abundances. Thus, the evidence suggest that *E. impressicollis* is truly restricted to the Maracaibo Province *sensu* Morrone et al. (2022), with confirmed presence records in the Sierra de Perijá in Venezuela, and apparent absence south of Lake Maracaibo (NeoMaps gradsects NM07 and NM26; Ferrer-Paris et al. 2013). Future surveys should be directed to the east of Lake Maracaibo and in the Guajira Peninsula to determine its true distribution limits.

Temporal and spatial patterns of abundance

The temporal variation in abundance of *Eurysternus* beetles in Rosario de Perijá between 2006 and 2009 was satisfactorily explained by changes in environmental conditions. That is, the low numbers of *Eurysternus* sampled in 2009 were not a sampling artifact, but were likely to reflect a real reduction of dung beetle abundance due to changes in vegetation and climatic conditions.

Vegetation condition was the most important variable to explain abundance in both species, while climatic conditions played a secondary role. Both species were positively related to high values of the enhanced vegetation indices, but differ in their relationship with leaf area index and climatic variables such as precipitation or temperature (Table 1). Both species have been reported in landscapes with forest/pasture mosaics (Lozano 2010), but quantitative data suggests higher abundance in dry forest and during rainy seasons than in pasture or during dry seasons (Navarro et al. 2011).

In the sampling area *E. impressicollis* was more abundant in localities with higher vegetation cover (denser, more humid forest), while *E. mexicanus* seems to prefer more deciduous, drier or fragmented forest, although this last species can also be found in a wide range of conditions across the country (Navarro et al. 2011). Also, the three known collection localities in Venezuela of *E. impressicollis* are located in more densely forested areas in Perijá. However, for *E. mexicanus* previous evidence (Navarro et al. 2011) suggest higher abundance in forested areas, which contrast with results presented here. The pattern reported here for *E. mexicanus* is more reliable because model was based in a higher number of data, and covering wider environmental conditions across the country.

Although we did not monitor species abundance through time, the models fitted with data from the 2006 survey had a good predictive performance when extrapolated to 2009 (Figure 2), when conditions were drier and vegetation was in poorer condition (Figures 3a – 3b). If the modeled relationship holds true, we would expect interannual and multiannual fluctuations in the abundance of these species reflecting the changes in these variables (Figures 3c – 3d). Again, these results agree with previous studies reporting fluctuations in abundance between rainy and dry seasons (Navarro et al. 2011), but a multi-season, and multi-year sampling program would be needed to prove the reliability of these predictions and to detect long term trends in their abundance.

Temporal and spatial variations in abundance, might reflect different preferences of the species or the result of interspecific competition. Both species seem to be more or less limited to forest vegetation and are less abundant or absent in less forested areas in the middle part of the gradsect. However, the fact that *E. impressicollis* was significantly more abundant than *E. mexicanus* in the extreme north of the gradsect, located in a less fragmented landscape than the extreme south which was a more perturbed area, suggest that *E. impressicollis* could be more competitive than *E. mexicanus* when habitat and climatic conditions are favorable. Clearly a more detailed study covering a wider range of forest densities is required to confirm this idea. Sampling did not include localities inside the more densely forested area, and patterns in more intact habitat might be different (Rangel- Acosta et al. 2016). Competitive exclusion can not be confirmed or ruled out with the baited trap method, because the interaction of the species within the individual dung-piles can not be observed. For example, both species were collected together

in many traps, but *E. mexicanus* was more often collected in the first 48 hours of sampling, while *E. impressicollis* was more often collected between 24 and 72 hours of sampling (data not shown). Future studies should test whether *E. impressicollis* can feed and breed in dungpiles already colonized by *E. mexicanus*.

These results provide a first quantitative account of one population of *E. impressicollis* in Venezuela. These results can inform future assessments of the conservation status of this species, and our recommendations could help guide future studies on the distribution and ecology of this species for monitoring and conservation. Additionally, the approach used here can be applied to analyze the impressive occurrence and count data accumulated in years of dung beetle monitoring across the world.

Declarations

All authors contributed to the study conception and design. Material preparation by Cecilia Lozano and Arlene Cardozo, data collection by Cecilia Lozano and Arlene Cardozo, and analysis were performed by [José Ferrer-Paris] and [Ada Sánchez-Mercado]. The first draft of the manuscript was written by [José Ferrer-Paris] and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Conflict of Interest

The authors declare that they have no conflict of interest.

References

1. Bates AE, Bird TJ, Stuart-Smith RD, Wernberg T, Sunday JM, Barrett NS, McCarthy M (2015) Distinguishing geographical range shifts from artefacts of detectability and sampling effort. *Divers. Distrib.* 21: 13–22.
2. Brown GR, Matthews IM (2016) A review of extensive variation in the design of pitfall traps and a proposal for a standard pitfall trap design for monitoring ground-active arthropod biodiversity. *Ecol. Evol.* 6: 3953–3964.
3. Camero-Rubio E, Lobo JM (2012) The distribution of species of *Eurysternus* Dalman, 1824 (Coleoptera: Scarabaeidae) in America: Potential distributions and the locations of areas to be surveyed. *Trop. Conserv. Sci.* 5: 225–244.
4. Davis AL, Scholtz CH (2001) Historical vs. ecological factors influencing global patterns of Scarabaeinae dung beetle diversity. *Divers. Distrib.* 7: 161–174.
5. Dénes FV, Silveira LF, Beissinger SR (2015a) Estimating abundance of unmarked animal populations: accounting for imperfect detection and other sources of zero inflation. *Methods Ecol. Evol.* 6: 543–556.
6. Dénes FV, Silveira LF, Beissinger SR (2015b) Estimating abundance of unmarked animal populations: Accounting for imperfect detection and other sources of zero inflation. *Methods Ecol. Evol.* 6: 543–

556.

7. Dunn RR (2005) Modern Insect Extinctions, the Neglected Majority. *Conserv. Biol.* 9: 1030–1036.
8. Ferrer-Paris JR, Lozano C, Cardozo-Urdaneta A, Thomas-Cabianca A (2016) Indicative response of *Oxysternon festivum* Linné (Coleoptera: Scarabaeidae) to vegetation condition in the basin of the Orinoco river, Venezuela. *J. Insect Conserv.* 20: 527–538.
9. Ferrer-Paris JR, Rodríguez JP, Good T, Sánchez-Mercado A, Rodríguez-Clark KM, Rodríguez GA, Solís A (2013) Systematic, large-scale national biodiversity surveys: NeoMaps as a model for tropical region. *Divers. Distrib.* 19: 215–231.
10. Fiske I, Chandler RB (2011) Unmarked: An R package for fitting hierarchical models of wildlife occurrence and abundance. *J. Stat. Softw.* 43: 1–23.
11. Funk C, Peterson P, Landsfeld M, Pedreros D, Verdin J, Shukla S, Michaelsen J (2015) The climate hazards infrared precipitation with stations – a new environmental record for monitoring extremes. *Sci. Data* 2: 1–21.
12. Gardner TA, Hernandez MIM, Barlow J, APC (2008) Understanding the biodiversity consequences of habitat change: The value of secondary and plantation forests for neotropical dung beetles. *J. Appl. Ecol.* 45: 883–893.
13. Genier F (2009) Le genre *Eurysternus* Dalman, 1824 (Scarabaeidae: Scarabaeinae: Oniticellini) révision taxonomique et clés de détermination illustrées. Bulgaria: Series Faunistica No 85, Pensoft Editors, Sofia.
14. Giménez-Gómez VC, Lomáscolo SB, Zurita GA, Ocampo F (2017) Daily activity patterns and thermal tolerance of three sympatric dung beetle species (Scarabaeidae: Scarabaeinae: Eucraniini) from the Monte Desert, Argentina. *Neotrop. Entomol.* 47: 4281.
15. Hallmann CA, Sorg M, Jongejans E, Siepel H, Hofland N, Sumser H, Kroon H (2017) More than 75 percent decline over 27 years in total flying insect biomass in protected areas. *PLoS Biol.* 12: e0185809.
16. Huete A, Didan K, Miura T, Rodriguez EP, Gao X, Ferreira LG (2002) Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sens. Environ.* 83: 195–213.
17. IUCN (2019) The International Union for Conservation of Nature's Red List of Threatened Species. Accessed in September 05, 2023, from <https://www.iucnredlist.org/>
18. Joseph LN, Elkin C, Martin TG, Possingham HP (2009) Modeling abundance using N-mixture models: The importance of considering ecological mechanisms. *Ecol. Appl.* 19: 631–642.
19. Kéry M, Dorazio RM (2008) Hierarchical modeling and inference in ecology: The analysis of data from populations, metapopulations and communities. Elsevier, Cambridge.
20. Kéry M, Royle JA (2016) Modeling abundance using multinomial N-Mixture Models. In *Applied Hierarchical Modeling in Ecology* (ed. by Kéry, M., & Royle, J. A.), pp. 313–392. Elsevier, Cambridge.
21. Kéry M, Schmidt BR (2008) Imperfect detection and its consequences for monitoring for conservation. *Commun. Ecol.* 9: 207–216.

22. Koch SO, Chown SL, Davis ALV, Endrády-Younga S, van Jaarsveld AS (2000) Conservation strategies for poorly surveyed taxa: a dung beetle (Coleoptera, Scarabaeidae) case study from southern Africa. *J. Insect Conserv.* 4: 45–56.
23. Lozano C (2010) Nuevos registros de escarabajos coprófagos para La Orchila, Sierra de Perijá, Venezuela. *Bol. Cent. Invest. Biol.* 44: 83–89.
24. Morrone JJ, Escalante T, Rodríguez-Tapia G, Carmona A, Arana M, Mercado-Gómez JD (2022) Biogeographic regionalization of the Neotropical region: New map and shapefile. *An Acad Bras Cienc.* Jan 31;94(1):e20211167. <https://doi.org/10.1590/0001-3765202220211167>
25. Myneni R, Knyazikhin Y, Par T (2015) MOD15A2 MODIS/Terra Leaf Area Index/FPAR 8-Day L4 Global 1km SIN Grid. NASA LP DAAC. Boston University and MODAPS SIPS - NASA. doi:<http://doi.org/10.5067/MODIS/MOD15A2.006>
26. Navarro IL, Roman K, Gomez H, Pérez A (2011) Variación estacional en escarabajos coprófagos (Coleoptera: Scarabaeidae: Scarabaeinae) de la Serranía de Coraza, Sucre (Colombia). *Rev. Colomb. Cienc. Anim.* 3: 102–110.
27. Nichols E, Spector S, Louzada J, Larsen T, Amequita S, Favil ME (2008) Ecological functions and ecosystem services provided by Scarabaeinae dung beetles. *Biol. Conserv.* 6: 1461–1474.
28. Rodríguez JP, Rojas-Suárez F, García-Rawlins A, Rojas-Suárez F (2015) Libro rojo de la fauna venezolana (2nd edn). Provita & Fundación Empresas Polar, Caracas, Venezuela.
29. Rodríguez JP, Sharpe CJ (2002) NeoMaps: The Neotropical biodiversity mapping initiative. *Cotinga* 17: 13–14.
30. Royle JA (2004) Generalized estimators of avian abundance from count survey data. *Animal Diversity and Conservation* 27: 375–386.
31. Royle JA (2004) N-Mixture models for estimating population size from spatially replicated counts. *Biometrics* 60: 108–115.
32. Rubio EC, Lobo JM (2010) Distribución conocida y potencial de las especies del género *Eurysternus* Dalman, 1824 (Coleoptera: Scarabaeidae) de Colombia. *Bol. Soc. Entomol. Arag.* 47: 257–264.
33. Running S, Mu Q, Zhao M (2017) MOD16A2 MODIS/Terra Net Evapotranspiration 8-Day L4 Global 500m SIN Grid V006 [Data set]. doi:10.5067/MODIS/MOD16A2.006
34. Scheffler PY (2005) Dung beetle (Coleoptera: Scarabaeidae) diversity and community structure across three disturbance regimes in eastern Amazonia. *J. Trop. Ecol.* 21: 9–19.
35. Schoolmeesters P (2023) World Scarabaeidae Database. In: Bánki O, Roskov Y, Döring M, Ower G, Vandepitte L, Hobern D, Remsen D, Schalk P, DeWalt RE, Keping M, Miller J, Orrell T, Aalbu R, Abbott J, Adlard R, Adriaenssens EM, Aedo C, Aescht E, Akkari N, et al. (eds) *Catalogue of Life Checklist (Version 2023-03-06)*. Available from <https://www.catalogueoflife.org/data/dataset/1027> [last accessed 03 Apr 2023].
36. Spector S (2006) Scarabaeine dung beetles (Coleoptera: Scarabaeidae: Scarabaeinae): An invertebrate focal taxon for biodiversity research and conservation. *Coleopt. Bull.* 5: 71–83.

37. Spector S, Nichols E, Gomez A (2008) Dysfunctional hotspots? Pan-tropical changes in dung beetle communities and declining ecosystem functions. Paper Presented at the Annual Meeting of the International Congress for Conservation Biology, Convention Center, Chattanooga.
38. Wan Z, Hook S, Hulley G (2015) MOD11A2 MODIS/Terra Land Surface Temperature/Emissivity 8-Day L3 Global 1km SIN Grid V006 [Data set]. doi:10.5067/MODIS/MOD11A2.006
39. Yang W, Shabanov NV, Huang D, Wang W, Dickinson RE, Nemani RR, et al. (2006) Analysis of leaf area index products from combination of MODIS Terra and Aqua data. Remote Sens. Environ. 104: 297–312.

Table 1

Table 1: Model predictions for *E. impresicollis* and *E. mexicanus*. Akaike Information Criterion (AIC) Nagelkerke's coefficient of determination (R^2_{nag}) and number of locations used to fit models is shown. PREC = total annual precipitation. LST = mean annual value of Land Surface Temperature. EVI = mean annual value of Enhanced Vegetation Index. LAI = mean annual value Leaf Area Index. ET = total annual value of Evapotranspiration. E = Sampling effort; ETs = Evapotranspiration value during sampling period.

E. impresicollis

λ (LAI + EVI + ET + LST + PREC) d(E + ETs)

AIC = 439.182; $R^2_{nag} = 0.50$

Number of sites = 60

Abundance			
Parameter	Estimate	SE	Z value
Intercept	-1.12	0.443	-2.54
LAI	1.15	0.226	5.11
EVI	2.93	0.367	8.00
ET	1.42	0.459	3.10
LST	2.14	0.488	4.40
PREC	0.96	0.244	3.93
Detection			
Intercept	-9.55	1.611	-5.92
E	8.68	1.834	4.73
ETs	-1.17	0.562	-2.08

E. mexicanus

λ (LAI + EVI + ET + LST + PREC) d(E)

AIC = 2119.734; $R^2_{nag} = 0.56$

Number of sites = 384

Abundance			
Parameter	Estimate	SE	Z value
Intercept	-0.771	0.2306	-3.34
LAI	-0.857	0.0672	-12.76
EVI	0.547	0.0694	7.88
ET	0.790	0.0650	12.15
LST	-0.373	0.0713	-5.24
PREC	-0.381	0.0420	-9.07

Detection			
Intercept	-1.388	0.229	-6.053
E	0.131	0.201	0.652

Figures

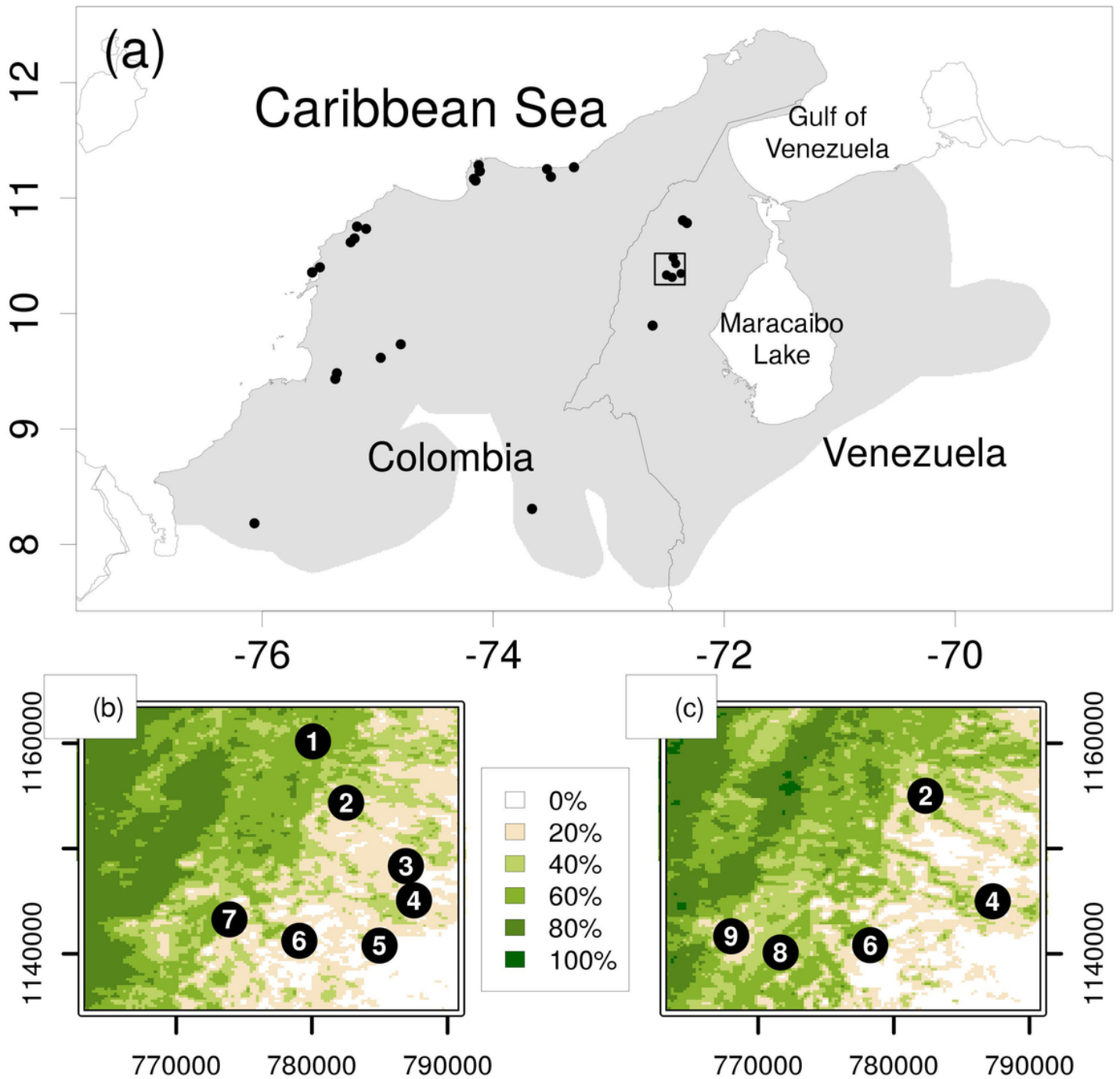


Figure 1

Study area. a) Known and expected distribution of *E. impresicollis*. The gray polygon represents the Maracaibo Province *sensu* Morrone et al. (2022) between Colombia and Venezuela. Circles indicate presence points recorded from literature, collections and NeoMaps surveys. Insets show percentage forest cover in the Rosario de Perijá (NM05) region and locations of groups of trap during surveys in 2006 (b) and 2009 (c).

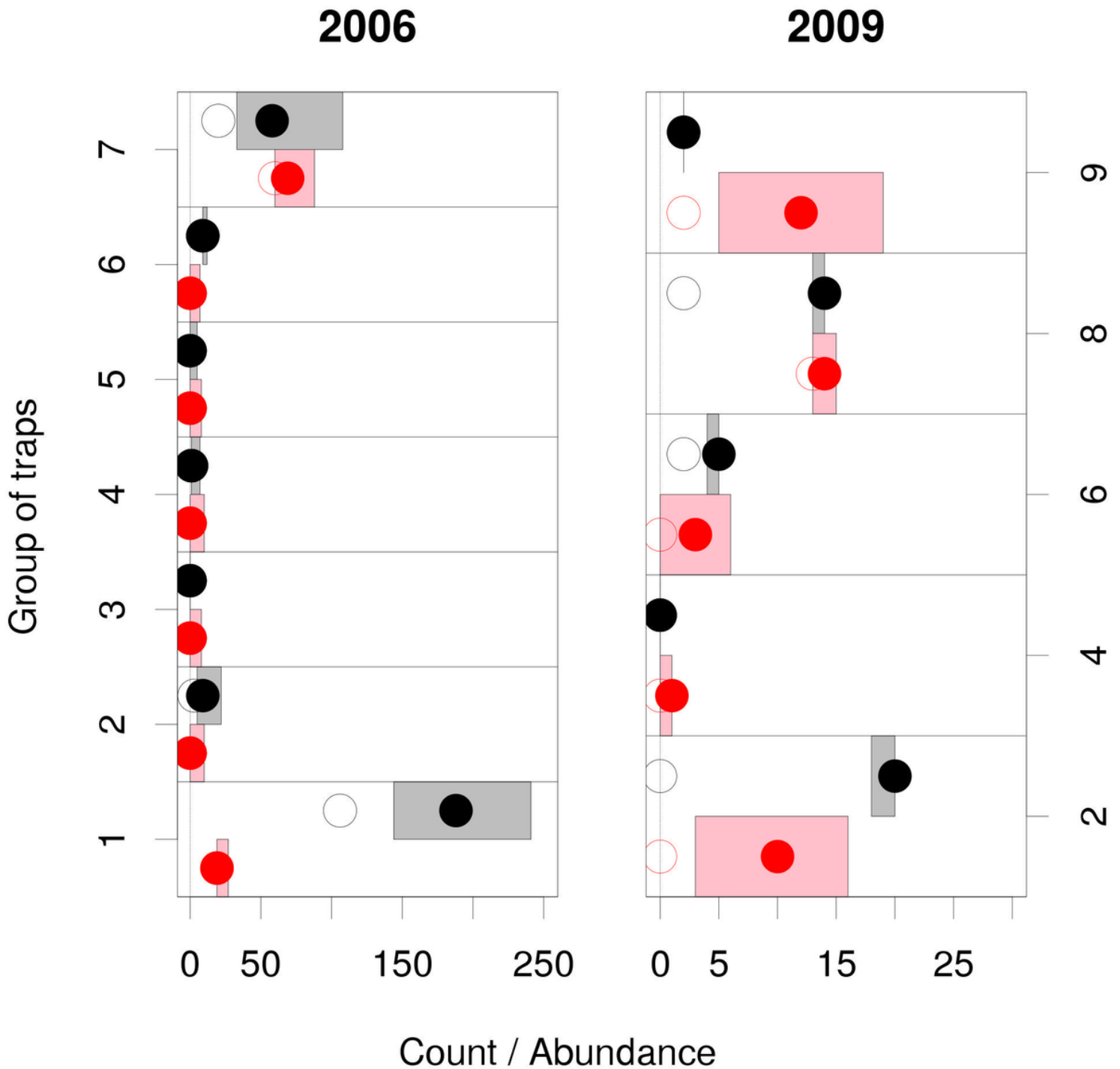


Figure 2

Observed and predicted abundance by group of traps for *E. impressicollis* (gray) and *E. mexicanus* (red). Open circles indicates observed counts, while close circles indicate the mean posterior abundance conditioned on observed sampling effort. Boxes show the 95% confidence intervals in predictions.

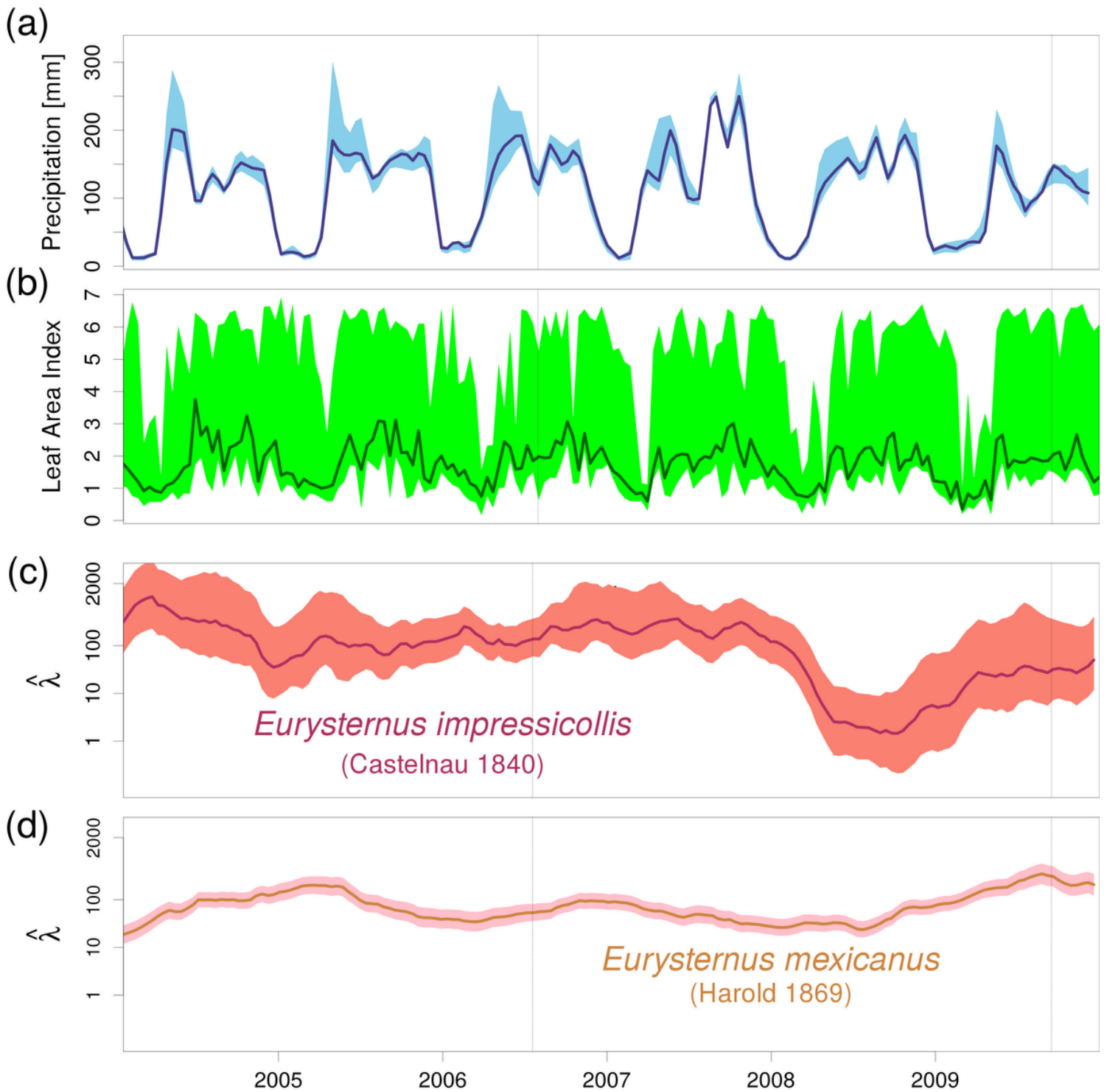


Figure 3

Time series of variables derived from remote sensors at 60 localities sampled in 2006, and model predictions of total abundance in these localities. For the covariate measurements, the lines indicate

median values and gray areas indicate minimum and maximum values of the sampled localities. For predictions of abundance, the lines represent the estimated total and the gray areas the approximate 95% confidence intervals of the predictions. (a) Precipitation (PREC); (b) Leaf Area Index (LAI); (c) abundance (λ) of *E. impresicollis*; and (d) abundance of *E. mexicanus*. Dotted lines indicated the date of NeoMaps surveys in 2006 and 2009.