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Potential distribution of *Akymnopellis chilensis* (Gervais, 1847) (Scolopendridae, Scolopendromorpha, Chilopoda) through Random Forest and MaxEnt in Chilean Ecosystems

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SUMMARY

Akymnopellis chilensis (Gervais, 1847) (Scolopendridae, Scolopendromorpha, Chilopoda), a centipede species endemic to Chile, plays a crucial role in soil ecosystems, but its distribution is still poorly studied. This study aims to predict its potential distribution using three variables sets to build two species distribution models (SDM). We ask: (1) which climatic and environmental variables best explain the distribution of this species, and (2) whether its predicted potential range extends beyond the currently known records. MaxEnt and Random Forest algorithms were performed using three sets of environmental variables: (1) core climate variables, (2) annual temperature and precipitation, and (3) seasonality of temperature and precipitation. All models showed good predictive performance (AUC > 0.92 in all cases) with high AUC values. Species distribution modelling in Chile is centred primarily between 30° and 40° S latitude. The results indicate that current records could underestimate its true distribution, and further studies are needed to validate the models.

INTRODUCTION

Chile encompasses a broad range of ecosystems that differ substantially in their climatic and edaphic conditions. (Martínez-Tilleria et al. 2017, Ministerio del Medio Ambiente 2018, Keith et al. 2022). Therefore, it becomes useful to understand the spatial patterns of edaphic fauna, which not only play important roles in nutrient cycling and soil formation but also contribute to ecosystem resilience and function (Alvial and Reculé 1999), and ecosystem services providers (Silva et al. 2019, Mishra and Singh 2020).

Among these organisms, centipedes (Myriapoda: Chilopoda) stand out as ecologically significant predators in soil communities (Voigtländer 2011). Their presence and abundance can serve as indicators of ecosystem health (Zapparoli 2007), and they are commonly found in the litter layer or beneath rocks, occupying diverse habitats across most terrestrial ecosystems (Lewis 1981, Jabin 2008). Despite their global distribution, including all continents except Antarctica (Bonato and Zapparoli 2011a), there remains a lack of detailed information on the habitat preferences and distribution patterns of many centipede species, particularly in South America (Kicaj 2023). The Chilean giant centipede, *Akymnopellis chilensis* (Gervais, 1847), is a notable example (Fig. 1B) inhabits a broad range of environments, from humid forests to semi-arid regions (Vega-Román et al. 2018). However, limited knowledge regarding its ecological niche and the environmental factors that determine its occurrence hinders our understanding of its requirements and its potential vulnerability to environmental conditions.

Given that *A. chilensis* is an edaphic predator and potentially sensitive to climatic and habitat variation, we hypothesize that its current distribution is narrower than its potential climatic niche, due to historical and sampling limitations. Identifying the main climatic and environmental drivers of its distribution will help distinguish between environmentally suitable areas that are currently unoccupied and areas where the species may be present but remains undetected due to sampling limitations, providing a clear basis for targeted monitoring and conservation strategies.

To address this knowledge gap, species distribution models (SDMs) offer a robust framework for predicting the potential geographic distribution of species using occurrence data and environmental predictors (Miller 2010, Sofaer et al. 2019, Franklin 2023). Techniques such as MaxEnt (Phillips et al. 2004) and Random Forest (Breiman 2001) have been widely applied in ecological research, each offering distinct advantages in terms of data requirements and predictive accuracy (Christin et al. 2019, Lissovsky and Dudov 2021, Valavi et al. 2022). MaxEnt is particularly effective with small sample sizes (Wisz et al. 2008, Boria and Blois 2018) and is grounded in the principle of maximum entropy (Phillips et al. 2004), while Random Forest is well suited for handling large datasets and capturing non-linear relationships (Salman et al. 2024).

Given that *Akymnopellis chilensis* is a soil-dwelling predatory myriapod strongly constrained by moisture availability and thermal stability, we hypothesize that its currently known distribution underestimates its potential climatic niche. Specifically, we expect climatic seasonality, rather than mean temperature or precipitation alone, to play a primary role in shaping its potential geographic range in Chile. In this study, we evaluate the potential climatic distribution of *A. chilensis* in Chile using species distribution models based on MaxEnt and Random Forest algorithms. Specifically, we aim to (1) identify the climatic variables that best explain its potential distribution, with particular emphasis on the role of temperature and precipitation seasonality relative to mean climatic conditions; and (2) assess whether the predicted potential distribution of *A. chilensis* extends beyond its currently known records, highlighting areas of climatic suitability that may reflect historical constraints or sampling limitations.

MATERIALS AND METHODS

Study Area

Chile is a southwestern country of the Americas and has a length of approximately 4,300 kilometers from north to south, with only 180 kilometers width. Its territory is delimited by strong geographic features: the Atacama Desert to the north, the Andes Mountains to the east, and the Pacific Ocean to the west and south (Santibañez et al. 2018). These features have historically shaped the distribution of terrestrial biota and generated high levels of endemism, acting as partial barriers to dispersal for many taxa (Sallaberry-Pincheira et al. 2011, Hernández-Mazariegos et al. 2023, Martin-Gallego et al. 2024).

Database

A bibliographic review of recorded scolopendromorph species in Chile served as the basis for the study. The literature review was conducted through websites "Web of Knowledge" (https://www.webofscience.com/wos/woscc/basic-search), "SciELO" (https://scielo.org), "CHILOBASE 2.0" (https://chilobase.biologia.unipd.it), Google Scholar (https://scholar.google.com), and the Myriatrix database (http://myriatrix.myspecies.info/), which has updated bibliography on myriapods worldwide. Keywords and thesauri used in the information search included: "Myriapoda + Chilopoda + Scolopendromorpha + Chile", "Myriapods + Chilopods+ Scolopendromorphs + Chile", "Scolopendromorpha + Chile", "Scolopendromorphs + Chile", and also, "Chile + target taxon".

We examined over 200 individual specimens from the collections of the Museum of Zoology at the Universidad de Concepción (MZUC-UCCC), the Chilean Museum of Natural History (MNHC), and the Laboratory of Ecological Entomology at the Universidad de La Serena (LEULS). The analysis of morphological traits followed the criteria established by Shelley (2008) and Vega-Román et al. (2018). Localities lacking geographic coordinates were georeferenced using the point–radius method (Wieczorek et al. 2004), which assigns a central coordinate and an associated uncertainty radius based on the original locality description. We defined a maximum uncertainty threshold of 1 km as a quality-control criterion, consistent with the spatial resolution of the environmental predictors (~1 km; 30 arc-sec). All georeferenced records fell within this threshold; therefore, no records were excluded, and positional uncertainty was not expected to influence environmental variable extraction or model outcomes. The coordinates and corresponding uncertainty radius were derived through Google Earth. After eliminating duplicate records, the combined data from the literature review and museum examination resulted in 31 unique occurrences (Table S1) with valid locality or geographical coordinates (Fig. 1A).

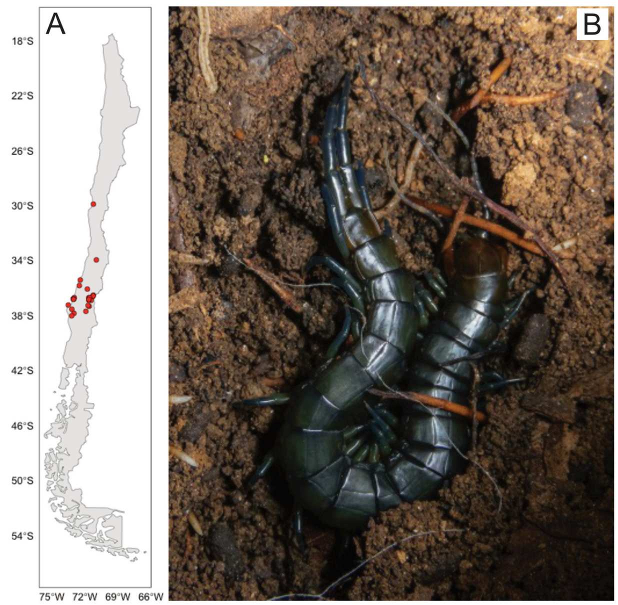

Figure 1. A) *Akymnopellis chilensis* records points in Chile. B) Habitus of *A. chilensis*. Claudio Maureira. https://inaturalist.mma.gob.cl/observations/61070039.

We did not use iNaturalist data, as accurate identification of *Akymnopellis chilensis* requires the examination of diagnostic morphological characters, such as the superposition of the cephalic plate over the 21st tergite, the paramedian groove of the 21st tergite, and the spine distribution on the femur of the anal appendages, which are not externally visible and cannot be assessed from photographs (Shelley 2008, Vega-Román and Ruiz 2014). Consequently, most records based solely on photographs of live individuals do not allow species-level identification with scientific certainty. Moreover, previous taxonomic revisions and our own examination of more than 200 museum specimens indicate that closely related species within the same genus exhibit high morphological similarity, particularly in external coloration and body size, rendering photographic identification unreliable.

Variable Selection

Nineteen bioclimatic variables were compiled from Worldclim database (Table S2), version 2.1 (Hijmans et al. 2005) with 30 arc-second spatial resolution. To avoid collinearity between variables we calculated the Pearson's r correlation for the 19 variables after standardizing the data (mean =0, SD =1) in R (R Core Team 2024) (Table S3). Parameter range of species occurrences are available in Table S4. Based on this analysis, we reduce the initial set to eight non-collinear variables with the lowest intercorrelations, representing the main climatic dimensions associated with temperature and precipitation regimes (Table 1). From these eight variables, we defined three alternative sets following an ecological meaning and temporal structure:

1) Core Climate Variables (CCV): set compromising a non-redundant combination of temperature and precipitation variables selected to characterize typical climatic conditions during ecological relevant periods of the year, including wet and dry phases, while minimizing predictor redundancy;

2) Annual Temperature and Precipitation (ATP): variables representing long-term thermal and hydric averages that define the general climatic envelope of the species;

3) Seasonality of Temperature and Precipitation (STP): variables reflecting the amplitude and irregularity of climatic fluctuations, which are particularly relevant for species sensitive to desiccation and thermal stress, such as soil-dwelling arthropods.

Table 1. Pearson's r correlation and its significance of bioclimatic variables used in SDMs. Bottom triangle represents p value and top triangle Person's r correlation. Bold printed values indicate high r.

	Bio 1	Bio 3	Bio 4	Bio 8	Bio 9	Bio 12	Bio 13	Bio 15
Bio 1		0.367	-0.192	**0.791**	**0.894**	-0.282	-0.156	0.268
Bio 3	<0.01		-0.55	0.581	0.124	**-0.668**	-0.589	0.561
Bio 4	<0.01	<0.01		-0.548	0.136	0.265	0.444	0.066
Bio 8	<0.01	<0.01	<0.01		0.471	-0.392	-0.403	0.179
Bio 9	<0.01	0.005	0.002	<0.01		-0.136	0.075	0.244
Bio 12	<0.01	<0.01	<0.01	<0.01	0.002		**0.919**	-0.443
Bio 13	<0.01	<0.01	<0.01	<0.01	0.089	<0.01		-0.22
Bio 15	<0.01	<0.01	0.135	<0.01	<0.01	<0.01	<0.01	

This grouping approach prioritizes ecological interpretability over dimensional reduction, allowing modelled relationships to be interpreted in terms of biologically meaningful climatic gradients (e.g., moisture availability, thermal stability, and climatic variability) rather than relying on an undifferentiated set of predictors (Table 2).

Species distribution model

Occurrence records were thinned to remove duplicates, and 10,000 background points were generated. Model robustness was evaluated via 5-fold spatial cross-validation (block method), with AUC used as the primary performance metric. Response curves were examined to assess ecological plausibility. Random Forest models were fitted for each variable set to assess the distribution patterns of *Akymnopellis chilensis*. Random Forest machine learning has established as one of the most extensively employed methodologies in the field of ecological modelling (Stupariu et al. 2022). Although Random Forest is often applied to large datasets, previous studies have shown that it can also perform well with relatively small sample sizes in species distribution modelling, providing robust predictions when appropriate validation procedures are applied (Mi et al. 2017). We built 500 trees for all variables sets; other parameters were set on default. Species distribution models for *Akymnopellis chilensis* were also constructed using MaxEnt (Phillips et al. 2006) in R. To reduce overfitting, only linear and quadratic features were used, and

Table 2. Bioclimatic variables set used by the SDMs and their Ecological Role.

Set	Code	Description	Ecological Role
1: Core Climate Variables (CCV)	Bio 3	Isothermality (BIO2/BIO7) (×100)	Describes the relative magnitude of daily versus annual temperature variation at a macroclimatic scale. May correlate with the distribution of soil-dwelling species, although such species are likely buffered from coarse-scale thermal variation by microhabitat conditions not captured by bioclimatic variables (Ashcroft and Gollan 2013, Keppel et al. 2017).
	Bio 4	Temperature Seasonality (standard deviation ×100)	Represents annual temperature variability; influences metabolic activity and reproductive timing, as centipedes are sensitive to abrupt thermal changes, although actual responses are likely mediated by microhabitat buffering (Castillo-Avila et al. 2025, Wan et al. 2025).
	Bio 8	Mean Temperature of Wettest Quarter	Indicates mean temperature during the wettest period; affects the availability of moist microhabitats and trophic activity, since chilopods are more active under humid conditions (Kicaj 2023).
	Bio 9	Mean Temperature of Driest Quarter	Mean temperature during the driest period; may be associated with distributional limits in regions where prolonged dry conditions reduce habitat suitability at a macroclimatic scale, (Kicaj 2023).
	Bio 13	Precipitation of Wettest Month	Associated with maximum soil and air humidity; promotes surface activity and prey availability for soil-dwelling predators (Kicaj 2023).
	Bio 15	Precipitation Seasonality (Coefficient of Variation)	Measures intra-annual variability of precipitation; high seasonality may restrict the species to areas with more constant humidity or shaded microhabitats (Kicaj 2023).
2: Annual Temperature and Precipitation (ATP)	Bio 1	Annual Mean Temperature	Determines the general thermal range suitable for physiological activity; moderate temperatures favour growth and survival centipedes (Kicaj 2023).
	Biol 12	Annual Precipitation	Indicates overall soil moisture and habitat humidity; a key factor for the persistence of populations that rely on moist substrates (Kicaj 2023).
3: Seasonality Temperature and Precipitation (STP)	Bio 4	Temperature Seasonality (standard deviation ×100)	Reflects the annual amplitude of temperature fluctuations; high variability may limit distribution to microclimatically buffered areas such as forests or ravines. (Castillo-Avila et al. 2025, Wan et al. 2025).
	Bio 15	Precipitation Seasonality (Coefficient of Variation)	Describes irregularity of rainfall patterns; affects soil moisture stability and the persistence of humid refuges required by the species (Kicaj 2023).

regularization multipliers (β) were optimized (Table S5). All models were performed on R language, the "randomForest" package for RF algorithm and "dismo" package (Hijmans et al. 2023) for MaxEnt algorithm (Script available in Supplementary Material).

Finally, we converted the continuous suitability and prediction into a binary prediction using the threshold that maximized the True Skill Statistic (TSS = Sensitivity + Specificity - 1) (Allouche et al. 2006). This step was only used to visualize areas of potential presence, not as a true presence–absence model, since our models were calibrated with presence-only data. TSS was computed using the threshold function in the dismo R package (Hijmans et al. 2023). Its values go from -1 to +1 with values > 0 indicating model performance better than random.

RESULTS

Across all predictors sets and modelling approaches, species distribution models showed consistently high predictive performance, indicating a robust signal of climatic suitability for *Akymnopellis chilensis*. Models showed good predictive performance with high AUC values (RF = > 0.95; MaxEnt = > 0.946) (Table 3). Considering the CCV set, RF explained 20.44% of the variation (MSE = 0.0369), with Precipitation Seasonality (Bio 15) and Precipitation of Wettest Month (Bio 13) being the most important variables according to %IncMSE. In contrast, permutation importance in MaxEnt identified Isothermality (Bio 3) and Precipitation Seasonality (Bio 15) as the main contributors. Considering the ATP set, RF explained 21.64% of the variation (MSE = 0.0363), with Annual Precipitation (Bio 12) and Annual Mean Temperature (Bio 1) ranking highest according to %IncMSE. Permutation importance in MaxEnt identified Mean Temperature (Bio 1) as the dominant driver. In the STP set, RF explained 12.77% of the variation (MSE = 0.040), with Precipitation Seasonality (Bio 15) ranking as the most important variable according to %IncMSE. In MaxEnt, Precipitation Seasonality (Bio 15) strongly dominated the model, contributing 86.9% and showing a permutation importance of 88.2%, highlighting the strong influence of precipitation seasonality on species distribution. Overall, RF tended to distribute importance more evenly across multiple predictors, whereas MaxEnt often concentrated importance on a single key variable, reflecting differences in how the algorithms weigh predictor influence (see Table 3).

Table 3. A) AUC scores for the three sets of covariates in each species distribution model (Random Forest, MaxEnt) for *A. chilensis* and Mean Decrease Accuracy (%IncMSE) of B) Random Forest Model for *A. chilensis* SDM.

A)

Set	Variable	%IncMSE (RF)	% Contribution (MaxEnt)	Permutation Importance (MaxEnt)
1: Core Climate Variables (CCV)	Bio 3	17.641	2.2	56.1
	Bio 4	15.197	3.8	3.0
	Bio 8	11.500	0.7	0.8
	Bio 9	13.625	6.8	7.0
	Bio 13	22.478	42.5	14.7
	Bio 15	24.449	44.0	56.1
2: Annual Temperature and Precipitation	Bio 1	15.057	26.7	82.4
	Bio 12	16.897	26.7	17.6
3: Seasonality Temperature and Precipitation (STP)	Bio 4	11.837	13.1	11.8
	Bio 15	18.424	86.9	88.2

B)

Set	Metric	Random Forest	MaxEnt
1: Core Climate Variables (CCV)	AUC	0.946	0.976
	Mean of squared residuals	0.037	--
	% Var explained:	20.44	--
2: Annual Temperature and Precipitation	AUC	0.978	0.926
	Mean of squared residuals	0.036	--
	% Var explained:	21.64	--
3: Seasonality Temperature and Precipitation (STP)	AUC	0.988	0.926
	Mean of squared residuals	0.040	--
	% Var explained:	12.77	--

Despite differences in algorithm structure, both modelling approaches consistently highlighted climatic seasonality as a key driver of habitat suitability for *A. chilensis*. In the CCV predictor set, MaxEnt response curves indicated that the probability of presence increased under intermediate values of Isothermality (Bio 3) and Precipitation Seasonality (Bio 15), followed by marked declines toward extreme values (Fig. 2). Temperature seasonality (Bio 4) showed a non-linear response, suggesting tolerance to moderate climatic variability but reduced suitability under highly seasonal conditions. The remaining CCV variables exhibited weak or non-informative response patterns and low relative contributions, suggesting a secondary role in shaping the species' distribution. According to the ATP set, MaxEnt response curves highlighted Annual Mean Temperature (Bio 1) and Annual Precipitation (Bio 12) as key drivers, exhibiting unimodal or threshold-like responses that indicate optimal environmental ranges for *A. chilensis* (Fig. 3A). In the STP set, MaxEnt response curves showed that precipitation seasonality (Bio 15) strongly dominated model responses, with a sharp increase in probability of presence beyond threshold values. Temperature Seasonality (Bio 4) also exhibited a non-linear response, with higher probabilities associated with intermediate levels of climatic variability (Fig. 3B), reinforcing the importance of seasonal climatic dynamics in shaping the species' distribution.

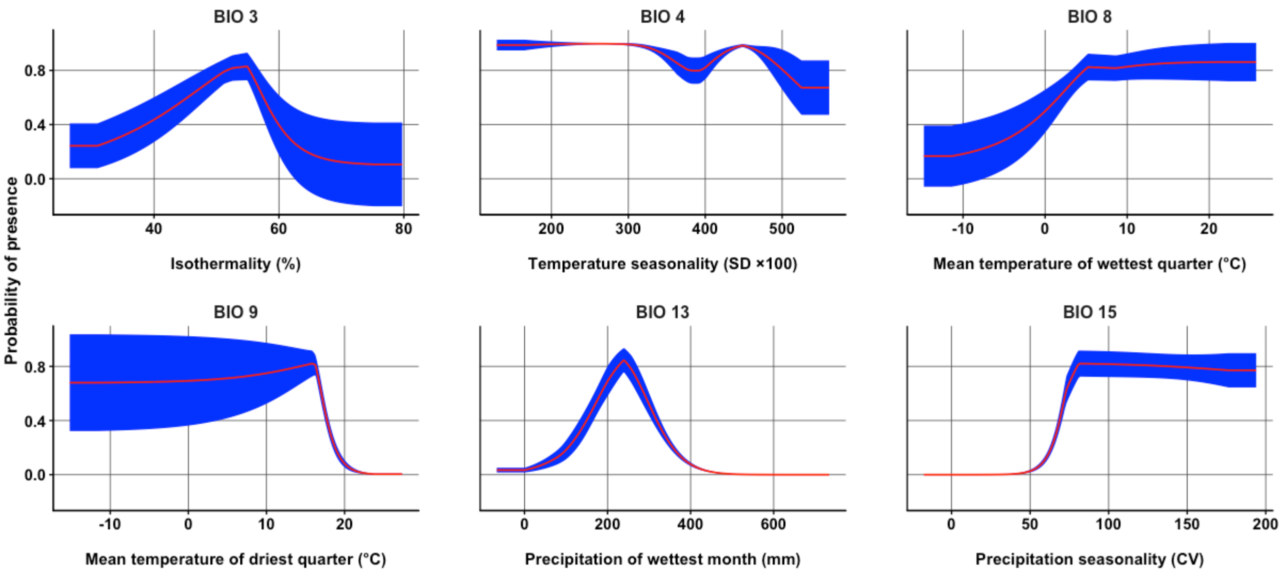

Figure 2. Response curves illustrating the relationship between the probability of presence for *A. chilensis* and the CCV bioclimatic predictors. The red line indicates the mean response across model replicates, while the blue shaded area represents the standard deviation (SD).

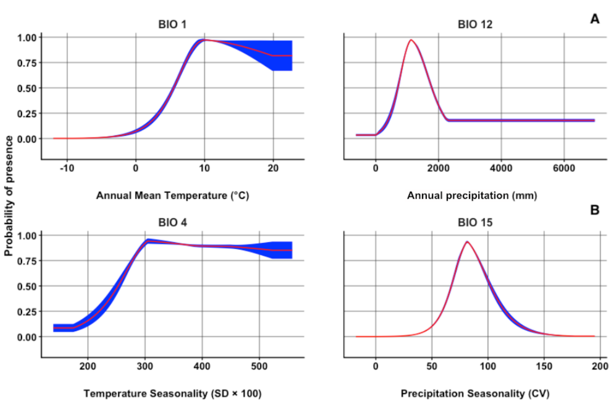

Figure 3. Response curves for the probability of presence of *A. chilensis* using the ATP (A) and STP (B) predictor sets. The red line indicates the mean response across model replicates, while the blue shaded area represents the standard deviation (SD).

Spatial predictions from both modelling approaches consistently identified central Chile as the core area of climatic suitability for *A. chilensis*, although the extent of suitable areas varied between algorithms and predictor sets. The areas predicted as suitable or with higher probabilities of occurrence for *A. chilensis* (Figs. 4 and 5) are mainly concentrated in central Chile, with high suitability and probability values in both coastal and Andean regions. The CCP and ATP predictor sets do not project potential distribution north of 30°S. In contrast, the STP set predicts an expansion of suitable areas from the Andean region toward central Chile (70°–68° W), with MaxEnt predicting these regions as highly suitable (> 65%), whereas Random Forest indicates relatively low probabilities of occurrence (~ 50%). Between 30°S and 40° S, Random Forest and MaxEnt display similar spatial patterns, identifying coastal and Andean zones with higher predicted suitability and probability values. MaxEnt additionally predicts suitable conditions toward the central part of the country (around 72° W). South of 40° S, suitability generally decreased across models, although ATP-based models showed localized areas of moderate suitability between 41° and 42° S. Neither Random Forest nor MaxEnt predicted suitable areas south of 50° S in the CCV and STP sets, whereas ATP models produced scattered and irregular patterns of low suitability.

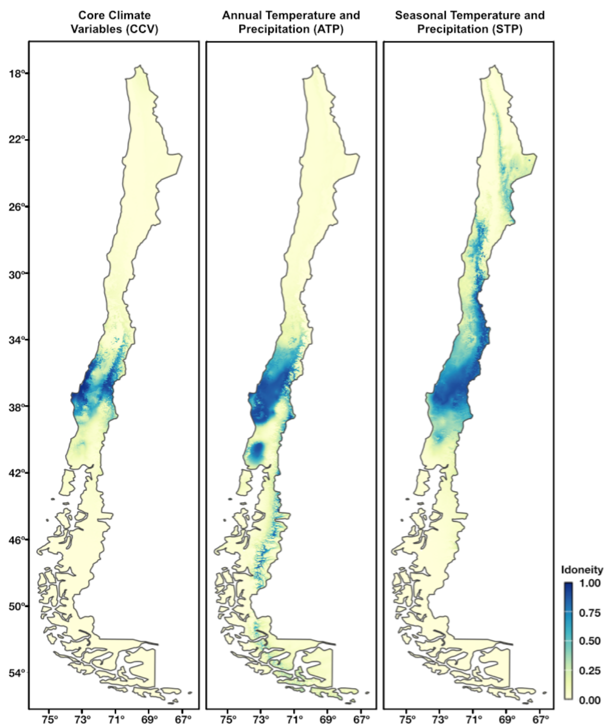

Figure 4. MaxEnt suitability models maps for *A. chilensis* using three environmental variables sets: Core Climate Variables (CCV), Annual Temperature and Precipitation (ATP) and Seasonal Temperature and Precipitation (STP).

Binary predictions further emphasized systematic differences between modelling approaches, with MaxEnt producing broader and more continuous suitability patterns than Random Forest. Across all predictor sets, MaxEnt predicted more extensive and continuous presence areas, often forming latitudinal bands, whereas Random Forest generated more spatially restricted and fragmented predictions concentrated mainly in central Chile (30°–40° S) (Figs. 6 and 7). Among predictor sets, CCV produced the narrowest predicted presence areas, while ATP and STP resulted in more extensive distributions in MaxEnt and moderately broader but fragmented patterns in Random Forest.

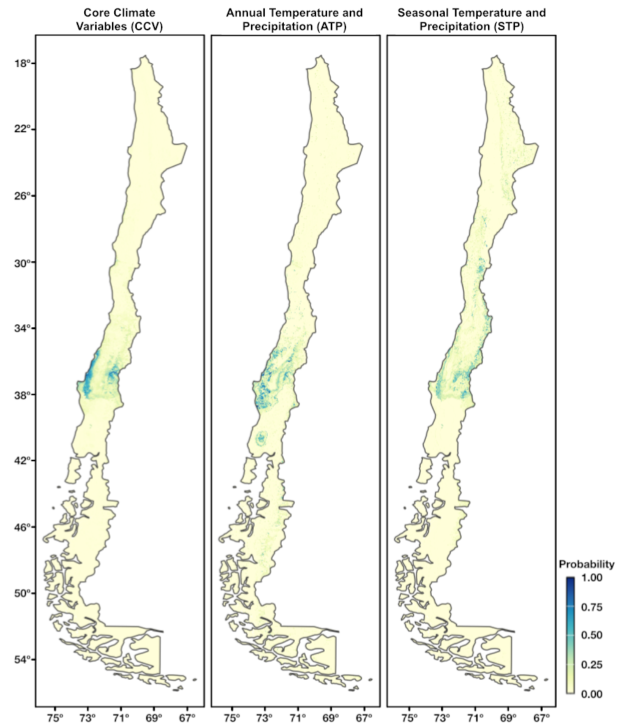

Figure 5. Random Forest probability maps for *A. chilensis* using three environmental variables sets: Core Climate Variables (CCV), Annual Temperature and Precipitation (ATP) and Seasonal Temperature and Precipitation (STP).

Taken together, these results indicate that the potential distribution of *A. chilensis* is broader than currently documented and is primarily shaped by climatic seasonality, particularly precipitation variability, rather than by mean climatic conditions alone.

DISCUSSION

Our results indicate that climatic seasonality plays a dominant role in shaping the potential distribution of *Akymnopellis chilensis* in Chile, supporting the hypothesis that the species' currently known distribution underestimates its true climatic niche. Both modelling approaches consistently highlighted variables related to temperature and, particularly, precipitation seasonality as key drivers of habitat suitability, whereas mean climatic conditions alone showed a weaker or secondary influence. This pattern suggests that temporal variability in climatic conditions, rather than absolute climatic values, constitutes a primary constraint on the distribution of this soil-dwelling predator. Such a result is consistent with biogeographic evidence for chilopods and other myriapods in Chile, whose distributions are strongly associated with moisture availability and climatic stability, reflecting a conserved ecological niche linked to humid and relatively stable environments (Parra-Gómez and Fernández 2022). From a mechanistic perspective, studies on soil-dwelling arthropods have shown negative responses of abundance and activity to increases in air and soil temperature, highlighting their sensitivity to short-term climatic fluctuations and hydric stress (Georgopoulou et al. 2016). At broader spatial scales, distributional patterns of myriapods have likewise been linked to climatic gradients, particularly those related to moisture and temperature regimes, supporting the idea that climatic variability is a key factor structuring their geographic ranges (Bedano et al. 2006).

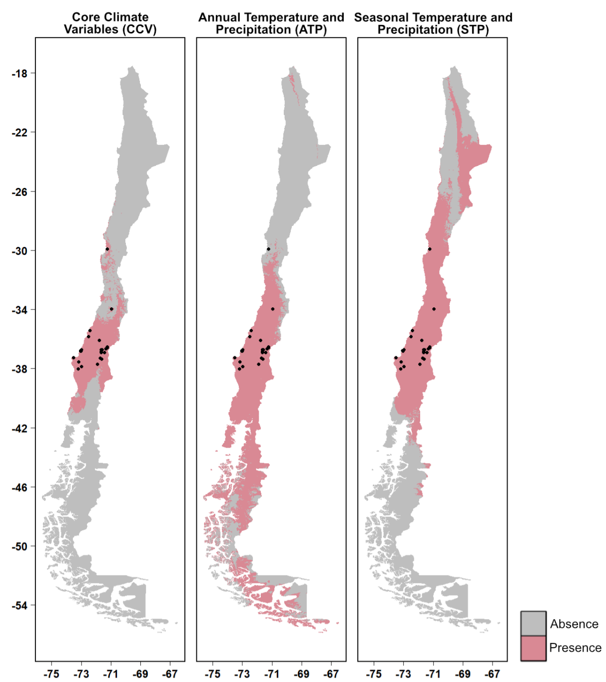

Figure 6. Presence-Absence model prediction of MaxEnt for *A. chilensis* using three environmental variables sets: Core Climate Variables (CCV), Annual Temperature and Precipitation (ATP) and Seasonal Temperature and Precipitation (STP). Black dots indicate records.

Differences observed between Random Forest and MaxEnt in terms of variable importance further contribute to our first objective by illustrating how algorithmic structure influences ecological inference when identifying key climatic drivers. In our results, Random Forest tended to distribute importance across several correlated temperature- and precipitation-related variables, whereas MaxEnt concentrated explanatory power on a smaller subset of predictors, most notably precipitation seasonality. Similar contrasts between these algorithms have been widely reported in species distribution modelling studies and are primarily attributed to methodological differences rather than underlying ecological inconsistencies (Zhao et al. 2022, Han et al. 2024). MaxEnt, through its regularization framework, often highlights dominant predictors, particularly when modelling species with restricted distributions or limited occurrence records, while Random Forest is more tolerant of multicollinearity and can partition importance among correlated variables (Mi et al. 2017, Kwon et al. 2025). Consequently, the fact that both approaches independently converged on seasonality-related climatic variables, despite differences in the specific predictors emphasized, reinforces the ecological relevance of climatic variability as a key determinant of *A. chilensis* distribution, rather than an artefact of model choice or sampling bias (Inman et al. 2021).

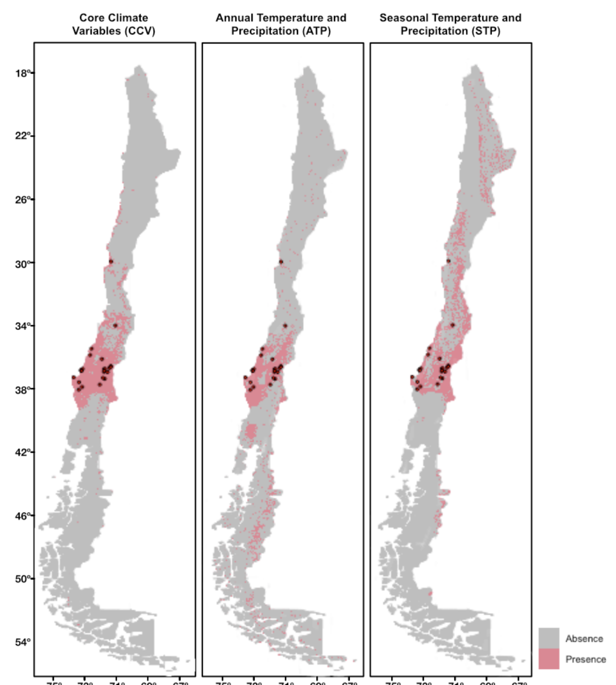

Figure 7. Presence-Absence model prediction of Random Forest for A. chilensis using three environmental variables sets: Core Climate Variables (CCV), Annual Temperature and Precipitation (ATP) and Seasonal Temperature and Precipitation (STP). Black dots indicate records.

Additional insight into how the key climatic variables identified under our first objective influence habitat suitability is provided by the MaxEnt response curves. These curves revealed predominantly non-linear relationships between habitat suitability and climatic predictors, particularly precipitation and temperature seasonality, a pattern that is commonly observed in species distribution models and reflects ecological thresholds rather than linear responses to environmental gradients (Merow et al. 2013). The existence of optimal climatic ranges is consistent with the biology of soil-dwelling arthropods, including myriapods, which are strongly constrained by moisture availability and climatic stability and show reduced performance under extreme thermal or hydric conditions (Parra-Gómez and Fernández 2022). Similar non-linear responses have been documented in studies examining the effects of climate and land-use conditions on soil microfauna, where extremes in temperature or moisture negatively affect habitat quality and soil health (Georgopoulou et al. 2016, Wallon et al. 2024). Overall, these findings provide support for interpreting the response curves obtained for *A. chilensis* as reflecting biologically plausible climatic optima rather than artefacts of the modelling process. The strong influence of seasonality variables suggests a preference for environments characterized by limited climatic variability rather than tolerance to a wide range of fluctuating conditions (Kampichler and Bruckner 2009). This pattern is consistent with previous studies indicating that many myriapods are closely linked to stable climatic regimes, with persistence across landscapes likely facilitated by the buffering effects of soil microhabitats (Riedel 2008). However, the associations identified here represent correlations with macroclimatic variables and do not directly reflect underlying physiological mechanisms.

Addressing our second objective, which aimed to assess whether the potential distribution of *A. chilensis* extends beyond currently known records, both modelling approaches consistently identified central Chile, between approximately 30° and 40° S, as the core area of climatic suitability. This region is characterized by Mediterranean-type climatic conditions and has been widely recognized as a biogeographic transition zone with pronounced environmental heterogeneity and increasing pressure from land-use change and other human activities (Hernández et al. 2016, Myers et al. 2000) The recovery of similar latitudinal patterns by both models suggests that this area represents a robust signal of suitability rather than an artefact of model choice. However, MaxEnt predicted broader and more spatially continuous suitable areas than Random Forest, a pattern that is consistent with the tendency of presence-only, correlative approaches to extrapolate suitability across environmentally similar regions (Simaiakis et al. 2012, Garreaud et al. 2017). Together, these results indicate that while the core distribution of *A. chilensis* is strongly centred in Mediterranean central Chile, the extent of suitable conditions may vary depending on model assumptions and algorithmic sensitivity.

The comparison between predicted suitable areas and available occurrence records suggests that the currently known distribution of *A. chilensis* may underestimate its true geographic range. Chile's myriapod fauna remains poorly studied, and many soils arthropod groups have received limited attention in biodiversity surveys (Pizarro-Araya and Ojanguren-Affilastro 2018). As a result, areas predicted as suitable by the models, but lacking records likely reflect gaps in sampling rather than true absence, underscoring the need for more systematic field surveys across different regions of the country (Kuralt and Kos 2018).

Taken together, our findings demonstrate that the potential climatic distribution of *Akymnopellis chilensis* is broader than currently documented and is primarily structured by climatic seasonality, particularly precipitation variability, rather than by mean climatic conditions alone. These results highlight the role of climatic variability as a first-order environmental filter shaping the geographic distribution of soil-dwelling predators in Mediterranean-type ecosystems. Although our models rely on broad-scale climatic predictors and do not explicitly incorporate microhabitat or edaphic variables, they provide a valuable framework for identifying climatically suitable areas where the species may occur but remains undetected due to historical or sampling limitations. More broadly, this study underscores the usefulness of species distribution models for revealing hidden biogeographic patterns in poorly known invertebrate taxa and for guiding future field surveys and conservation assessments in regions undergoing rapid environmental change.

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