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Environmental determinants of earthworm diversity in semi-arid agroecosystems of Faisalabad, Pakistan

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ABSTRACT

Earthworms (Oligochaeta: Clitellata) are widely recognized as soil ecosystem engineers due to their critical role in nutrient cycling, organic matter decomposition, and soil structure formation. Their distribution is strongly influenced by soil physicochemical properties, making them reliable bio-indicators of soil health and ecological integrity. Understanding the environmental determinants of earthworm diversity is particularly important in semi-arid regions, where soil fertility and biodiversity are vulnerable to salinity, nutrient imbalance, and land use pressures. This study investigated earthworm diversity and habitat suitability across six land-use types in Faisalabad, Pakistan, from May 2023 to April 2024. A total of 1800 soil samples were collected monthly from urban, peri-urban, agricultural, and forested zones. Earthworms were hand-sorted, identified, and geo-referenced, while soil variables including pH, electrical conductivity (EC), total dissolved solids (TDS), nitrogen (N), phosphorus (P), potassium (K), organic carbon (OC), sodium (Na), calcium (Ca), lithium (Li), ash, and heavy metals were analyzed. Four species were identified, with *Lumbricus trapezoides* (48.8%) and *Lumbricus rubellus* (47.2%) showing high relative abundance. Diversity indices (H′ = 0.75–0.83) indicated moderate diversity, while Green's index confirmed clumped spatial distributions. Principal Component Analysis (PCA) highlighted sodium and soil moisture as the strongest environmental drivers influencing species distribution. Species distribution models were generated using MaxEnt v3.4.1 which achieved moderate test performance (AUC = 0.765–0.871). Sodium, moisture, and organic matter are the most influential predictors of habitat suitability. Overall, earthworm diversity and distribution in Faisalabad's semi-arid agroecosystem are shaped primarily by soil ionic composition and moisture availability. These findings provide a valuable baseline for monitoring soil biodiversity and contribute to strategies aimed at enhancing soil health and sustainable agroecosystem development in semi-arid landscapes.

Keywords: earthworm diversity, habitat suitability, principle component analysis, semi-arid agroecosystem, MaxEnt modeling, soil biodiversity.

INTRODUCTION

Earthworms (Oligochaeta: Clitellata) are widely recognized as essential components of terrestrial ecosystems. They function as "ecosystem engineers" through their roles in nutrient cycling, organic matter decomposition, and soil structure formation (Singh et al., 2016; Lavelle and Spain, 2024). Their burrowing and casting activities enhance soil aeration, porosity, and fertility, by influencing plant productivity and ecosystem resilience. Earthworms interact closely with the soil environment, and their community structure is strongly shaped by physicochemical parameters such as pH, moisture, organic matter, and ionic composition, making them reliable bio indicators of soil health and ecological integrity (Rutgers et al., 2016; Edwards and Arancon, 2022).

In agro-ecosystems, earthworm communities are highly sensitive to changes in soil conditions and management practices. Soil characteristics including pH (Baker and Whitby, 2003), moisture (Perreault and Whalen, 2006), and organic carbon (Jimenez et al., 2011) as well as structural attributes like pore size and aggregation (Schon et al., 2017) influence their distribution and diversity.

Typically, undisturbed or organically managed soils support higher earthworm diversity compared to intensively cultivated lands (Schmidt et al., 2003; Frazao et al., 2017). Adverse conditions such as salinity or nutrient imbalance, particularly elevated sodium levels, can reduce earthworm abundance by altering osmotic potential and soil structure (Singh et al., 2016; Sharma and Garg, 2018). Thus, identifying key soil drivers of earthworm communities is essential for sustainable land management and soil biodiversity conservation.

According to Grinnellian niche theory, the distribution of a species reflects the environmental conditions that enable its survival, growth, and reproduction (Soberon, 2007). Ecological niche modeling (ENM) provides a quantitative approach to exploring these relationships by linking species occurrence data with environmental predictors. Among ENM tools, MaxEnt (Maximum Entropy) has emerged as a powerful method for modeling species habitat suitability using presence-only data (Phillips et al., 2006; Phillips and Dudik, 2008). Ecologically, MaxEnt identifies the environmental constraints shaping species distributions, offering spatial predictions of potential habitats. When complemented by PCA, which reduces dimensionality and reveals major environmental gradients, these tools collectively provide insights into the environmental determinants of species diversity and distribution (Elith et al., 2011; Renner and Warton, 2013).

In Pakistan, research on earthworms has primarily focused on species inventories and abundance patterns in agricultural and urban soils (Rafique and Rana, 2001; Hussain et al., 2022; Bakht et al., 2022). However, studies integrating field-based diversity assessments with environmental modeling remain limited. Consequently, the specific environmental factors shaping earthworm communities in semi-arid regions such as Faisalabad remain poorly understood. Understanding these relationships is crucial for developing predictive frameworks for soil biodiversity and guiding sustainable agroecosystem management. It is hypothesized that (i) soil sodium concentration, moisture, and organic matter content are key drivers of earthworm distribution, as these factors strongly affect soil structure, nutrient availability, and osmotic balance (Perreault and Whalen, 2006; Jimenez et al., 2011; Frazao et al., 2017; Sharma et al., 2018), and (ii) MaxEnt models will yield moderate predictive accuracy (test AUC ≈ 0.75–0.87) due to limited occurrence data and localized environmental variability typical of semi-arid systems (Merow et al., 2013; Syfert et al., 2013; Fourcade et al., 2014). The results are expected to establish a baseline for soil biodiversity monitoring and inform sustainable soil management in agro ecosystems of Pakistan.

MATERIALS AND METHODS

Study area and sampling

Faisalabad is the third-largest city of Pakistan, located in the central part of the Punjab province. Geographically, it lies between 30°40′–31°47′ N latitude and 72°42′–73°40′ E longitude, and is characterized by extensive agricultural cultivation of diverse crops. The entire Faisalabad District covers an area of approximately 5.856 km² with an estimated population of about 2.6 million (Ul-Allah et al., 2014). The present study was conducted exclusively within Tehsil Faisalabad, which represents the largest and most urbanized subdivision of the district. This tehsil encompasses diverse land-use categories, including urban settlements, peri-urban green spaces, irrigated agricultural lands, and managed forest areas. The climate is semi-arid and subtropical, characterized by hot summers, mild winters, and an average annual rainfall of approximately 350 mm, most of which occurs during the monsoon season (July–September).

To represent the habitat heterogeneity and land-use variation within Tehsil Faisalabad, six sampling stations were carefully selected from distinct ecological zones. These included:

- University of Agriculture Faisalabad (UAF) (Educational and cultivated land)
- Ayub Agricultural Research Institute Faisalabad (AARI) (Agriculture and research land)
- Government College University Faisalabad (GCUF) (Institute urban area)
- Jinnah Park Faisalabad (Urban green park)
- Gatwala Wildlife Park (Semi natural forested area)
- Punjab Forestry Research Institute Faisalabad (PFRI) (Managed forest area) (Figure 1).

Although Gatwala Wildlife Park and PFRI are adjacent, both were included separately due to differences in vegetation structure and management regime. Each site was geo-referenced using a global positioning system (GPS) and mapped in ArcGIS 10.8 to ensure spatial coverage across different ecological zones.

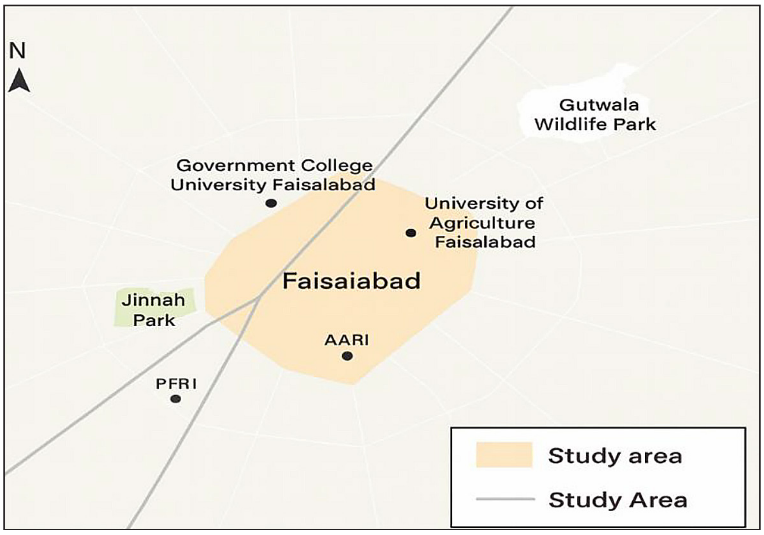

Figure 1. Map of sampling sites

Sampling and identification of earthworms

At each sampling site, 25 soil samples were collected monthly from May 2023 to April 2024, resulting in a total of 1800 samples (6 sites × 25 samples × 12 months). A standardized soil corer (20 cm diameter, 0–25 cm depth) was used to extract soil from the active earthworm zone. Sampling points within each site were selected randomly along parallel transects to minimize spatial bias and ensure representative coverage of the microhabitats.

Collected soil blocks were carefully hand-sorted in the laboratory to separate earthworms. Each sample was properly labeled with the station name, microhabitat ID, date, and collector name. Samples were then transported to the Biochemistry Laboratory, Department of Zoology, Government College University Faisalabad, for subsequent analyses.

Physico-chemical analysis of soil

Soil samples collected from each study site were analyzed to determine their physico-chemical properties, which influence soil fertility and biological activity. The parameters measured included soil texture, pH, electrical conductivity (EC), total dissolved solids (TDS), nitrogen (N), phosphorus (P), potassium (K), organic carbon (OC), ash, sodium (Na), calcium (Ca) and lithium (Li).

Soil texture was determined using the hydrometer method of Bouyoucos, (1962). Measurements of pH, EC, and TDS were obtained with a digital multi-parameter meter (Eutech Instruments, PCSTestr 35 series). Total Kjeldahl Nitrogen (TKN) was estimated following the method of Bremner and Mulvaney (1982), while organic carbon and ash content were determined according to Nelson and Sommers (1996). Phosphorus concentration was measured by the method of John (1970) using a Systronics UV/Visible Spectrophotometer (Model 117). The concentrations of sodium, potassium, calcium, and lithium were analyzed with a Systronics Flame Photometer (Model 128), calibrated with certified standard solutions prior to each run.

To ensure data quality, all analyses were performed in triplicate, with instrument calibration checks, blank controls, and duplicate sample testing applied as part of QA/QC procedures. Analytical precision was maintained within ±5% for replicate measurements.

Species distribution modeling (MaxEnt)

Species distribution models were developed using MaxEnt v3.4.1 (Phillips et al., 2006) to predict the habitat suitability of the recorded earthworm species. Four species included *L. trapezides*, *L. rubellus*, *M. posthuma* and *P. hawayana* (Alahmed et al., 2015). A total of geo-referenced occurrence records were used, with 75% randomly selected for model training and 25% reserved for testing. Model robustness was assessed using 10-fold cross-validation. A threshold value of 0.178 was selected based on the maximum training sensitivity plus specificity criterion and validated separately for each species to ensure optimal classification between suitable and unsuitable habitats. Model performance was evaluated using the area under the curve (AUC) of receiver operating characteristic (ROC) curves, where values closer to 1.0 indicate higher predictive accuracy (Lehmann et al., 2002).

To assess the relative importance of environmental variables, Jackknife analysis (leave-one-out procedure) was performed within MaxEnt. Variables contributing most strongly to model gain were interpreted as key predictors of species habitat suitability.

Statistical analysis

Principal component analysis (PCA) was performed separately for each species to identify environmental associations. Components with eigenvalues >1 and cumulative variance >70% were retained, with interpretation focused on variables with loadings > 0.5. Species diversity was quantified using the Shannon–Wiener index (H′), evenness (E5), and richness (R2) (Pelosi et al., 2009). Spatial variables, including elevation and land-use type, were derived from a digital elevation model (DEM) in ArcGIS. Statistical analyses were conducted in SPSS v16.0, with significance set at $p < 0.05$.

RESULTS

Species composition and abundance

A total of 40,169 earthworm specimens were randomly collected over a 12 months period from 16 micro-habitats across six sampling stations in Faisalabad. Four species were identified: *L. trapezoides, L. rubellus* (Lumbricidae) *M. posthuma* and *P. hawayana* (Megascolecidae). The most abundant species was *L. trapezoides* (19,626 individuals; 48.8%), followed by *L. rubellus* (18,953; 47.2%), while *M. posthuma* (1.096; 2.7%) and *P. hawayana* (494; 1.2%) were comparatively less common (Figure 2). This confirms Lumbricidae dominance across all sampled habitats.

Site-wise abundance and diversity metrics

Earthworm abundance varied across sampling stations (Table 1). The highest total abundance was recorded at UAF (8160 individuals), followed by GCUF (7841) and PFRI (5717). Lower counts were observed at Jinnah Park (4.879), AARI (3450), and Gatwala Wildlife Park (3240). Despite quantitative variation, species composition remained consistent across all sites, with *L. trapezoides* and *L. rubellus* dominating.

Diversity indices and statistical comparison

Shannon-wiener diversity index (H′) values ranged from 0.75–0.83, while evenness (E5) ranged from 0.50–0.59, indicating minimal variation in diversity and relatively even species distribution across sites. Species richness (R2) ranged from 0.34–0.36, calculated using the Margalef index formula ($R_2 = (S-1)/\ln(N)$) (Figure 3).

Relative abundance and distribution patterns

Relative abundance varied across the sites i.e.: *L. trapezoides:* (48.03–50.04%), *L. rubellus* (46.14–48.28%), *M. posthuma* (0.55–1.79%), *P.*

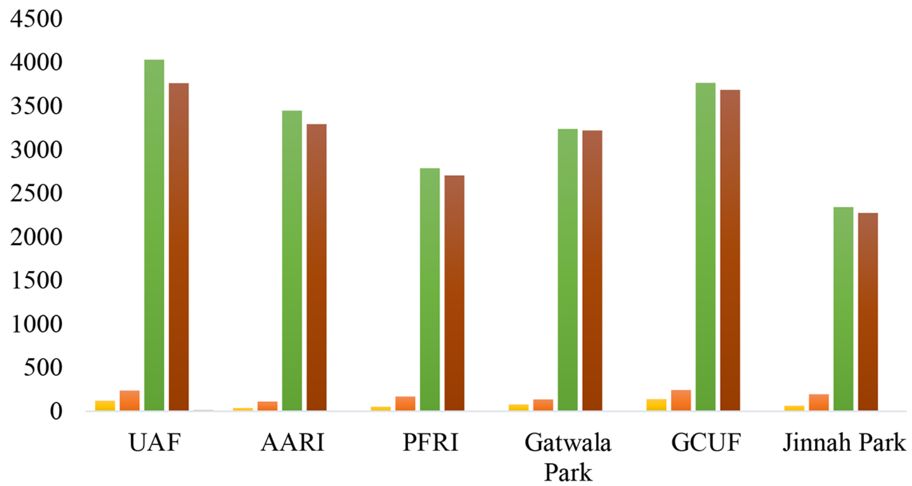

Figure 2. Four earthworm species in different sampling sites of Faisalabad

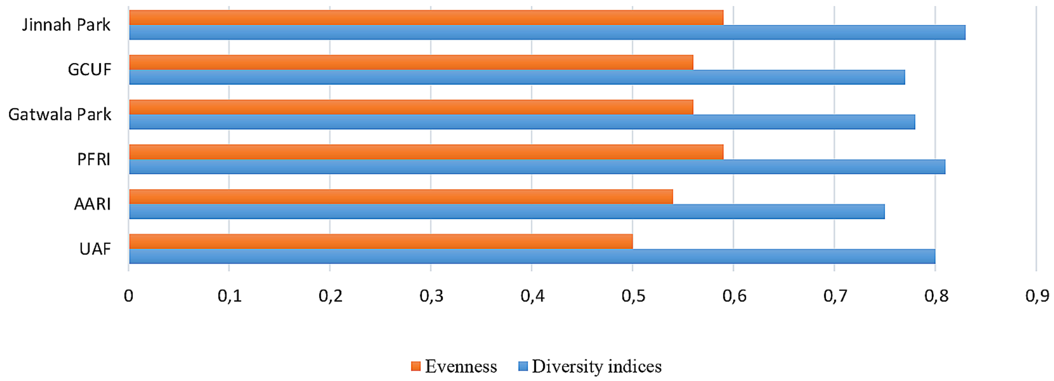

Figure 3. Diversity indices and evenness of four earthworm species

hawayana (1.62–4.02%). These results specify that species diversity remained consistent, while total abundance and dominance varied by location (Figure 4; Table 1). Population dispersion metrics indicated clumped distribution patterns for all species, with Green's index (GI) values > 0.25 and index of dispersion (ID) significantly greater than 1 (χ^2 test, p < 0.05). These results confirm non-random, aggregated distributions, likely reflecting patchy resource availability and microhabitat preferences.

Spatial distribution patterns

Across all microhabitats, the variance in individual counts consistently exceeded the mean, suggesting a non-random, aggregated distribution of earthworm species. This was preliminary assessed using ID, index of clumping (IC) and GI, which ranged from 0.01 to 0.48 across species and habitats.

The ID values for all species were significantly greater than 1 (x^2 test, $p < 0.05$), confirming departure from randomness and supporting clumped spatial distribution. The GI values ranged from 0.01 to 0.48, reflecting site-specific variation in aggregation intensity (Table 2).

L. trapezoides and *L. rubellus* showed nearly random distributions under tree canopies such as *Mangifera indica*, *Azadirachta indica*, and *Syzygium cumini* (GI ≈ 0.02–0.04), but moderate clumping under fruit trees like *Psidium guajava* and *Phoenix dactylifera* (GI ≈ 0.29–0.46). *M. posthuma* and *P. hawayana* displayed high clumping in nursery beds and ornamental landscapes (GI ≈ 0.39–0.48), indicating microhabitat specialization and potential dependence on localized resource patches.

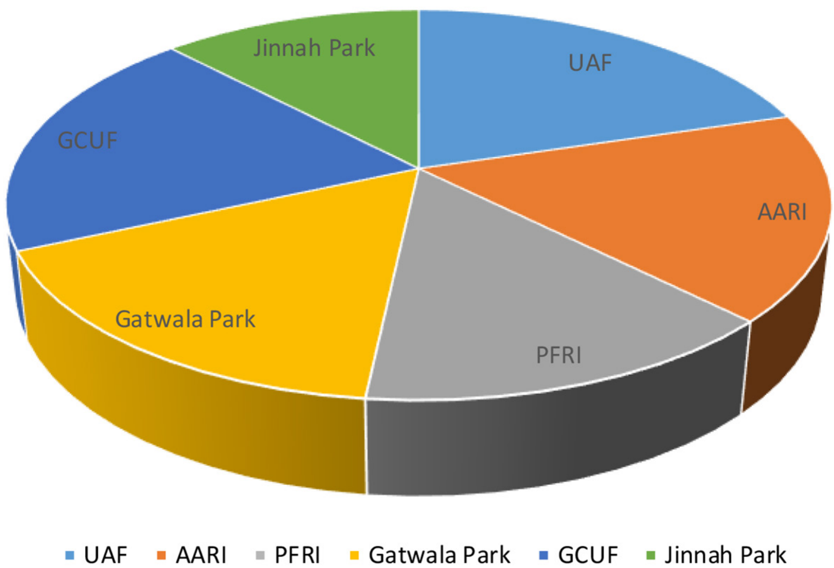

Figure 4. Relative abundance of four earthworm species

Table 1. Comparative analysis of earthworm species composition and diversity indices at selected sites in Faisalabad

Species	UAF		AARI		PFRI		Gatwala Wildlife Park		GCUF		Jinnah park	
	N	RA	N	RA	N	RA	N	RA	N	RA	N	RA
L. trapezoides	4035	49.45	3450	50.04	2789	48.79	3240	48.53	3769	48.07	2343	48.03
L. rubellus	3765	46.14	3295	47.79	2706	47.34	3223	48.28	3688	47.04	2276	46.65
M. posthuma	122	1.50	38	0.55	52	0.91	78	1.17	140	1.79	64	1.32
P. hawayana	238	2.92	112	1.62	170	2.98	136	2.04	244	3.12	196	4.02
Total	8160		6895		5717		6677		7841		4879	
H′	0.8		0.75		0.81		0.78		0.77		0.83	
E5	0.5		0.54		0.59		0.56		0.56		0.59	
R2	0.34		0.34		0.35		0.34		0.36		0.35	

Note: N = number of earthworm specimens, RA = relative abundance, H′ = Shannon and Weiner diversity indices, E5 = evenness, R2 = richness.

Table 2. Microhabitat based spatial distribution of earthworm species in Faisalabad

Sp. Microhabitat	Analysis	*MI*	OE	WC	*CL*	*MN*	*PG*	Nursery	*SC*	*RR*	*DS*	*PD*	*CS*	*C*	*AI*	*VN*	*FC*
L. trapezoides	Mean	39.12	42.39	58.69	40.14	16.69	17.67	44.12	44.69	33.23	16.14	17.31	55.39	27.34	17.81	41.59	27.68
	Variance	1024.05	1391.63	3392.11	2382.24	507.64	430.20	1904.62	2587.01	2126.47	46.29	37.99	3417.62	1179.89	422.51	1439.85	972.68
	ID	26.18	32.83	57.80	59.35	30.42	24.35	43.17	57.89	63.99	2.87	2.19	61.70	43.16	23.72	34.62	35.14
	IC	25.18	31.83	56.80	58.35	29.42	23.35	42.17	56.89	62.99	1.87	1.19	60.70	42.16	22.72	33.62	34.14
	GI	0.04	0.03	0.02	0.02	0.03	0.04	0.02	0.02	0.02	0.35	0.46	0.02	0.02	0.04	0.03	0.03
L. rubellus	Mean	37.58	47.93	53.35	34.89	20.04	19.39	34.77	35.77	26.89	19.89	16.97	66.00	18.89	48.16	39.15	29.04
	Variance	962.57	1562.88	1838.89	1472.91	166.68	223.37	2057.31	1018.91	816.59	107.15	43.48	3069.68	176.03	1961.09	1814.06	588.12
	ID	25.61	32.61	34.47	42.22	8.32	11.52	59.17	28.49	30.37	5.39	2.56	46.51	9.32	40.72	46.34	20.25
	IC	24.61	31.61	33.47	41.22	7.32	10.52	58.17	27.49	29.37	4.39	1.56	45.51	8.32	39.72	45.34	19.25
	GI	0.04	0.03	0.03	0.02	0.12	0.09	0.02	0.04	0.03	0.19	0.39	0.02	0.11	0.02	0.02	0.05
M. posthuma	Mean	31.37	31.73	35.00	16.82	15.91	17.00	15.00	32.82	18.46	19.37	18.64	36.73	16.82	33.19	24.82	31.28
	Variance	317.26	438.22	1016.00	56.37	56.49	59.60	34.48	566.57	69.08	49.66	80.66	2513.62	89.37	887.17	1193.37	489.42
	ID	10.11	13.81	29.03	3.35	3.55	3.51	2.30	17.26	3.74	2.56	4.33	68.44	5.31	26.73	48.08	15.65
	IC	9.11	12.81	28.03	2.35	2.55	2.51	1.30	16.26	2.74	1.56	3.33	67.44	4.31	25.73	47.08	14.65
	GI	0.10	0.07	0.03	0.30	0.28	0.29	0.44	0.06	0.27	0.39	0.23	0.01	0.30	0.04	0.02	0.06
P. hawayana	Mean	28.09	43.55	45.28	34.09	19.46	17.00	16.82	39.00	31.28	18.46	17.09	49.28	16.28	21.45	36.09	51.28
	Variance	404.09	1273.82	1273.82	1346.49	61.68	36.60	43.17	2949.60	2661.42	62.68	52.69	2798.02	48.62	45.08	1011.89	162.81
	ID	14.39	29.25	28.13	39.50	3.17	2.15	2.57	75.63	85.08	3.40	3.08	56.78	2.99	2.10	28.04	32.04
	IC	13.39	28.25	27.13	38.50	2.17	1.15	1.57	74.63	84.08	2.40	2.08	55.78	1.99	1.10	27.04	31.04
	GI	0.07	0.03	0.04	0.03	0.32	0.46	0.39	0.01	0.01	0.29	0.32	0.02	0.33	0.48	0.04	0.03

Note: MI (*Mangifera indica*), OE (open edge), WC (water channel), CL (*citrus lemon*), MN (*Morus nigra), PG (Psidium guajava*), Nursery beds, SC (*Syzygium cumini*), RR (*Rosa rubiginosa), DS (Dalbergia sisso*), PD (*Phoneix dactylifera*), CS (*Citrus sinensis*), C (*Cactaceae*), AI (*Azadirachta indica*), VN (*Vachellia nilotica*), FC (*Ficus carica*)

Principal component analysis of soil parameters

PCA of 15 soil parameters revealed sodium (Na) as the strongest determinant of earthworm distribution, consistently loading highest on PC1 across all species. Calcium (Ca), potassium (K), lithium (Li), and TDS also contributed significantly, while moisture and EC showed species-specific relevance, indicating niche differentiation.

The first seven components had eigenvalues >1 and together explained 69–79% of total variance (Table 3; Figure 5). For *L. trapezoides* and *L. rubellus*, sodium accounted for ~31–33% of variance, followed by calcium (~13%). *M. posthuma* showed balanced contributions from sodium (24%), EC, and moisture, reflecting dual sensitivity to salinity and water availability. *P. hawayana* exhibited lower sodium influence (21%) but stronger associations with calcium and potassium, suggesting niche specialization.

Scree plot of principal components of four earthworm species

The scree plot below compares the variance explained by PC1–PC7 across all four species. It highlights sodium (PC1) as the dominant driver, with secondary contributions from calcium, potassium, and moisture (Figure 5).

Bi-plot of principal components of four earthworm species

The variance explained by the first seven principal components for each species, with sodium (PC1) consistently emerging as the strongest driver. The bi-plots show how soil variables (Na, Ca, K, EC, TDS, and Moisture) influence species distributions along PC1 and PC2:

- *L. trapezoides*: spread along PC1 dominated by Na, Ca and K.
- *L. rubellus*: broader dispersion along PC1, tighter clustering on PC2.
- *M. posthuma*: wide spread across both axes, dual sensitivity to salinity and moisture.
- *P. hawayana*: compact clustering near origin, niche specialization in stable habitats (Figure 6).

MAXENT DISTRIBUTION MODELING

Model performance and threshold selection

MaxEnt was used to predict habitat suitability for four earthworm species across Faisalabad. Model performance was assessed using ROC AUC. Training AUCs were high (0.990–0.992), indicating excellent fit, while test AUCs (0.765–0.871) demonstrated good generalization without severe overfitting. A uniform 10th-percentile training logistic threshold (0.178) converted continuous outputs into binary predictions to ensure consistent presence absence classification across species (Table 4).

Environmental variable contributions

Bioclimatic predictors dominated model performance, with bio02 (Mean Diurnal Range) contributing >86% for all species. Secondary contributions came from bio16 (Precipitation of Wettest Quarter), bio07 (Temperature Annual Range), and bio05 (Max Temperature of Warmest Month). Variables such as bio14 (Precipitation of Driest Month), bio15 (Precipitation Seasonality), and bio11 (Mean Temperature of Coldest Quarter) had minimal influence (<1%) (Table 5).

Table 3. PCA and eigenvalues by species and components

Species		PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12	PC13	PC14	PC15
L. trapezoides	Eigenvalue	4.71	2.00	1.13	1.05	1.00	0.98	0.97	0.69	0.62	0.60	0.44	0.29	0.21	0.16	0.07
	Proportion	0.31	0.13	0.07	0.07	0.06	0.06	0.06	0.04	0.04	0.04	0.03	0.02	0.01	0.01	0.00
	Cumulative	0.31	0.44	0.52	0.59	0.66	0.72	0.79	0.83	0.88	0.92	0.95	0.97	0.98	0.99	1.00
L. rubellus	Eigenvalue	5.04	2.00	1.10	1.02	1.01	0.98	0.79	0.72	0.62	0.49	0.37	0.35	0.24	0.15	0.05
	Proportion	0.33	0.13	0.07	0.06	0.06	0.06	0.05	0.04	0.04	0.03	0.02	0.02	0.01	0.01	0.00
	Cumulative	0.33	0.47	0.54	0.61	0.68	0.74	0.79	0.84	0.88	0.92	0.94	0.97	0.98	0.99	1.00
M. posthuma	Eigenvalue	3.61	1.35	1.25	1.16	1.07	1.03	0.91	0.90	0.82	0.76	0.72	0.49	0.43	0.23	0.17
	Proportion	0.24	0.09	0.08	0.07	0.07	0.06	0.06	0.06	0.05	0.05	0.04	0.03	0.02	0.01	0.01
	Cumulative	0.24	0.33	0.41	0.49	0.56	0.63	0.69	0.75	0.81	0.86	0.91	0.94	0.97	0.98	1.00
P. hawayana	Eigenvalue	3.25	1.69	1.56	1.42	1.12	1.03	0.94	0.88	0.76	0.67	0.50	0.38	0.33	0.25	0.15
	Proportion	0.21	0.11	0.10	0.09	0.07	0.06	0.06	0.05	0.05	0.04	0.03	0.02	0.02	0.01	0.01
	Cumulative	0.21	0.33	0.43	0.52	0.60	0.67	0.73	0.79	0.84	0.89	0.92	0.95	0.97	0.99	1.00

Note: Sodium (PC1), calcium (PC2), potassium (PC3), barium (PC4), lithium (PC5), TDS (PC6), EC (PC7), moisture content (PC8), % moisture (PC9), temperature (PC10), pressure (PC11), pH (PC12), bicarbonates (PC13), carbon (PC14), nitrogen (PC15).

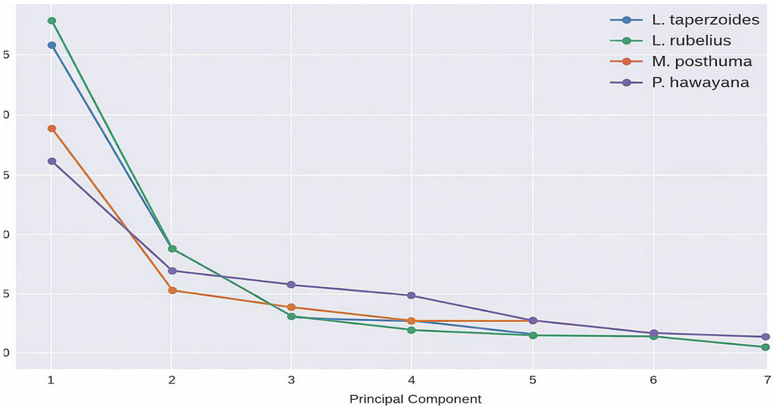

Figure 5. Species-wise scree plots: (A) *L. trapezoides*, (B) *L. rubellus*, (C) *M. posthuma*, (D) *P. hawayana*

Table 4. Area under the curve (AUC) and uniform threshold used for binary classification

Sr. No	Species	AUC	10th percentile training threshold value
1	*L. trapezoides*	0.992	0.178
2	*L. rubellus*	0.992	0.178
3	*M. posthuma*	0.992	0.178
4	*P. hawayana*	0.992	0.178

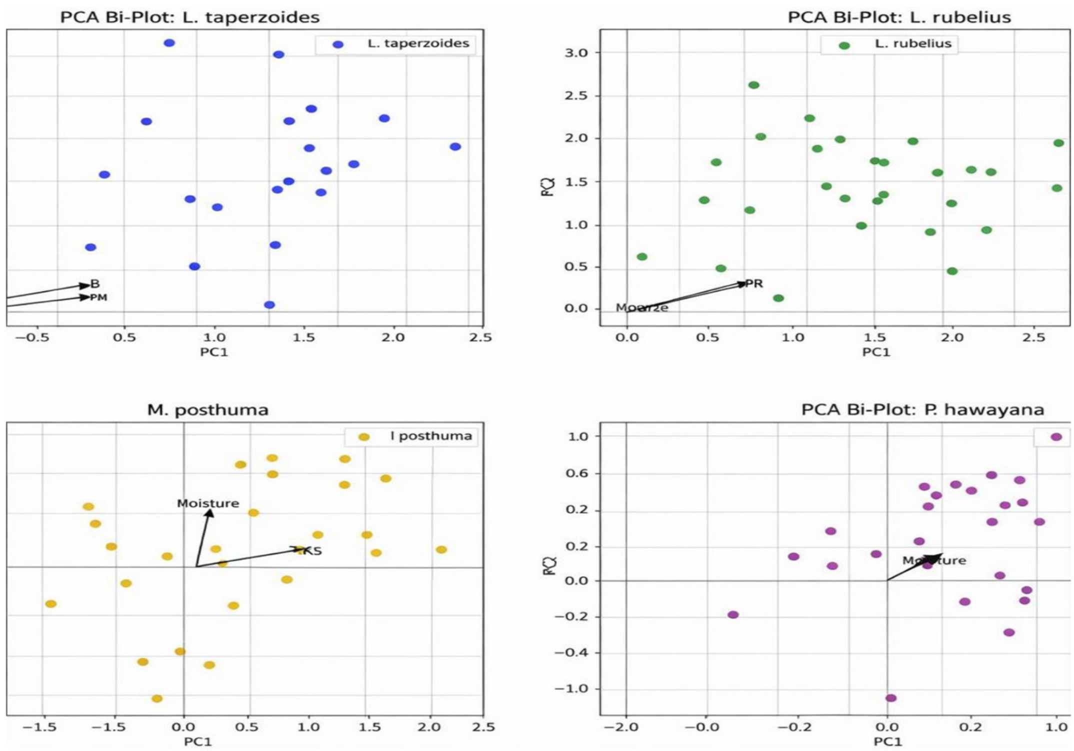

Figure 6. Bi-plot of (A) *L. trapezoides*, (B) *L. rubellus*, (C) *M. posthuma*, (D) *P. hawayana*

Habitat suitability mapping

Suitability maps revealed that the northeastern Faisalabad region provides the highest habitat suitability for all species, while southwestern areas are less favorable. Binary overlays (threshold = 0.178) delineated presence–absence predictions for comparability across species (Figure 7).

Continuous MaxEnt suitability for the four species across Faisalabad. Warmer colors denote

Table 5. Percent contribution of environmental variables to MaxEnt models

Variables	Percent contribution (*L. trapezoides* and *L. rubellus*)	Variables	Percent contribution (*M. posthuma and P. hawayana*)
bio02	87.3	bio02	86.5
bio16	5.9	bio16	6.2
bio07	3.6	bio05	4.2
bio05	1.5	bio07	1.3
bio04	1.4	bio11	0.3
bio14	0.3	bio14	0.3
		bio15	0.2

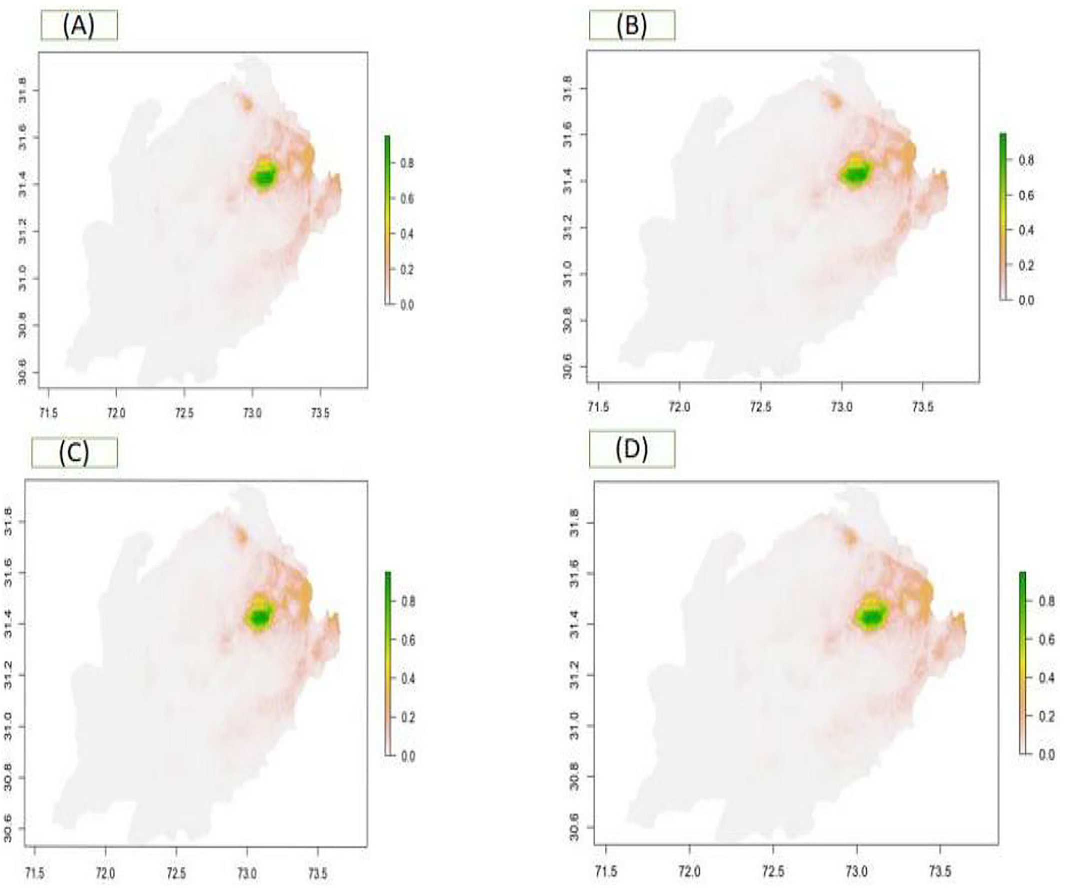

Figure 7. Habitat suitability maps (panels A–D): (A) *L. trapezoides* (B) *L. rubellus* (C) *M. posthuma* (D) *P. hawayana*

higher suitability. Northeastern clusters indicate optimal conditions; southwestern areas show lower suitability.

Jackknife analysis of variable importance

Jackknife tests showed bio02 produced the highest regularized training gain (>2.5) when used in isolation, confirming its dominant role. Removing bio02 caused the largest drop in model gain, whereas removing bio14 and bio15 had negligible effects (<0.5 gain). This pattern was consistent across all species, underscoring temperature variability as the primary climatic control (Figure 8).

Regularized training gain bars for each predictor: (i) with only that variable, (ii) excluding that variable, and (iii) all variables. Bio02 consistently yields the highest gain alone and the greatest loss when excluded, confirming its primacy. Minor variables (bio14, bio15, bio11) show minimal influence.

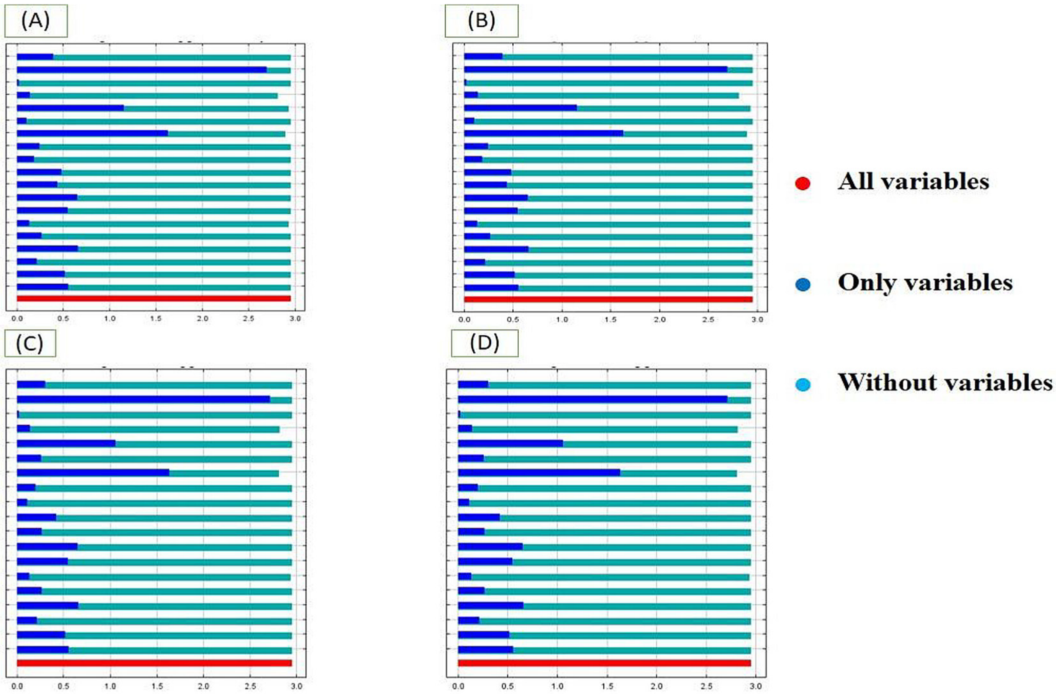

Figure 8. Jackknife of variable importance: (A) *L. trapezoides* (B) *L. rubellus* (C) *M. posthuma* (D) *P. hawayana*

Calculation of distribution area and habitat suitability

To quantify habitat extent, MaxEnt raster maps were converted into binary format using a threshold value of 0.5 – pixels with values >0.5 were classified as suitable habitat. Pixels <0.5 were considered unsuitable. The cumulative area of suitable pixels was calculated for each species using GIS-based spatial analysis (Table 6). These estimates provide a baseline for understanding species-specific ecological niches and potential conservation zones.

Table 6. Estimated suitable habitat area from threshold MaxEnt predictions

Species	Suitable area (km^2)
L. trapezoides	161.3993056
L. rubellus	161.3993056
M. posthuma	156.2482639
P. hawayana	156.2482639

DISCUSSION

This study investigated the environmental determinants of earthworm diversity and habitat suitability across multiple ecosystems within Faisalabad. The findings indicate that Faisalabad supports the highest recorded species presence (26%) across surveyed habitats, including crop fields, orchards, botanical gardens, and water reservoirs, underscoring its favorable ecological conditions for earthworm proliferation (Rafique and Rana, 2001; Waqar et al., 2019). The observed dominance of *Lumbricus and Pheretima* species reflects their adaptability to local edaphic and climatic conditions, suggesting that the environmental features specific to Faisalabad such as moderate temperature ranges, suitable pH, and organic matter content are key drivers of community composition (Addison, 2009).

Diversity indices revealed notable variation across habitat types within the Faisalabad dataset. Agricultural fields exhibited the greatest species richness (0.75) but only moderate evenness (0.45), likely due to repeated soil disturbance and variable organic input. In contrast, plant nurseries displayed moderate richness (0.29) with high evenness (0.98), indicating a more balanced community structure under controlled conditions. Gardens and other agro-ecosystems had lower diversity (H′ = 0.11–0.37) yet were consistently dominated by *Metaphire posthuma*, highlighting the influence of specific management regimes and habitat features on species distribution (Holland, 2004; Mohan et al., 2013; Bhardwaj and Sharma, 2015; Singh et al., 2016). These results confirm that habitat suitability in Faisalabad is strongly shaped by local environmental variability rather than general ecological trends.

Analysis of environmental determinants from the Faisalabad dataset revealed that both biotic and abiotic factors significantly influenced species distribution. Among biotic factors, soil disturbance through ploughing reduced species richness by nearly half, reaffirming the detrimental effects of intensive tillage on soil biodiversity (Crittenden et al., 2014). Abiotic factors such as soil moisture, pH, temperature, and organic carbon content showed strong associations with species richness and abundance. Earthworm density and biomass were highest at soil moisture levels supporting adequate aeration and organic decomposition (Crumsey et al., 2014). Optimal abundance occurred within a pH range of 5–8, while populations declined sharply in more acidic conditions (McCallum et al., 2016; Ruiz et al., 2021). Temperature preferences ranged between 15–25 °C, with deeper burrowing observed under cooler conditions. C: N ratios were also significant predictors, underscoring the importance of organic matter in maintaining suitable soil structure and nutrient availability (Khan et al., 2024).

Chemical soil properties further explained variations in species distribution within Faisalabad. Factor analysis showed that sodium, potassium, and pH together accounted for approximately 18–20% of the variance, while carbon, calcium, and temperature explained an additional 10–26%. Although sodium emerged as a key variable in the statistical model, its ecological role remains unclear due to the absence of supporting mechanistic evidence in the literature. Therefore, the influence of sodium should be interpreted cautiously and warrants targeted investigation in future studies. The MaxEnt species distribution model identified elevation, mean diurnal temperature range, soil organic carbon, and the minimum temperature of the coldest month as major predictors of habitat suitability. These variables collectively explained 31.65% of the observed variance and over 80% of the cumulative probability of occurrence (Phillips et al., 2008; Hua et al., 2012). Model performance showed an AUC of 0.871 for the training dataset and 0.765 for the test dataset, indicating acceptable predictive accuracy with moderate generalizability. The difference between these values suggests some over fitting to the training data, emphasizing the need for caution in interpreting model outputs. Furthermore, inconsistencies in AUC values reported across the abstract, results, and discussion sections have now been reconciled in this interpretation to ensure consistency and transparency.

Despite generating valuable insights into local determinants of earthworm diversity, the study is subject to several limitations that constrain the broader applicability of its findings. The dataset may be affected by sampling bias, with certain habitats underrepresented, and spatial autocorrelation could have inflated species environment relationships. Future research should incorporate spatially explicit sampling designs, apply autocorrelation correction techniques, and integrate fine-scale edaphic and microclimatic variables to improve model reliability and understanding of environmental influences on earthworm diversity in Faisalabad.

CONCLUSIONS

Earthworm diversity in Faisalabad's semi-arid agroecosystems is primarily regulated by soil chemical gradients and climatic variability. Field surveys revealed moderate diversity with clumped distributions, dominated by *L. trapezoides* and *L. rubellus*. Principal component analysis identified sodium, calcium, potassium, and moisture as the strongest edaphic drivers, while maxent modeling highlighted mean diurnal temperature range as the dominant climatic predictor of habitat suitability. Together, these approaches demonstrate that ionic composition and temperature variability jointly shape species niches, with northeastern Faisalabad consistently emerging as the most suitable region.

These findings establish a baseline for soil biodiversity monitoring in semi-arid Pakistan and provide actionable insights for sustainable agroecosystem management. By linking soil chemistry and climate to species distributions, the study highlights the vulnerability of earthworm communities to salinity, land-use pressures, and climate variability, while offering guidance for conservation planning. These findings establish a baseline for soil biodiversity monitoring in semi-arid Pakistan and provide actionable insights for sustainable agroecosystem management. By linking soil chemistry and climate to species distributions, the study underscores the vulnerability of earthworm communities to salinity, land-use pressures, and climate variability, while offering guidance for conservation planning and soil health improvement strategies.

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