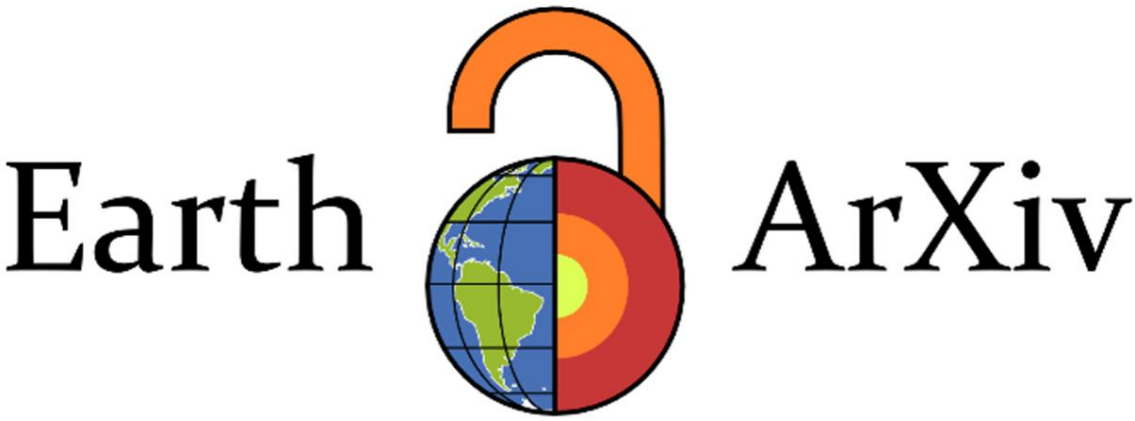

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Soil-informed multivariate decision support to assess urban ecosystem service potential

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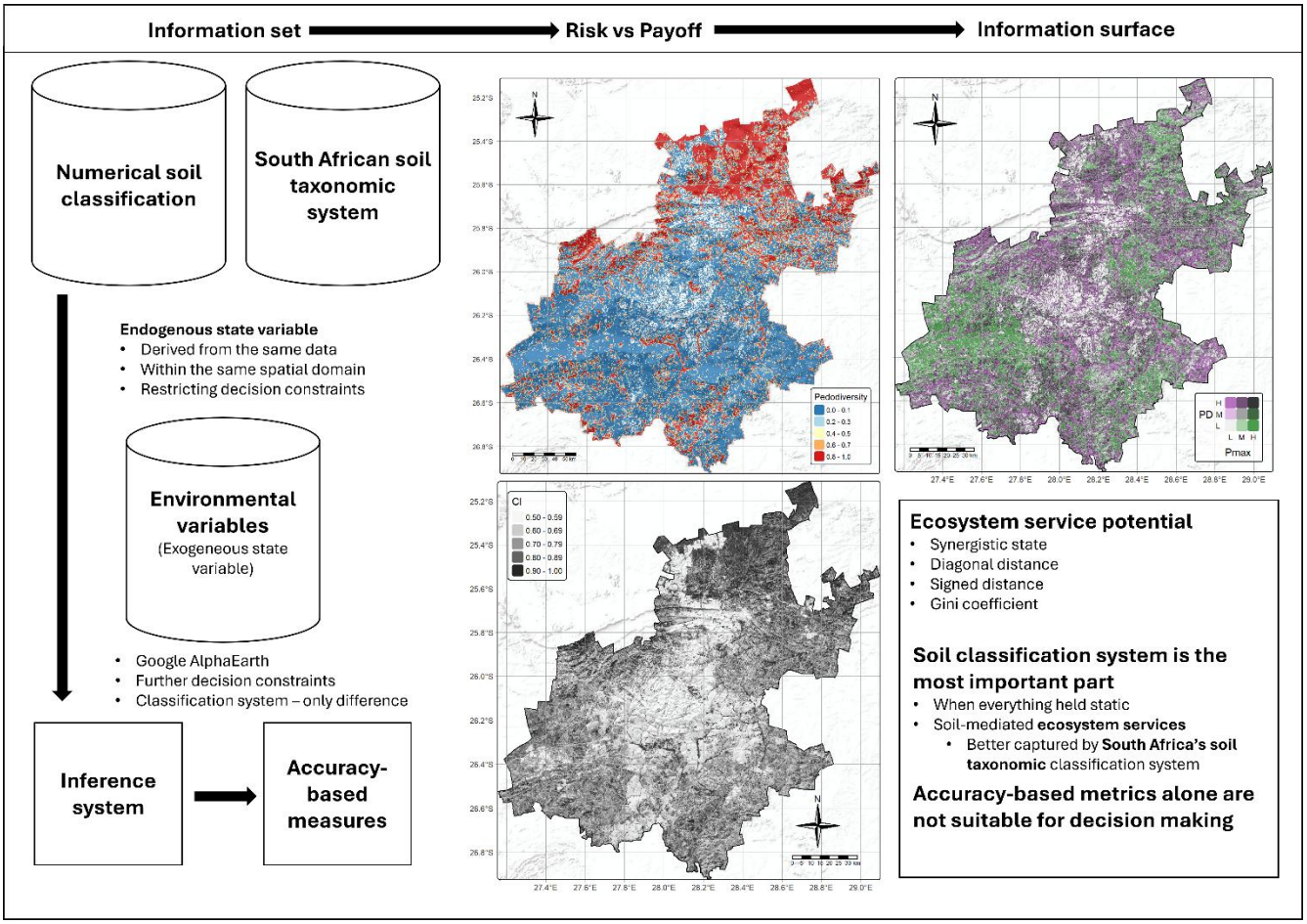

Abstract

Metropolitan expansion across Africa requires robust soil information to support ecosystem services and urban resilience. However, digital soil mapping often prioritises predictive accuracy over identifying where information is reliable for decision making. This study evaluated numerical and South African Soil Taxonomy within a decision framework to assess where ecosystem service inferences can be made with confidence in Gauteng, South Africa. Although both approaches achieved comparable subsoil accuracy (71% vs. 80%), their information spaces differed markedly. The numerical classification captured high-frequency variation but generated pedodiversity through class fragmentation, producing weakly constrained spatial patterns (synergistic state = 21%). In contrast, the taxonomic system preserved pedological coherence through process-based transitions, maintaining pedodiversity with higher predictive confidence (synergistic state = 63%). These results show that classification choice, not accuracy alone, determines where reliable soil information exists. We recommend integrating classification, probability, and uncertainty into a pedologically grounded decision-support framework for rapidly urbanising landscapes. Current digital soil mapping approaches prioritize predictive accuracy without explicitly identifying where soil information is reliable for decision making. This study demonstrates that classification structures govern the translation of pedodiversity into actionable knowledge, showing that higher accuracy does not necessarily yield more reliable ecosystem service inference. By integrating classification, probability, and uncertainty, this work introduces a framework for identifying decision-relevant soil information in rapidly urbanising landscapes.

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Keywords: Decision support; Pedodiversity; Pedology; Urban soil

1. Introduction

Rapid metropolitan expansion across Africa is reshaping environmental systems at unprecedented rates (Awumbila, 2017). Urban growth is frequently characterised by high population density, informal settlement expansion and uneven infrastructure development, placing substantial pressure on soil that sustains ecosystem services essential to urban resilience and human well-being (Bhatta, 2010). Urban soil regulates stormwater and flooding (Anni et al., 2020), it supports food production and soil health in urban and peri-urban agriculture (Wu & Congreves, 2024), mitigates urban heat (Li & Wang, 2021), and provides materials for construction (Reddi et al., 2012), cultural practices, and recreation (O'Riordan et al., 2021). At the same time, industrial and mining activities and pollution are widespread in many African cities, frequently contaminating soil and adjacent agricultural and natural systems, with direct implications for public health and ecosystem integrity (Karthika et al., 2022).

Decisions about land use, infrastructure placement, green-space design and environmental remediation are often made under conditions of limited, uneven and uncertain and soil information (Grimm et al., 2008). Soil maps are thus not only descriptive products but also strategic inputs that influence how ecosystem service potential, environmental risk and management trade-offs are perceived. This places increase importance on how soil information is generated, represented and interpreted, particularly where there is high population density.

Soil-mediated ecosystem services emerge from the direct and indirect diversity of soil across space and depth (Adhikari & Hartemink, 2016; Fu et al., 2022). Pedodiversity or the spatial variety of soil types, properties or gradients capture this heterogeneity and reflect the capacity of soil to support multiple functions and ecosystem services (Deng et al., 2025; Ibáñez et al., 1995). Topsoil hosts biological activity, carbon inputs, and nutrient cycling, while subsoils regulate drainage, chemical buffering, carbon stabilization, and long-term water storage (Ferré et al., 2025; Fu et al., 2022; Wen et al., 2024). In urban environments, these contrasts are amplified or diminished: topsoil is often disturbed or engineered, whereas subsoils may retain pedogenetic structure and continue to govern critical hydrological and geochemical functions (Pouyat et al., 2020).

Digital soil mapping (DSM) has advanced the production of spatially explicit soil property maps, including bare soil, carbon stocks and contaminant distributions (Fiorentino et al., 2025; Liu et al., 2022; Villa et al., 2018). Traditional evaluation emphasizes statistical metrics such as overall accuracy or Cohen's kappa coefficient (Cohen, 1960). While necessary, these metrics

provide limited insight into whether mapped soil information is meaningful or reliable for decision-making, particularly in urban soil that are highly modified and decoupled from classical soil–landscape relationships (e.g., Anthrosols and Technosols) (Pouyat et al., 2020). Accurate maps may therefore be insufficient for identifying soil multifunctional areas or balancing trade-offs among ecosystem services.

Decision-making in soil systems occurs under incomplete and asymmetric information, where the true soil organization is only partially observed and unevenly understood (Regan et al., 2002). Conventional and digital classification frameworks imperfectly represent underlying soil processes and spatial organization, mediating access to latent soil states and shaping interpretations of ecosystem service potential (Berger, 2010; Morgan & Henrion, 1990). As a result, decision-theory is rarely applied to soil classification and DSM products. Where different classification systems do more than label soil: they structure pedodiversity, shape interactions with ecosystem services and generate distinct decision contexts even from identical observations.

The aim of this study was to evaluate how a numerical and the South African taxonomic soil classification systems structure ecosystem service potential in an urban landscape, specifically by identifying where inferred soil information is sufficiently reliable in Gauteng Province, South Africa. By treating DSM inputs and outputs as structured information that explicitly incorporates uncertainty, the study emphasizes practical utility over prediction alone, highlighting how classification systems influence decision-making for urban planning and ecosystem management.

2. Methods and materials

2.1 Study site (spatial domain, Ω)

Gauteng Province (Figure 1) is located in the Highveld, a high-altitude grassland region of central South Africa (approximately 26.3° S, 28.1° E). Although the smallest province by area, Gauteng is the most densely populated region in the country, with an average population density exceeding 850 people km^{-2} (Statistics South Africa, 2016). It contains the major metropolitan areas of Johannesburg and Pretoria, together with rapidly expanding cities such as Soshanguve and Vereeniging. The province has a mean elevation of approximately 1,500 m , a mean annual temperature of ~20 °C, and a mean annual precipitation of ~650 mm (Harris et al., 2020). Gauteng was selected as the study area because it represents a highly

heterogeneous urban–agro–natural mosaic, making it well suited for examining spatial relationships between soil functions, ecosystem services, and metropolitan expansion under conditions of strong anthropogenic disturbance.

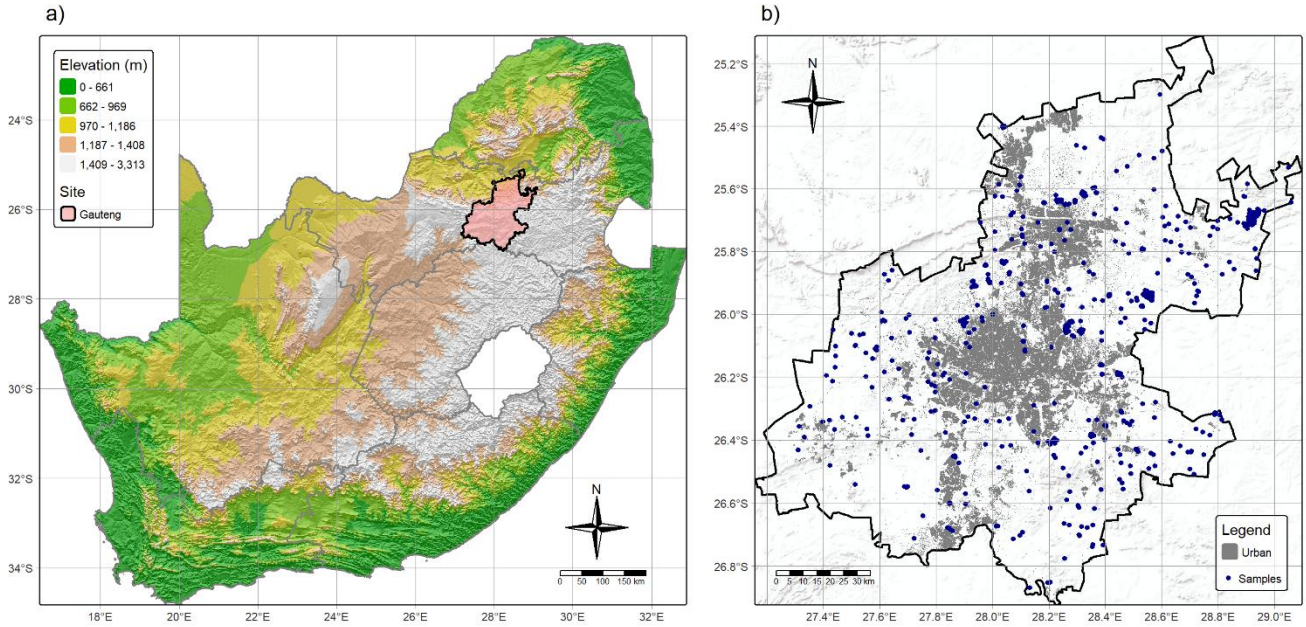

Figure 1: Gauteng Province located in South Africa (a) and Gauteng Province with major urban areas (grey) and soil observations (b).

2.2 Data set and collection (information set, I)

2.2.1 Soil data (endogenous state observations, Y)

Soil profile data was obtained from the South African Land Type Survey (LTS; Land Type Survey Staff, 2006), comprising 565 observations (Figure 1b). The numerical classification system was previously developed by Flynn et al. (2021), who clustered soil profiles into five topsoil and nine subsoil classes (Table 1) using a medoid-based clustering approach. Clustering was performed using the CLARA (Clustering Large Applications) algorithm, which applied k-medoids clustering to identify representative medians that minimizes overall within-cluster dissimilarity (Kaufman & Rousseeuw, 1986). The algorithm used Euclidean distance across six chemical and five physical soil properties and was designed to provide a scalable and outlier-robust classification at the national scale.

Table 1: Topsoil and subsoil diagnostic horizons clustered by the Flynn et al. (2021), number of members (n) and their properties that were observed in Gauteng.

Horizon	Cluster	*n*	Properties
Topsoil	A1	36	Low clay, low SOC, mildly acidic, moderate CEC
	A2	50	High SOC, high base saturation,
	A3	404	Intermediate leaching and moderate CEC
	A4	58	High base saturation, high activity clay
	A5	17	Very high CEC and high clay
Subsoil	B1	181	Light texture, dominated by coarse sand
	B2	26	Light texture, dominated by fine sand
	B3	23	High clay, high CEC, mildly alkaline
	B4	15	Low CEC, moderate base saturation
	B5	237	Very high clay, slightly alkaline, high Fe
	B6	45	High clay, alkaline, high Mg
	B7	2	Coarse sand, low CEC
	B8	11	Low CEC, clay and base saturation
	B9	23	High CEC and Fe, low clay and base saturation

The LTS dataset contains modal soil profile descriptions, measured soil properties and diagnostic horizons classified using the 1991 South African taxonomic “Blue Book” classification (Soil Classification Working Group, 1991). The Blue Book system was used because it is the most widely adopted and fully integrated classification framework within the LTS at the time of analysis. For analytical consistency and interpretability, diagnostic horizon names were harmonized by translating them to their closest United States Department of Agriculture (USDA) Soil Taxonomy (Soil Survey Staff, 2014) equivalent or Latin descriptors, and classes were grouped based on shared morphological characteristics or land-use management relevance. Grouping was necessary because a large number of horizons in the South African system were represented by only a single observation. Although their inclusion may contribute to class imbalance and potential bias, it was necessary to preserve pedological detail and maintain a comparable number of soil classes relative to the numerical classification system.

Table 2: Topsoil and subsoil diagnostic horizons classified by the Soil Classification Working Group, (1991), number of members (n) and their properties that were observed in Gauteng.

Horizon	Diagnostic	*n*	Concept
Topsoil	Mollic	19	High SOC, high base saturation, well structured
	Ochric	521	Topsoil that does not meet requirements of others
	Vertic	24	Swelling and cracking clay

Subsoil	Rhodic	199	Uniform red, slightly acidic with or without clay increase
	Xanthic	131	Uniform yellow, slightly acidic with or without clay increase
	Cambic	88	Young horizons with or without free carbonates/lithic contact
	Luvic	71	Clay increase, moderate to strong structure
	Aquic	52	Horizons that are wet for most of the year
	Plinthic	18	Horizons with clear Fe/Mn concretions (not continuous)
	Hardpan	3	Soil with a continuous hard layer
	Podzolic	3	Fe/Al and SOC accumulation with or without a Placic pan

147

148 2.2.2 Environmental variables (exogeneous state variables, X)

149 All 64 AlphaEarth (Brown et al., 2025) embedding layers at a 10 m spatial resolution were
150 used for model training and spatial predictions. These embeddings are derived from multi-
151 sensor Earth observation data and encode nonlinear representations of surface reflectance,
152 texture and spatiotemporal context learned through self-supervised deep learning. Rather than
153 representing individual spectral bands or indices, the embedding vectors provide a compact
154 description of land-surface characteristics, capturing complex interactions among spectral,
155 spatial, and temporal features. All embeddings were obtained from the median of the year 2024
156 at a 10 m resolution and are uncorrelated so no feature selection was performed, making them
157 suitable for spatial predictions in heterogeneous urban environments.

158 ## 2.3 Model development

159 The mapping was implemented in a decision-making framework with incomplete information
160 (Figure 2), in which soil classification outputs represent probabilistic surfaces about latent soil
161 configurations and their associated ecosystem service potential. Identical soil observations (Y),
162 environmental covariates (X), spatial domain (Ω) and the inference system (algorithm) were
163 used for both numerical and taxonomic classification systems, ensuring that differences in
164 outcomes reflect classification structure rather than data availability or model configuration.

165 Soil class predictions ($\hat{S}$) were generated through the inference mechanism (machine
166 learning), derived from posterior class probability surfaces (π_i), which quantify the likelihood of
167 each class at location x. Spatial predictions were therefore treated as probability distributions
168 over soil classes rather than deterministic soil states. These probability distributions form the

information upon which land-use decision makers implicitly assess ecosystem service potential. Therefore, model evaluation emphasized not only predictive performance, but also the extent to which inferred patterns preserve pedological coherence and spatial structure relevant to ecosystem service interpretation.

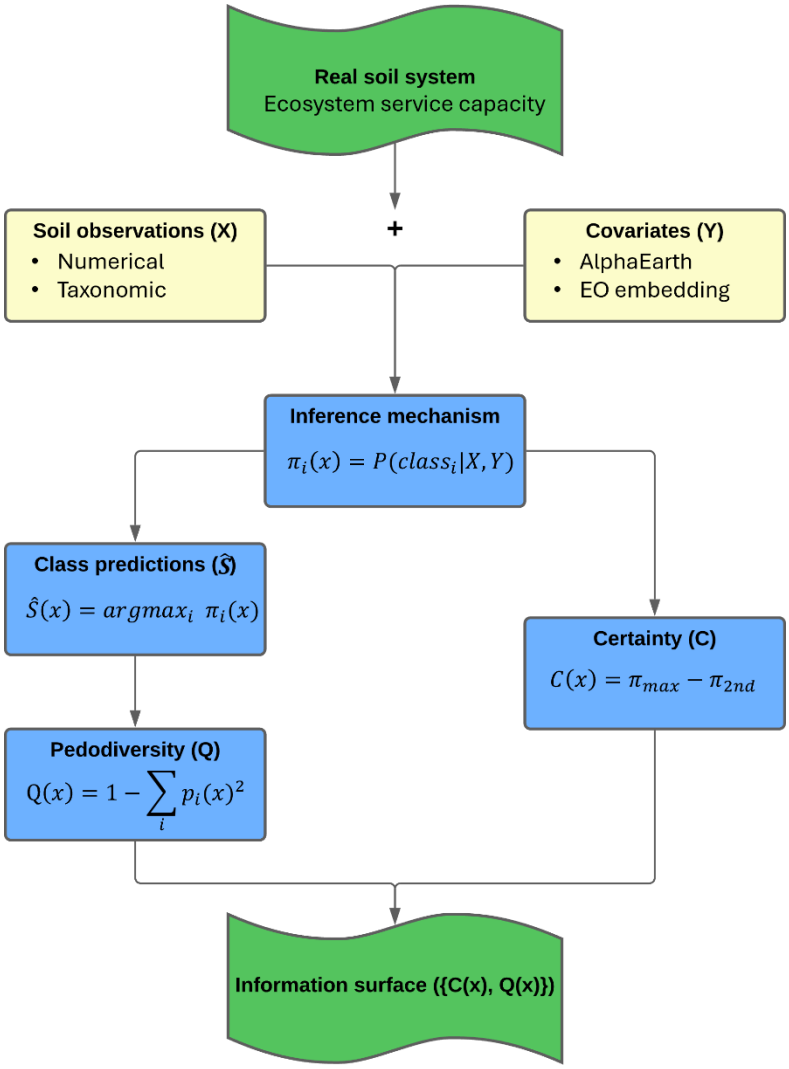

Figure 2: Conceptual workflow for evaluating ecosystem service potential derived from soil classification systems.

2.3.1 Soil class predictions ($\hat{S}$)

To predict soil classes $\hat{S}$, a gradient tree boosting (GTB) model was implemented in Google Earth Engine (GEE; Gorelick et al., 2017). A GTB is a generalised additive model in which base learners are small decision trees, and each successive tree corrects the residuals of the previous ensemble (Hastie et al., 2009). The construction improves regularization, accuracy and reduces overfitting (Friedman & Hastie, 1998), while nonlinear interactions enable the

model to capture complex relationships between soil classes and AlphaEarth covariates (Kuhn & Johnson, 2013). Additionally, it is stochastic, making it well suited for modelling complex soil–environment relationships (Flynn et al., 2019).

For each location x, posterior class probabilities $\pi_i(x)$ were produced by the model, and the predicted soil class was defined as:

$$\hat{S}(x) = \ argmax_i \ \pi_i(x).$$

Model performance was evaluated using an 80:20 train-test split, with predictive accuracy and Cohen's κ as accuracy-based metrics. Both classification systems were predicted with the same GTB parameters of 100 sequential trees, a learning rate of 0.01 and a subsampling rate of 0.7 per tree.

2.3.2 Uncertainties and certainties (model certainty, *C*)

Uncertainty was derived from the posterior soil-class probability distribution and calculated as a confusion index (*CI*: Burrough et al., 1997):

$$\mathrm{CI} = \ 1 - (\pi_{\max} - \pi_{2\mathrm{nd}}),$$

where $\pi_{\max}$ and $\pi_{2\mathrm{nd}}$ denote the highest and second-highest posterior class probabilities at location x. While reporting certainty is not common in soil science, it is essential here because the joint behaviour of additional model outputs and potential synergistic states requires quantification. Model certainty (*C*) was formulated as the inverse of the *CI* (*C* = 1 – *CI*). Low values indicate broad probability distributions and low classification confidence, while high values indicate high confidence. Certainty values were normalized to [0, 1].

2.3.3 Pedodiversity (payoff, *Q*)

Pedodiversity (*Q*) was considered a payoff because it represents the realised capacity of a landscape to support multiple soil-mediated ecosystem functions simultaneously (i.e., a reward). Under the assumption that all soil types possess a dissimilarity of one, pedodiversity was quantified using the Simpson Diversity Index (Simpson, 1949),

$$Q(x) = 1 - \sum_i p_i\,(x)^2,$$

where $p_i(x)$ represents the local proportion of soil class i within a 50 x 50 m window centred at pixel x. Proportions p_i were derived from the predicted soil classes, reflecting the spatial soil horizon patterns. The window size was thought to represent manageable land units in Gauteng's landscape mosaic. By construction, *Q* captures taxonomic pedodiversity and is maximised when multiple soil classes coexist evenly within the window.

2.3.4 Information space ({*C, Q*})

The joint behaviour of pedodiversity and model certainty defines a bounded information space, Ω = $\{C(x), Q(x)\}$, within which ecosystem service outcomes were evaluated. Both quantities were normalised to the unit interval [0, 1], enabling joint interpretation without scale dominance. Within this bivariate space, this relationship determines the utility of soil information for decision-making.

Synergistic states occur along the diagonal of this information space, where certainty and pedodiversity coincide (Table 3), indicating soil heterogeneity that is inferred with commensurate confidence. Improvements in soil classification therefore shift information toward higher joint values, expanding the region of reliable decision states. However, high pedodiversity and high certainty rarely co-occur because structural heterogeneity and inferential certainty often require opposing constraints; for example, increasing the number of soil classes often decreases classification confidence, while aggregating classes to increase certainty suppresses detectable diversity. Decision-making is thus conditioned by the synergistic region of the information space rather than by its theoretical joint maximum.

Table 3: representation of synergistic information states between model certainty (C) and pedodiversity (Q), including their statistical interpretations.

Certainty (*C*)	Pedodiversity (*Q*)	Interpretation & Decision
High	High	**Stable hotspot:** reliable evidence of diverse soil functions (high reward). High confidence for strategic urban planning and conservation.

Low	High	**Speculative reward:** high potential value but high classification risk. Information gap requires further site-specific sampling before investment.
High	Low	**Predictable matrix:** low diversity but high reliability. Suitable for standard, low-risk land-management protocols and infrastructure development.
Low	Low	**Information void:** unreliable data and low functional potential. High risk with low reward.

2.3.5 Ecosystem services potential and alignment

Certainty and pedodiversity were first calculated separately for each soil horizon and classification system, then summed across topsoil and subsoil to obtain profile-like measures reflecting the integrated information available from the information set (I). Resulting information surfaces were summarised using quantiles to support comparison across classification systems. While this aggregation does not capture full vertical profile complexity, it represents the maximum information content accessible with the given constraints.

Diagonal distance measures the absolute misalignment between the quantile-based C and Q classes, where values of zero indicate perfect alignment and larger values indicate increasing misalignment. Signed diagonal distance characterises the direction of this misalignment: negative values indicate Q exceeds C (high pedodiversity, low certainty), while positive values indicate C exceeds Q (low pedodiversity, high certainty). Diagonal occupancy was calculated as the proportion of pixels occupying synergistic states (low–low, mid–mid, high–high), quantifying landscape-wide concordance.

The Gini coefficient of diagonal distance values was used to quantify the degree of spatial alignment. Low Gini values indicate that alignment is broadly distributed across the landscape, reflecting widespread consistency between certainty and pedodiversity, whereas high Gini values indicate that alignment is spatially concentrated in specific locations, such as soil transition zones or anthropogenically disturbed urban environments (Cowell, 2011). The Gini coefficient was calculated as:

$$G = \frac{1}{2n^2\mu}\sum_{i=1}^{n}\sum_{j=1}^{n}|d_i - d_j|,$$

where d_i is the diagonal distance at pixel i, μ is the mean diagonal distance across all pixels, and n is the total number of pixels. Indices i and j refer to pairwise comparisons among pixels. This information space was evaluated on these parameters and spatially on the bivariate information surface that certainty and pedodiversity formed.

3. Results

3.1 Model performance

3.1.1 Inferred soil states

Model evaluation showed that the GTB framework produced superficially comparable predictive accuracy across both classification systems; however, accuracy-based metrics were not stable indicators of information quality (Table 4). For topsoil, numerical and taxonomic systems showed similarly high overall accuracy (87–97%) but low agreement (κ = 0.24–0.43), moderate confusion index (CI = 0.52–0.62), and a very low mean pedodiversity (Q = 0.03–0.09). Specifically, the numerical system exhibited lower κ and accuracy while simultaneously producing a lower confusion index, indicating that these metrics can give a misleading impression of the reliability of the spatial prediction quality. These results were not intuitive as the numerical system with the lower κ and accuracy, with the higher number of topsoil classes, had a lower uncertainty.

Table 4: Agreement (κ), accuracy, mean confusion index (CI) and mean pedodiversity (Q) of the numerical and taxonomic predictions.

System	Class	κ	Accuracy (%)	Mean CI	Mean Q
Numerical	Topsoil	0.24	87	0.52	0.09
	Subsoil	0.47	80	0.77	0.22
Taxonomic	Topsoil	0.43	97	0.62	0.03
	Subsoil	0.57	71	0.86	0.45

The subsoil results were similar to the topsoil results in that some of the metrics were counter-intuitive, with the numerical system having a higher accuracy (80% vs 71%) but a lower κ of 0.47 compared to 0.57. The pedodiversity was also unexpected, with a mean pedodiversity of 0.22 compared to 0.45 for the taxonomic system, despite the latter having one less soil class. However, several classes were not predicted under either system, with two numerical subsoil classes (B7 and B8) and one taxonomic class (Vertic) absent from the model outputs. Collectively, these results demonstrate that accuracy and singular metrics alone do not reflect the structural and functional relevance of inferred soil patterns; rather, the soil patterns themselves are influencing the discrepancies in these metrics.

3.1.2 Information space

The information surface revealed marked differences in landscape alignment between classification systems (Table 5). The numerical classification exhibited a high mean diagonal distance (1.15), indicating substantial misalignment between pedodiversity and certainty, whereas the taxonomic system showed substantially lower misalignment (0.45). Consistent with this, only 21% of the numerical system occupied synergistic states, compared with 63% under the taxonomic system. Signed diagonal distance values were negative for both systems, indicating a general tendency for pedodiversity to exceed confidence, but this bias was markedly stronger under the numerical classification. Analysis of misalignment distribution further showed that the taxonomic system localized misalignment into specific areas (Gini = 0.68), while the numerical system distributed misalignment more uniformly across the landscape (Gini = 0.34).

Table 5: Summary of numerical and taxonomic information space showing diagonal distance, signed diagonal distance (+ or -), area occupied by synergistic state and gini coefficient.

Statistic	Numerical system	Taxonomic system
Diagonal distance	1.15	0.45
Signed diagonal distance	-0.78	-0.33
Synergistic state	21%	63%
Gini coefficient	0.34	0.68

3.2 Spatial predictions

3.2.1 Topsoil surfaces

Topsoil predictions, dominated by a single diagnostic horizon of A3 (96% of Gauteng) and Ochric (98% of Gauteng), differed only slightly between the numerical (Figure 3a) and taxonomic (Figure 3b) classification systems. In contrast, the numerical CI surface revealed distinct spatial patterns with lower CI values occurring in urban and peri-urban landscapes (Figure 3c). The taxonomic system, however, displayed more spatially uniform CI values with higher overall magnitudes peaking in the east (Figure 3d). At this scale and resolution, small patches of predictions from less predominant classes were difficult to observe.

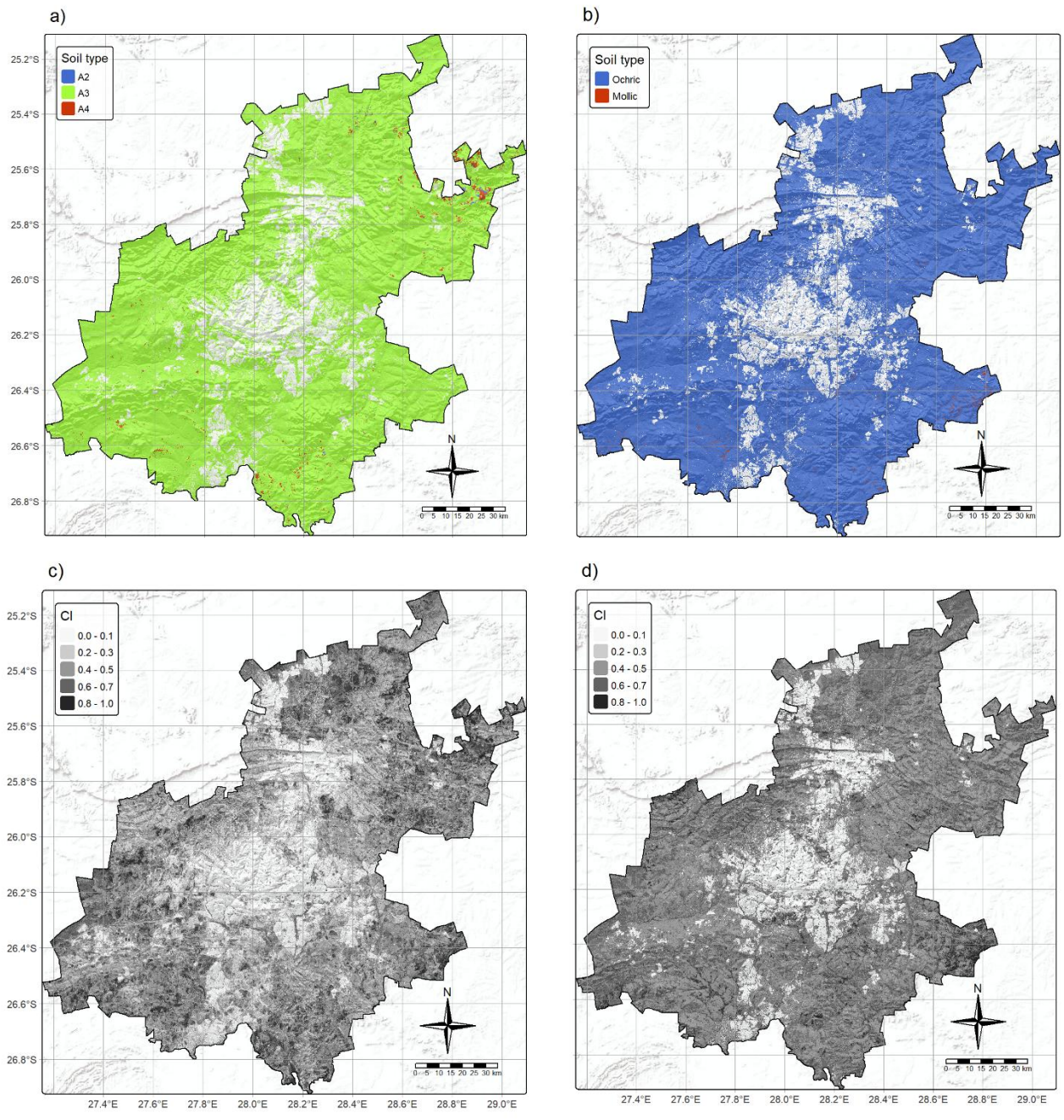

Figure 3: Spatial distribution of topsoil information for Gauteng derived from the (a) numerical soil class predictions; (b) taxonomic soil class predictions;(c) The numerical classification uncertainty; and (d) the taxonomic classification uncertainty.

3.2.2 Subsoil surfaces

Subsoil spatial predictions differed markedly between numerical and taxonomic classification systems. The numerical system produced largely homogeneous subsoil patterns dominated by a single horizon (Figure 4a) much like its topsoil counterpart. Horizon B4 occupied

316 approximately 94% of the predicted area, while the remaining classes were confined to small,
317 spatially fragmented patches. In contrast, the taxonomic system displayed multiple, spatially
318 structured subsoil horizons (Figure 4b). Rhodic horizons occupied approximately 58% of the
319 Gauteng, while Xanthic, Luvic, and Cambic horizons each accounted for substantial and
320 comparable portions (≈20%) of the remaining landscape. The taxonomic system showed more
321 pedological relationships with Aquic horizons in valleys, Luvic in foothills, Cambic on erosion-
322 deposition positions, and Rhodic/Xanthic on more planar positions.
323 The numerical system exhibited spatially structured CI values, with higher values
324 concentrated in northern regions and lower values nearer to urban areas (Figure 4c). The
325 taxonomic system showed higher overall CI values with less spatial organisation across the
326 study area (Figure 4d). These results suggest an inverse relationship between classification
327 and uncertainty patterns: the numerical system produced spatially fragmented soil classes
328 despite having coherent uncertainty structures, whereas the taxonomic system exhibited
329 spatially coherent soil classes but disorganised uncertainty.

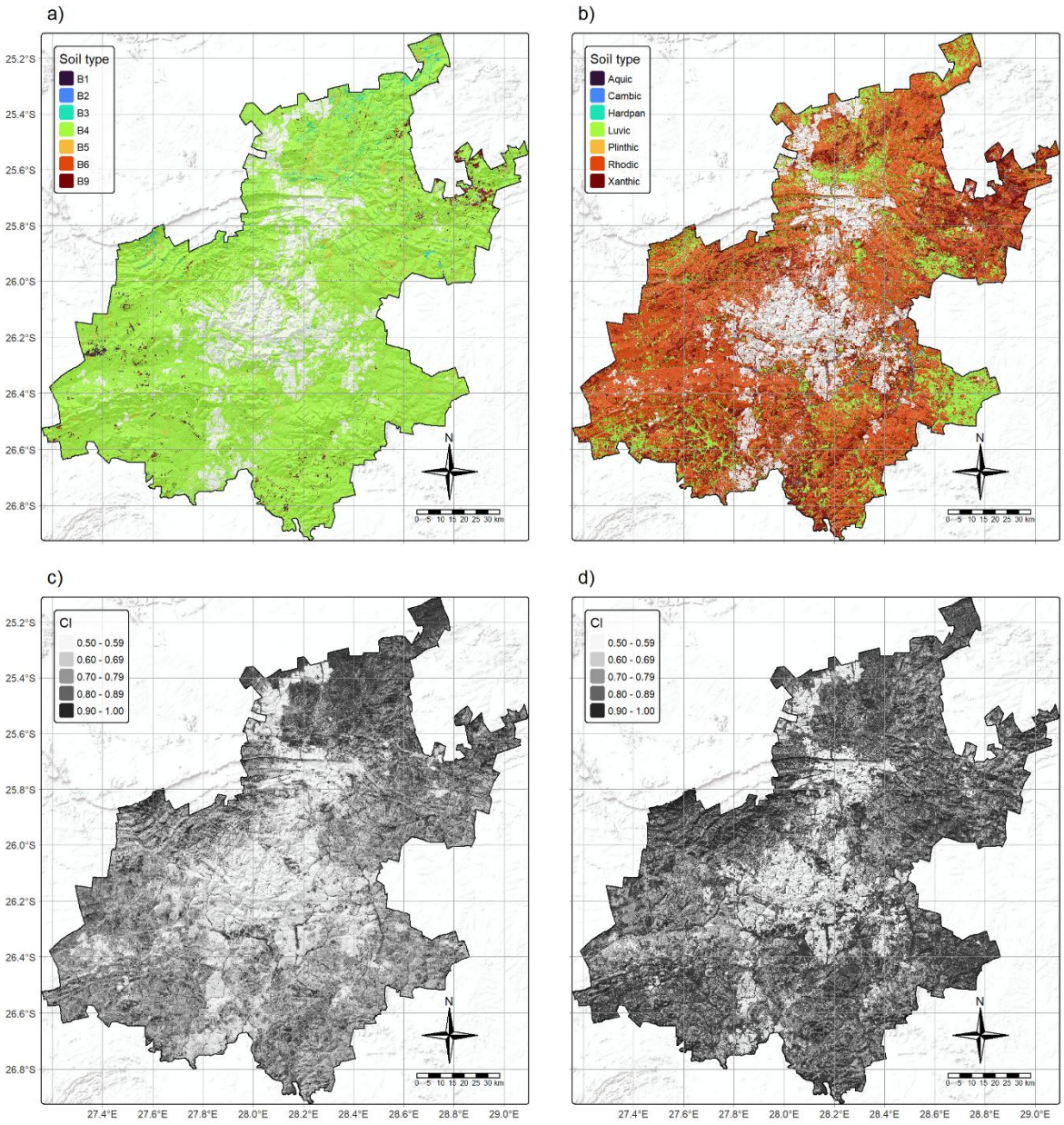

Figure 4: Spatial distribution of subsoil information for Gauteng derived from the (a) numerical soil class predictions; (b) taxonomic soil class predictions;(c) The numerical classification uncertainty; and (d) the taxonomic classification uncertainty.

3.2.3 Information surface

The maps of the information surfaces coincide well with the information space statistics. The combined topsoil–subsoil information surface derived from the numerical classification system revealed a strong trade-off between pedodiversity and model certainty (Figure 5a). High pedodiversity occurred predominantly where certainty was low, while areas of high certainty

were consistently associated with low pedodiversity. A synergistic state was rare, indicating limited representation of structurally diverse soil profiles inferred with balancing confidence.

In contrast, the taxonomic classification system exhibited a distinctly different organisation of the information space (Figure 5b). Pronounced synergistic states was evident, with extensive areas where moderate to high pedodiversity coincided with moderate to high certainty. This synergistic information condition forms larger and more spatially coherent patches than in the numerical system. Pedodiversity patterns align with geomorphic and landscape units, and certainty surfaces show corresponding spatial structure, resulting in reduced fragmentation and improved spatial continuity.

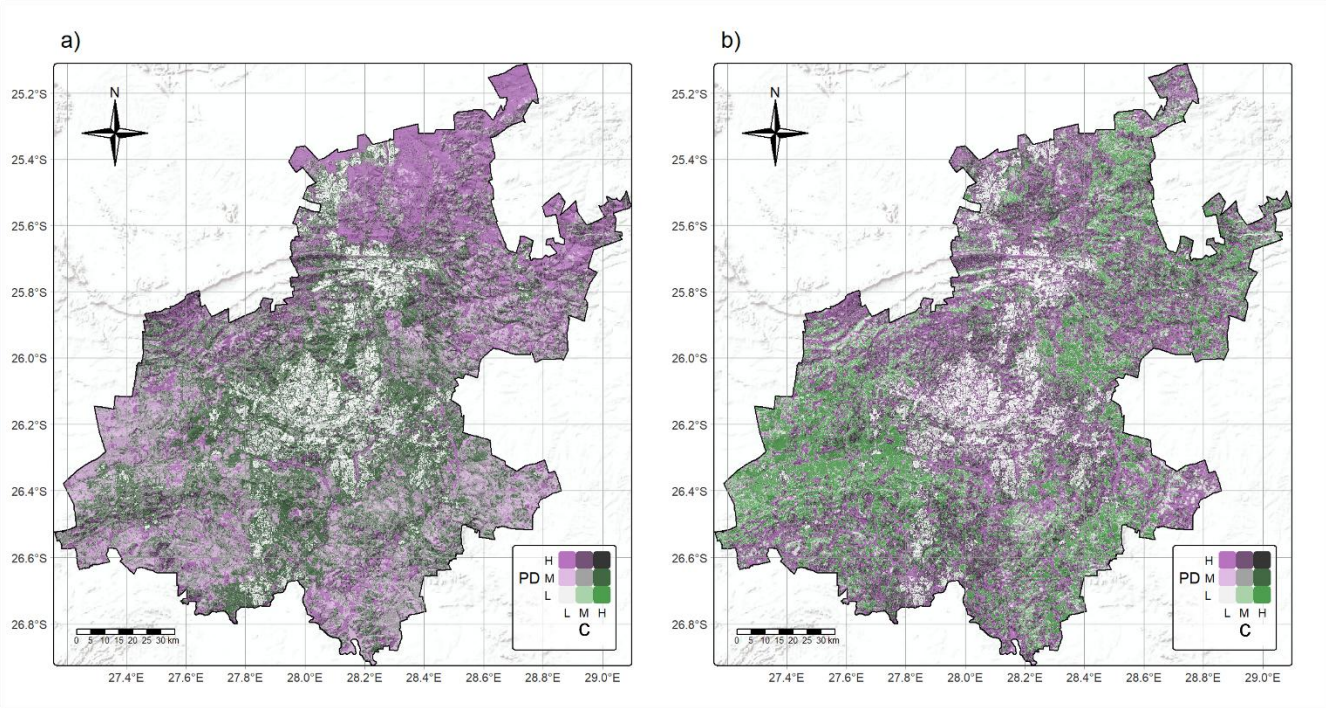

Figure 5: Information space of pedodiversity and certainty of the numerical (a) and taxonomic (b) classification systems.

4. Discussion

Soil classes were predicted for Gauteng, South Africa, using both a numerical system and the national taxonomic soil classification system. To enhance the interpretability and decision relevance of these outputs, the DSM framework was reframed as a decision-making framework, wherein soil maps function as information structures for ecosystem service potential under uncertainty. Class predictions, posterior probabilities, and derived metrics were jointly analysed to evaluate which classification system yielded greater pedodiversity (the reward) while maintaining high certainty in spatial inference.

Overall predictive accuracy only moderately differed between classification systems, yet coincided with similar studies conducted in South Africa (Flynn et al., 2025; van Zijl et al., 2019; G. Van Zijl & Le Roux, 2014; G. M. Van Zijl et al., 2013). This indicates that, based on model performance alone, both models would be considered reasonable outcomes. However, their spatial organisation of information differed substantially. The numerical classification achieved its accuracy primarily through class fragmentation, which produced significant trade-offs between detail and reliability. In contrast, the taxonomic system maintained comparable predictive performance while preserving spatial structure, allowing moderate to high pedodiversity to be inferred with greater certainty. Collectively, these results demonstrated that conventional accuracy metrics alone were insufficient for assessing the decision relevance of these soil maps.

These differences have direct implications for urban ecosystem service assessment. In the heterogeneous landscape of Gauteng, pedodiversity represents the structural capacity of soil to support multifunctional services such as stormwater regulation in Pretoria (Nhamo et al., 2025) or food production in peri-urban areas (Cattivelli & Pinna, 2025), while certainty reflects the confidence with which this capacity can be inferred. Under the numerical system, high pedodiversity is frequently associated with low certainty, particularly in areas of strong anthropogenic disturbance such as soil sealing (García et al., 2014) where AlphaEarth embeddings capture high spectral–spatial variability. This creates an information bottleneck, limiting confidence in identifying multifunctional soil where decision support is most critical affecting a large population.

By contrast, the taxonomic system encoded process-based transitions through diagnostic horizons, enabling structurally diverse soil groups to be represented with greater spatial unity. This is evidenced by the high spatial alignment of the information surface, even within the complex urban fabric of Johannesburg. By filtering high-frequency surface variability that disrupted numerical clustering, the taxonomic system produced a more stable information structure characterized by a lower Gini coefficient. Consequently, greater confidence can be placed in these synergistic states when assessing soil functions that directly affect both urban and rural populations, such as erosion control (Rugendo et al., 2023), toxic pollutants (Ewis et al., 2022), and crop productivity (Ma et al., 2023).

The limited information observed in the topsoil and numerical subsoil predictions likely reflects a weak correspondence between these soil layers and the 10 m AlphaEarth

embeddings. In urban environments, as evidenced by the numerical system's high Gini coefficient, topsoil is frequently disturbed, while subsoil classified numerically expresses variability that is poorly aligned with surface-derived remote sensing. As a result, inference is constrained not only by the classification but by the correlation of the information itself. Expanding the information set (I), through multi-resolution covariates, depth-explicit observations, or management indicators would facilitate more inferred soil states and improved spatial alignment in bivariate space.

The prevalence of synergistic information states reflected intrinsic properties of the taxonomic classification system itself. High alignment of the information surface indicates that diagnostic horizons organized soil variation in a way that preserved structural heterogeneity without introducing high interpretive ambiguity. In this way, synergistic states not only indicate good mapping outcomes but also show how well taxonomic classes capture soil structure into stable, interpretable areas. By producing frequent synergistic states, the taxonomic system provided a more efficient information structure for interpreting ecosystem service potential.

Nevertheless, several limitations warrant investigation. Reducing complex urban soil systems to bivariate dimensions may obscure finer-scale functional trade-offs, such as depth-specific contaminant transport, localised soil sealing, or preferential flow in anthropogenically disturbed profiles. The scale of this study may have also limited the representation of soil classes within the urban–rural mosaic; a multi-resolution approach might be required to improve the spatial alignment and representation of the numerical subsoil.

Furthermore, reliance on a static soil dataset limits the representation of rapid land-use feedbacks and surface modifications characteristic of expanding metropolitan areas. While the taxonomic framework successfully filtered surface noise to maintain structural consistency and synergistic states, it may have missed functionally important anthropogenic soil types that the "Blue Book" (Soil Classification Working Group, 1991) does not capture well. The updated South African soil classification system (the "Green Book") (Soil Classification Working Group, 2018), however, provides more detailed diagnostics for these anthropogenic soil types, offering a pathway to further improve diagonal occupancy and information utility in urbanised landscapes.

These results demonstrate that the choice of soil classification is not a neutral modelling decision, but a fundamental determinant of how raw data is transformed into actionable knowledge. By framing DSM within a decision-making framework, this study showed that

"accuracy" is often a secondary metric to spatial alignment. In this sense, a "better map" is defined not by reduced residuals, but by its ability to maximise synergistic states across the landscape, providing a reliable basis for assessing ecosystem service potential in complex urban–agro–natural mosaics. By favouring process-based taxonomic logic over purely numerical clustering, we fundamentally expanded the decision space available to stakeholders in this study. This shift from "prediction-centric" to "information-centric" mapping provided a novel blueprint for navigating land-use trade-offs in an increasingly uncertain environmental future within the ever-urbanising landscapes.

5. Conclusion

This study evaluated a numerical and South Africa's taxonomic soil classification systems as information structures for assessing ecosystem service potential in the expanding metropolitan landscape of Gauteng Province, South Africa. By shifting the evaluation from predictive accuracy to a bivariate information space, the results showed that classification choice is a primary determinant of the decision context for urban resilience. While the numerical system captured multivariate variation, its high degree of class fragmentation led to weakly constrained spatial patterns (synergistic state = 21%), limiting its utility for stable ecosystem service inference. In contrast, the taxonomic framework preserved pedological coherence through process-based transitions. This produced a fundamentally more robust information structure, achieving a synergistic state of 63%. This high spatial alignment between pedodiversity and certainty enables stakeholders to identify, with high confidence, the land units best suited for critical functions such as erosion control, pollutant buffering and urban agriculture. These findings demonstrate that "better maps" for urban governance are not defined by accuracy alone, but by their capacity to provide actionable information through synergistic states. Interpreting DSM outputs through this framework shifts the focus toward identifying where soil information is reliable enough to support multifunctional land-use decisions under uncertainty. Future research should expand this framework to diverse geographic regions and modify it for specialized applications such as precision agriculture, sampling regimes, or soil health monitoring; thereby operationalising the bivariate information space as a versatile tool for soil resource governance.

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