ADVANCED LAND COVER ACCURACY ASSESSMENT IN SOUTH AFRICA: A STATISTICAL APPROACH TO SAMPLE SIZE DETERMINATION

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SUMMARY

Land cover datasets are fundamental for monitoring and achieving the United Nations Sustainable Development Goals (SDGs), supporting applications such as food security assessment, water resource management, urban planning, climate action, and biodiversity conservation. Given their extensive use in policy formulation and scientific analysis, the reliability of national land cover products depends critically on the implementation of statistically rigorous accuracy assessment procedures. In South Africa, however, national land cover datasets have historically relied on rule-of-thumb sampling approaches, with no formally established, probability-based framework for determining optimal sample sizes for independent accuracy validation.

This study addresses this methodological gap by evaluating statistically grounded approaches for determining minimum acceptable sample sizes for land cover accuracy assessment within the South African context. Using KwaZulu-Natal Province as a representative and heterogeneous study area, the research investigates and compares simple random sampling and stratified random sampling designs. The province was selected due to its diverse climatic conditions, land-use patterns, and ecological zones, which collectively reflect the broader heterogeneity of South Africa's land cover.

Sample size requirements for simple random sampling were derived using established probability-based formulas under defined confidence, precision, and expected accuracy parameters. Stratified random sampling was implemented to account for unequal class area distributions, incorporating class weights, assumed user accuracies, and minimum sample thresholds per class. The study finds that simple random sampling, while unbiased, is impractical in heterogeneous landscapes because it requires very large sample sizes, making it operationally infeasible at sub-national scales. In contrast, stratified random sampling is more efficient and realistic, as it allocates validation points proportionally to land-cover class extent while ensuring rare classes are represented. Stratified random sampling offers a robust,

repeatable approach for land cover accuracy assessment in South Africa and forms the foundation for national validation guidelines aligned with global best practices.

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1. INTRODUCTION

Land cover datasets play a pivotal role in achieving the United Nations Sustainable Development Goals (SDGs) by providing essential spatial information to support monitoring, planning, and evidence-based decision-making across multiple sectors. Accurate land cover information supports initiatives such as food security (SDG 2) through mapping agricultural areas and crop dynamics; supports water resource management (SDG 6) by enabling monitoring of wetlands and water catchment conditions; and contributes to sustainable urban development (SDG 11) through the assessment of urban expansion and green-space distribution. Land cover data are also fundamental to climate action (SDG 13), facilitating carbon stock estimation and deforestation monitoring, as well as to biodiversity conservation (SDG 15) by detecting habitat loss and ecosystem fragmentation. Furthermore, land cover information informs infrastructure planning (SDG 9) and supports poverty reduction efforts (SDGs 1 and 10) by guiding equitable land use policies and rural development strategies (UN, 2015; Estes et al., 2022; FAO, 2021).

Given this critical role, the reliability and accuracy of land cover datasets are of paramount importance. National land cover datasets in South Africa, as in many countries, are primarily produced using remotely sensed imagery. It is widely acknowledged in the literature that land cover data derived from remotely sensed imagery must undergo statistically rigorous accuracy assessments before being used in scientific analyses or policy decision-making (Stehman & Czaplewski, 1998; Congalton, 2005; Wulder et al., 2006; Huang et al., 2017). Accuracy assessment is defined as the process of estimating the correctness of a remotely sensed classification (land cover product in this instance) by comparing it with reference information that is assumed to represent the true land cover. This reference information is typically derived from data sources of higher spatial resolution or greater reliability than the map being evaluated (Caetano et al., 2006).

The evolution of validation of map products from remotely sensed imagery can be broadly characterised by four major stages: initial visual appraisal, spatial area summaries, early error matrix analysis, and the contemporary use of statistically rigorous accuracy assessment approaches. Despite these methodological advances, South Africa currently lacks a statistically grounded framework for determining optimal sample sizes for the accuracy assessment of national land cover products. Consequently, national practices remain largely confined to spatial area summaries and early error matrix analysis. To ensure methodological robustness, comparability and alignment with international best practices, there is a clear need for South Africa to advance towards statistically rigorous accuracy assessment approaches that reflect the current state of the discipline.

2. AIM OF THE STUDY

Haub et al. (2015) emphasise that the validating map products derived from remotely sensed data should be a mandatory component of geospatial analysis. Independent and systematic accuracy assessments of land cover products are essential for enhancing their reliability and credibility. However, despite the importance of these evaluations, there is currently no universally accepted method for the accuracy assessment and validation of land cover products. South Africa, in particular, has historically lagged in consistently prioritising such investigations. Its national land cover datasets series (1990, 1995, 2000, 2013/14, 2018, 2020 and 2022) have not employed a statistically determined sample size for accuracy verification. Instead, sampling sizes have typically been based on educated rules of thumb, which may compromise the robustness of the results.

This gap motivates the present study, which seeks to identify an appropriate statistical minimum acceptable number of sample points required for independent accuracy assessment of land cover maps in South Africa. Achieving this aim involves addressing the key objective of defining what constitutes an acceptable sample size for land cover accuracy assessment and validation within the South African context, drawing on international guidance (Olofsson et al. 2014; Stehman & Foody 2019) and practical protocols to adapt probability-based sampling

3. STUDY AREA

The study area is KwaZulu-Natal province (Figure 1), selected as a representative region for determining the minimum number of accurate sampling points. This province was chosen because it encompasses a broad range of land-cover classes found across South Africa, offering a comprehensive representation of the country's land-cover heterogeneity. Its diversity in climatic conditions, topography, land-use patterns, and ecological zones allows for the inclusion of both natural and anthropogenic land-cover types, making it particularly suitable for evaluating classification performance in heterogeneous landscapes.

KwaZulu-Natal features a mix of natural grasslands, wetlands, and cultivated land, reflecting sharp contrasts between natural and intensively managed environments. The province exhibits high land-cover variability, including coastal and inland wetlands, dense settlements, subsistence and commercial agriculture, indigenous forests, grasslands, and urban areas. The presence of both fragmented and continuous land-cover patterns provides a robust testing environment for assessing class-level accuracy, especially for rare and spatially heterogeneous classes.

In addition to its land-cover diversity, KwaZulu-Natal was selected for its manageable spatial extent, which enables efficient implementation of statistically rigorous sampling and reference data interpretation without compromising national representativeness. Using this province ensures that the minimum sample-size determination captures the complexity of South Africa's land cover while remaining operationally feasible.

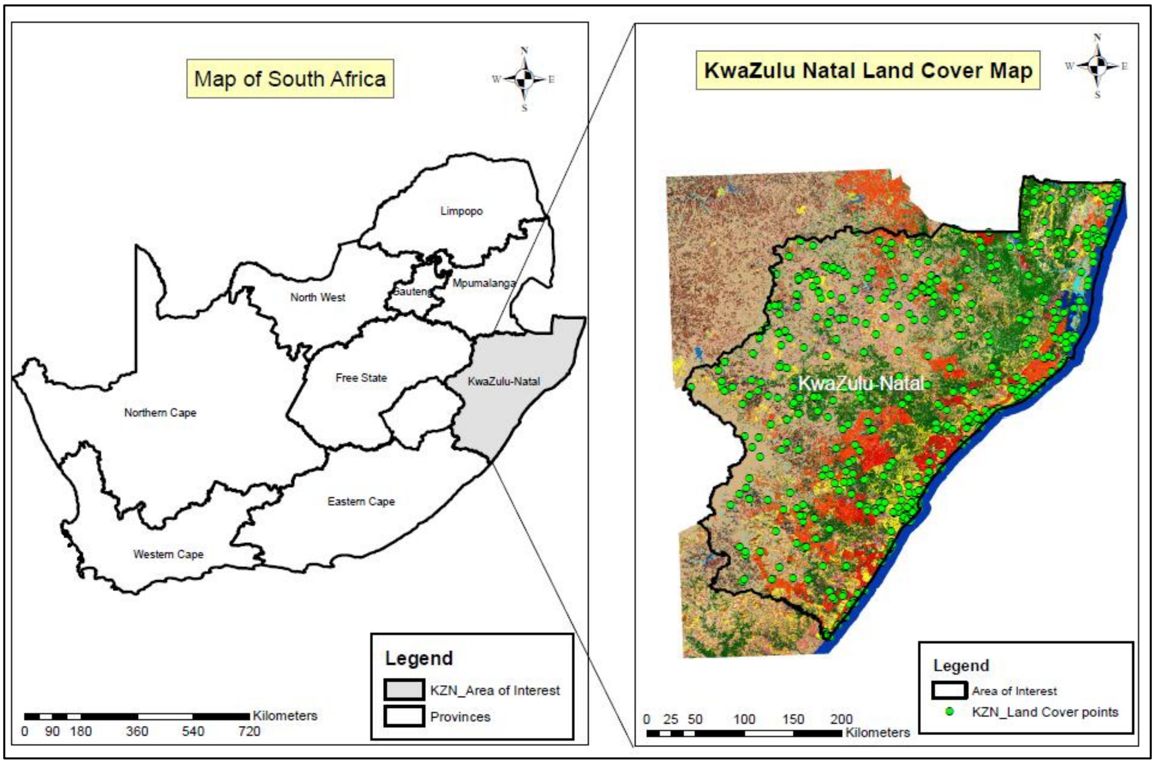

Figure 1: Study area of KwaZulu-Natal province

4. METHODOLOGY

To implement a statistically rigorous accuracy assessment, both the sampling design and the response design must be clearly defined (Foody, 2009; Wulder et al., 2006). Sampling design refers to the protocol used to select reference data, including the definition of sampling units and the determination of sample size. Several authors emphasise that adequate sample size representation is critical for deriving meaningful accuracy assessments, as both under-sampling and over-sampling can lead to biased, imprecise or inefficient results (Congalton, 2005; Carrão et al., 2007; Foody, 2009; Stehman, 2009; Stehman et al., 2012). Sample size determination is grounded in probability theory and has a direct influence on the precision and confidence of accuracy estimates. Statistically robust sampling designs seek to achieve low variance and high confidence levels, while ensuring that samples are spatially representative. Commonly documented sampling strategies include simple random sampling, stratified random sampling, systematic sampling, cluster sampling, and multi-stage sampling, the latter representing combinations of these approaches. While each strategy has methodological merits, their suitability varies depending on the objective of the accuracy assessment, the characteristics of the mapped phenomenon and practical implementation constraints.

This study focuses exclusively on simple random sampling and stratified random sampling because these methods are the most widely recommended and theoretically robust probability-based approaches for land cover accuracy assessment. Simple random sampling provides an unbiased and statistically defensible basis for estimating overall map accuracy, as every location within the study area has an equal probability of selection. Its statistical properties are well understood, making it particularly suitable for deriving sample size formulas, estimating variance, and ensuring transparency and replicability in national-scale assessments (Stehman & Czaplewski, 1998; Congalton & Green, 2019). The random sampling was based on the following formula

$$n = \frac{z^2 \rho q}{E^2}$$

Where:

- n = required number of sample points (per class when you design per-class sampling).
- z = z-score for the desired confidence level (e.g., 95% → 1.96), refer to table 1
- p = expected accuracy (proportion), e.g., 0.5 or 0.80.
- q=1-p
- E = allowable (absolute) error on the estimated accuracy (in proportion, e.g., 0.05 = ±5%).

Table1: The standard normal distribution confidence level values with relation to the -z-percentile score.

Desired Percentage of confidence level (%)	Z - value
80	1.28
85	1.44
90	1.65
95	1.96
99	2.58

Stratified random sampling is included because land cover datasets are inherently heterogeneous, with class areas often highly unbalanced. Rare or spatially limited classes, such as wetlands, rivers, or specific vegetation types, may be under- or over-represented under simple random sampling, leading to unreliable class-specific accuracy estimates. Stratified random sampling addresses this limitation by allocating samples within predefined land cover classes, thereby improving the precision of class-level accuracy and area estimates while maintaining statistical rigour (Stehman, 2009; Olofsson et al., 2014). This approach is particularly advantageous for national land cover validation, where accurate estimation of both overall and per-class accuracies is required. For stratified random sampling determination, the following formula was applied:

$$n = \frac{(\Sigma w_i s_i)^2}{[s(\hat{o})]^2 + (1 / N)\Sigma W_i S_i^2} \approx \left(\frac{\Sigma w_i s_i}{s(\hat{O})}\right)^2$$

Where:

- N = Total number of units in the region of interest,
- $s(\hat{o}) =$ Desired standard error of the estimated overall accuracy. Typical values are 0.01, 0.002 or 0.003 depending on how precise you want the accuracy estimate to be.
- $w_i =$ Proportion of total map area occupied by class i
- $s_i =$ Standard deviation for class i, computed as $s_i = \sqrt{u_i(1 - u_i)}$, where
- U_i = Expected user's accuracy for class *i.* If unknown, a value such as 0.5 (maximum uncertainty) may be used

Complementary to sampling design is the response design, which defines the procedure for assigning reference land cover classes to sampled units (Stehman & Czaplewski, 1998; Olofsson et al., 2014). Response design addresses how agreement or disagreement between the mapped product and the reference classification is evaluated. A fundamental requirement of response design is that the reference data must be more accurate than the dataset being assessed to ensure the validity of the accuracy estimates (Congalton, 2005). For this study, 25cm ground sample distance aerial imagery from the Chief Directorate: National Geospatial Information (CD: NGI), together with Google Earth Engine aerial imagery were used to determine reference accuracy points.

Within the response design framework, a critical methodological decision concerns the choice of spatial sampling unit, such as whether to use individual pixels or polygon-based units. Huang et al. (2017) note that no consensus exists on the optimal sampling unit, as this choice is largely dependent on the objectives, scale and characteristics of the study area. A pixel-based sampling unit was selected because the national land cover products under assessment are generated through pixel-based image classification, making the pixel the most direct and conceptually consistent unit for validation. Pixel-based sampling enables straightforward comparison between mapped and reference classes, avoids complications associated with mixed or arbitrarily defined polygon boundaries, and supports statistically rigorous, probability-based sampling designs. This approach is widely recommended for national and regional land cover accuracy assessments where class-level accuracy and error matrix analysis are required (Congalton & Green, 2019; Stehman & Czaplewski, 1998).

5. RESULTS

Beyond methodological considerations, the map accuracy validation process must be carefully planned and implemented as efficiently as possible to minimise time and cost constraints. Central to this efficiency is the determination of an appropriate sample size, without which meaningful accuracy assessment cannot be achieved. The literature contains numerous rule-of-thumb recommendations regarding sufficient sample sizes for land cover accuracy assessment. For example, Wulder et al. (2006) suggest a minimum of 100 sample points per class, while Nilsson (1998) advocates for 50 samples per class, increasing to 75–100 samples when the mapped area exceeds 500km² or when the number of land cover classes exceeds 12. Similar recommendations of 75–100 samples per class are provided by Hashemian et al. (2004). The Food and Agriculture Organisation of the United Nations (FAO, 2016) proposes a minimum sample size ranging from 20 to 100 samples per class, while Congalton (2005) recommends between 50 and 100 samples per class.

Despite these guidelines, rule-of-thumb approaches alone are insufficient for statistically rigorous accuracy assessment. To meet statistical requirements, sample size determination must be based on probability sampling principles that balance theoretical robustness with practical feasibility. Samples should be spatially representative of the region of interest and yield accuracy, and area estimates with minimal standard errors, supported by approximately unbiased variance estimators (Olofsson et al., 2014; Caetano et al., 2006; Tateishi et al., 2007; Foody, 2008).

In response to these considerations, this study used both simple random sampling and stratified random sampling methods. These approaches are grounded in established probability theory and are evaluated for their suitability in deriving statistically robust, practical, and replicable sample size estimates for national land cover validation in South Africa.

5.1 Random sampling results

Using the provided formula and parameters, the required number of random sample control points is calculated as follows.

Given**:**

- $z=1.96$ (95% confidence level)
- $p=0.80$ (expected accuracy)
- $q=1-p = 0.20$
- $E=0.05$ (allowable error)

Calculation:

$n=(0.05)^2(1.96)^2\times0.80\times0.20 / (0.05)^2$

n= 246 points per class (for 11 land cover classes)

Total number of points requires 246 *11 = 2706

Results summary:

A minimum of 246 random sample control points is required to estimate land cover classification accuracy with an expected accuracy of 80%, a ±5% allowable error, and 95% confidence. When applying per-class sampling, this value represents the required number of samples per land cover class, which equates to 2706 minimum sample points required for this study.

5.2 Stratified sampling results

Table 2 presents the stratified random sampling allocation for KwaZulu-Natal, designed to support statistically robust land cover accuracy assessment while ensuring adequate representation of all land cover classes. The allocation is based on a stratified sampling framework that combines proportional allocation with a minimum sample size threshold to address class imbalance and heterogeneity.

The column Pixels represents the total number of pixels for each land cover class within KwaZulu-Natal, while w_i denotes the class weight, calculated as the proportion of each class relative to the total number of pixels in the province. The parameters u_i and s_i represent the assumed class-specific accuracy and corresponding standard deviation, respectively, where $s_i = \sqrt{[u_i(1 - u_i)]}$. These values account for varying levels of thematic uncertainty across classes and allow for differentiated allocation where classes with higher uncertainty receive relatively more samples.

The Points per class column reflects the final number of sample points allocated to each class after applying two constraints: (1) proportional allocation based on class weight and uncertainty, and (2) a minimum threshold of 30 sample points per class. This ensures that smaller or rarer classes, such as Artificial, Consolidated, and Wetlands, are sufficiently represented to enable reliable class-level accuracy estimates, while larger classes retain proportionally higher sample counts.

Overall, this approach balances statistical rigour with practical feasibility by maintaining proportionality for dominant land cover classes while preventing under-sampling of minor classes. The resulting total sample size of 401 points is considered adequate for provincial-scale accuracy assessment and supports both overall and class-specific accuracy reporting.

Table 2: Stratified sampling formula parameter calculations

Class Name	Pixels	w_i	u_i	s_i	Points per class
Natural wooded land	64,179,988	0.2013	0.85	0.3571	**44**
Planted Forest	23,030,846	0.0722	0.80	0.4000	**30**
Natural Grassland	113,925,749	0.3573	0.75	0.4330	**71**
Natural	18,148,674	0.0569	0.70	0.4583	**30**
Artificial	1,981,437	0.0062	0.90	0.3000	**30**
Wetlands	6,076,756	0.0191	0.80	0.4000	**30**
Consolidated	527,914	0.0017	0.85	0.3571	**30**
Unconsolidated	2,996,977	0.0094	0.75	0.4330	**30**
Cultivated	61,878,569	0.1941	0.80	0.4000	**46**

Total	292,747,910	1.0000	—	—	**401**

6. DISCUSSION

The selection of an appropriate sampling strategy is a critical methodological consideration in land cover accuracy assessment, particularly in landscapes characterised by pronounced spatial heterogeneity (Congalton, 2005; Foody, 2002; Stehman, 2009). As shown in Figure 2, the distribution of pixel counts across land cover classes is highly uneven, with classes such as Natural Grassland, Natural Wooded Land, and Cultivated occupying a substantial proportion of the study area, while classes including Wetlands, Artificial, Consolidated, and Unconsolidated cover relatively small spatial extents. This imbalance is further quantified in Table 2, which presents class-wise pixel counts, proportional weights, and the resulting stratified sample allocation.

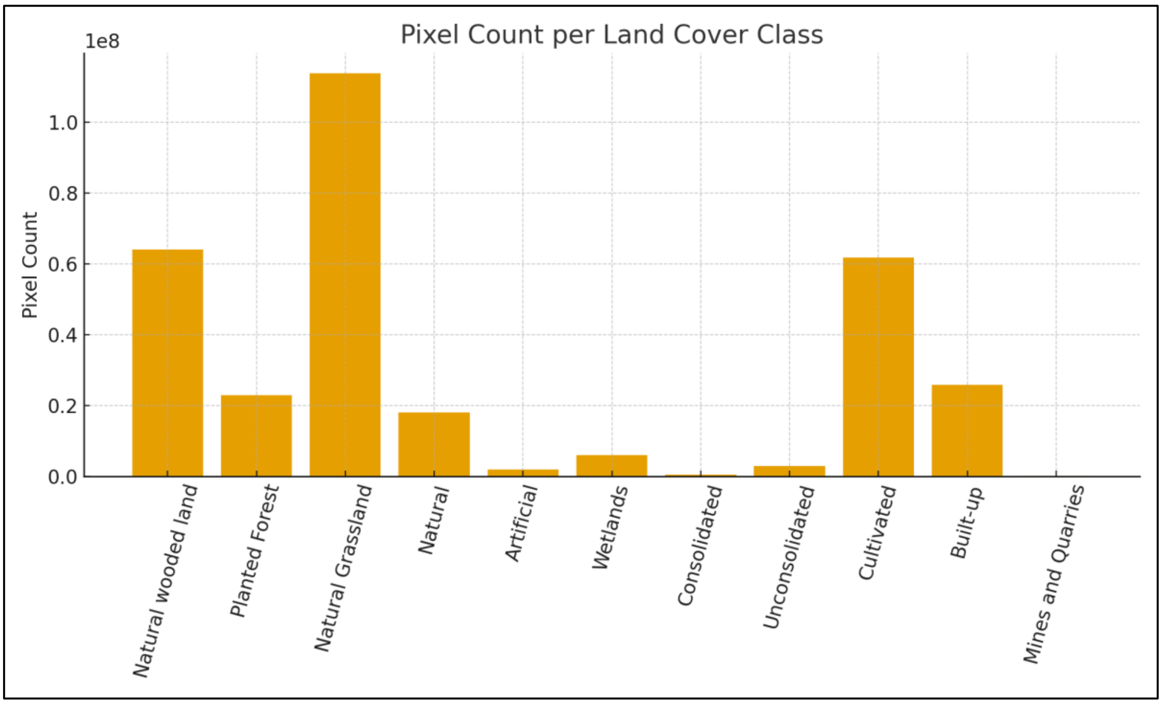

Figure 2: Pixel count representation of land cover classes in the KwaZulu-Natal province from the South African land cover 2022 product.

Under a simple random sampling design employing a blanket allocation of equal sample sizes per class, such disparities in class area coverage are not explicitly accounted for. Consequently, smaller classes may be over-represented relative to their spatial importance, while larger classes, despite their dominant contribution to overall map accuracy and area estimates, may be insufficiently sampled. In heterogeneous environments, this approach often results in an excessive total number of validation points to achieve acceptable precision, thereby placing unnecessary demands on resources for reference data collection and interpretation. While such an approach may be appropriate for national-scale assessments where broad generalisation is required, it is less suitable for provincial or regional studies where operational efficiency and cost-effectiveness are critical considerations.

In contrast, the stratified sampling approach adopted in this study explicitly incorporates class area information derived from the land cover map. As illustrated in Table 2, sample sizes are allocated proportionally to the relative spatial extent of each class, while a minimum sample threshold is enforced to ensure that rare or fragmented classes are still adequately represented. This modified allocation balances statistical rigour with practical feasibility by concentrating sampling effort where it contributes most to overall accuracy, without neglecting minority classes. Such an approach is particularly well suited to landscapes like those examined in this study, where a small number of dominant classes account for the majority of land cover, and numerous minor classes exhibit high internal variability.

The stratified design is therefore more realistic in terms of both resource requirements and long-term maintenance of reference points, especially when repeated accuracy assessments are required. By aligning sampling effort with the spatial structure of the landscape, stratified sampling enhances the reliability and interpretability of class-level and overall accuracy estimates. This finding is consistent with established best practice in land cover validation, which advocates for stratified designs as a means of improving statistical efficiency and reducing uncertainty in area and accuracy estimates (Stehman, 2009; Olofsson et al., 2014; Congalton & Green, 2019).

To determine the most suitable sampling strategy for future applications, accuracy assessments using both simple random and stratified sampling designs could be conducted independently and compared. Such a comparative evaluation would provide empirical evidence on the trade-offs between precision, resource requirements, and operational feasibility, thereby informing the selection of an optimal sampling approach for similar heterogeneous landscapes and supporting evidence-based methodological decisions in land cover quality assessment.

7. CONCLUSION

The study shows that sampling design affects the feasibility, efficiency, and statistical robustness of land-cover accuracy assessments. Simple random sampling, although unbiased and suitable for large-scale applications, often requires impractically large sample sizes in heterogeneous landscapes, making it resource-intensive and unsustainable for sub-national validation. Conversely, stratified random sampling offers a more practical solution by allocating points proportionally to class area while ensuring minimum thresholds for rare classes. This approach improves class-specific accuracy, supports reliable area-based reporting, and balances rigour with operational efficiency. The findings highlight the need to align sampling design with landscape complexity, study scale, and resource constraints, recommending stratified sampling as a defensible, repeatable framework for heterogeneous environments. Future research should compare alternative designs across scales to refine national validation guidelines.

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