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Classification of Farming Enterprises of Land Reform Beneficiaries in KwaZulu-Natal

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ABSTRACT

The establishment of farmer typologies in agriculture has gained popularity in recent years and is key to guiding planning, execution, and monitoring of intervention strategies and programmes that improve productivity. Using Principal Components Analysis, Hierarchical Clustering, and K-Means Clustering, this study sought to develop farmer typologies and characterise them among land reform farming enterprises. The data was collected from 262 land reform farmers in KwaZulu-Natal using a structured questionnaire. The data set was tested for reliability using the Kaiser-Meyer-Olkin Measure of Sampling Adequacy and Bartlett's Test of Sphericity. The study found that land reform enterprises in KwaZulu-Natal can be classified into six clusters. The six farmer typologies are summarised as High value farms — driven by farm size, marketing costs and total asset value; Highly capitalised farms — driven by high income, high production costs and high labour costs; Family labour farms — driven by high number of family members and entity directors' dependent on farm income; Resource-constrained farms — determined by high lease rental amount and reduced access to credit; Retention farms — driven by aging farmers with vast experience; and Non-farm based income farms — driven by high dependence on non-farm income, gender and farmer's level education. The Principal Components Analysis explained 63,94% of the total variation in the sample. The remaining 36,06% can be explained by other methods not captured by the PCA model. The established clusters enabled the resolution of the main aim of this study, as the established typologies will be key to the planning and implementation

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of intervention programmes that increase profitability in land reform. Future policies assisting small-scale and land reform farmers should design support packages targeting the homogenous groups of farmers with similar characteristics for maximum impact.

Keywords: Classification, Enterprise, Land Reform, Typology.

1. INTRODUCTION

An understanding of the various types of farming enterprises for land reform beneficiaries is critical to recommend appropriate policy proposals that uplift farmers. Most of the land reform farmers are smallholders. Empirical evidence confirms the existence of different farm types among smallholders, rendering “one-size fits all” interventions, programmes, and techniques ineffective (Chipfupa & Wale, 2018). According to López *et al*. (2008), a technique for analysing data and obtaining technical-economic results from farms across various regions is necessary for any attempt at agricultural production planning aimed at characterising production models. In general, reports on assisted farms acquired through the land reform programme are presented by the government and stakeholders on various formal and informal platforms.

Many of these farmers have received agricultural development support but remain unproductive (Mokgomo *et al*., 2022; Rusenga, 2022). Nevertheless, the public outcry continues to highlight the challenging lack of support for farmers who obtained their farms through the land reform programme. This public outcry calls into question the government’s interventionist, one-dimensional approach over the years, which may have contributed to farmers’ ongoing need for such assistance.

Kirsten *et al*. (2016) contend that infrastructure investments, such as roads, water, and electricity, are also necessary to support farmers on reformed land, as land alone is insufficient. Xaba and Roodt (2016) attribute the failure of land reform farms to inadequate design and planning at the project-conception level. Claassens (2017) also concurs that poor outcomes and a slow pace of land reform are reported across many government platforms. This means the land reform programme needs to be returned to the planning and design stage to ensure that the services, timing, size, and approach provided to farmers on reformed land are appropriate to yield a positive impact.

This study contributes to the body of knowledge on the typology of agricultural enterprises for farmers on reformed land in KwaZulu-Natal. Currently, there is a dearth of knowledge about the classification of farmers supported by the land reform programme and the dominant characteristics that determine each category. Pienaar (2013) advocates that understanding farm typologies helps those who administer policies analyse farm functionality and provide useful recommendations to optimise farming operations. National and provincial governments are committed to supporting the smallholder farming sector through various interventions, including food security and land reform programmes (Tshuma, 2014; Mokgomo *et al*., 2022). One of the main strategies used by governments in developing countries to improve the standard of living for small-scale farmers is agricultural development assistance (Giller *et al*., 2021; Ortiz-Miranda *et al*., 2022; Mokgomo *et al*., 2022). Mokgomo *et al*. (2022) further argue that, though agricultural support was provided, there is currently very little empirical data on how well the program is working. However, Mokgomo *et al*. (2022) concede that agricultural development assistance provided by the South African government is effective in reducing food insecurity and improving the agricultural production and income of beneficiary small-scale farmers. Thus, this study will greatly assist the government and other role players in designing appropriate intervention programmes to support land reform farmers in post-settlement support, thereby leading to the long-term sustainability of their enterprises.

In addition to any support provided, it is helpful to take a broad view of the key features of agricultural policies, their underlying policy environment, and their role in the dynamics of structural transformation to fully understand the justification and forms of support for smallholder agriculture (Losch, 2020). Lack of policy cohesion and coordination has led to duplication, uncoordinated efforts, and inadequate progress towards national and international food security development targets (Mokgomo *et al*., 2022). As a result, this study identifies the farmer typologies that exist in land reform farms. This will help ensure that stakeholders in the land reform sector can consider typologies to understand the types of farmers, their characteristics, and their SWOT attributes, including areas that need intervention and areas of strength that can be learned and emulated elsewhere. This concurs with Chipfupa and Wale (2018), who confirmed that one must understand the diversity of farmers and the intricacy of their farming systems to align their needs with available support programmes. In farmer typologies, the extension system must accurately target agricultural inputs, advisory services, credit access, and critical information to the identified farms (Goswami *et al*., 2014). The selection of beneficiaries for many public extension programmes may also be guided by such established farm typologies (Goswami *et al*., 2014).

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2. CLASSIFICATION OF FARMING ENTERPRISES

Bidogeza *et al*. (2009) and Carelsen *et al*. (2021) argue that smallholder farmers are not a homogeneous farming group. Their characteristics as farmers vary; they respond differently to incentives, work in different agricultural systems, have varied opportunities, and face distinct farming constraints (Chipfupa & Wale, 2018). Because farms are grouped into relatively homogeneous categories called farm types, farm typologies serve as a tool for understanding the complexity of farming systems by providing a simplified picture of variation within the system (Alvarez *et al*., 2018). Thus, it is possible to classify farmers by identifying consistencies among their diverse social aspects of farming (Pienaar, 2013). Chipfupa and Wale (2018) argue that the discrepancies typically observed between smallholder farmers operating in the same community, with comparable resource endowments and confronting comparable institutional and infrastructure constraints, are rarely explained by research. Hence, there is a need for empirical studies that yield actionable outcomes to inform policy and intervention mechanisms.

Typology can be useful in modelling and simulation studies to assess the possible consequences of interventions in farming systems (Makate *et al*., 2018). Kirsten and Van Zyl (1998) classify South African agriculture into two types of farmers: subsistence farmers and large-scale commercial farmers. Jayne *et al*. (2016) classify farmers into three main categories based on their production scale: namely, small-scale, medium-scale, and commercial-scale.

One of the prominent categories of classification in farming is through geographic location. This classification refers to the acquisition of farmland in different areas with varied agro-ecological characteristics (Ducastel & Anseeuw, 2017). Cousins (2016) argues that the government, through the Comprehensive Rural Development Programme (CRDP), classified farmers into two typologies: by landholding size and by production size. Unlike Cousins (2010), who categorises farms by class based on scale of production, Gumede (2000) believes that farms can be classified by the size of the enterprise. This is the volume, measured in units, of the enterprise streams within a business (Gumede, 2000).

Popova *et al*. (2019) enterprises according to performance indicators of their economic activities, including, but not limited to, volume and profitability levels. Another typology of enterprise classification is based on access to financial and physical resources (Ducastel & Anseeuw, 2017). Mkuhlani *et al*. (2019) classified farmers into three broad categories: mixed farming, horticultural farming, and off-farm income-dependent farmers. Tuyen (2010) classified farmers based on land holdings, income, labour, housing, and machinery, and, based on these factors, established three broad categories: better-off, medium, and poor farmers. This typology is closely linked to Sarker *et al*. (2021) classification, which groups farmers into four main categories based on resource availability: well-resourced, moderately resourced, resource-constrained, and severely resource-constrained. In terms of classes, Cousins (2010) identified six classes of farmers; namely: Small to Medium-scale Capitalist Farmers (SSCF), Petty Commodity Farmers (PCP), Worker Peasants (WP), Allotment Holding Wage Workers, Capitalists who rely on Non-Farm Income, and Supplementary Food Producers (SFP).

TABLE 1 depicts a summary of established farmer typologies in South Africa and the classification methods used by different authors, i.e., Cousins (2010), Aliber *et al*. (2009), Jayne *et al*. (2016), Chipfupa and Wale (2018), Olofsson (2020), and Yazdan-Bakhsh and Feil (2021). By employing variables from established typologies, this study aims to develop farmer typologies and characterise them across farming enterprises to inform intervention strategies for improved profitability.

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TABLE 1: Established Farmer Typologies in Literature

Author	**Established Typology**	**Factors Determining Typology**
Department of Agriculture, Fisheries, and Forestry (DAFF, 2015) as cited by Yazdan-Bakhsh & Feil (2021)	1. Subsistence farmers. 2. Smallholder farmers. 3. Commercial farmers.	a. Land size. b. Production orientation.
Department of Agriculture, Fisheries, and Forestry (DAFF, 2013) as cited by Olofsson (2020)	1. Part-time smallholder (agriculture contributes only a small share of livelihood). 2. Middle-of-the-spectrum smallholder (relies on agriculture as the main source of livelihood). 3. Commercial smallholders (not obliged to register for VAT or income tax).	a. Degree of commercialisation. b. Importance of agriculture in a household's livelihood. c. Poverty level.
National Planning Council (NPC, 2013)	1. Subsistence farmers (<0.5 ha). 2. Smallholder farmers (0.5–5 ha). 3. Commercial farmers (more than 5ha).	a. Land size.
Department of Rural Development and Land Reform (DRDLR, 2009) as cited by Yazdan-Bakhsh & Feil (2021)	1. Landless households; commercial-ready subsistence producers. 2. Expanding commercial smallholders. 3. Well-established black commercial farmers. 4. Financially capable, aspirant black commercial farmers.	a. Land size. b. Production orientation. c. Assets.
Aliber *et al*. (2009)	1. Subsistence. 2. Semi-subsistence.	a. Labour. b. Source of income.

	3. Emerging commercial farmers (or semi-commercial farmers).	
Olofsson (2020)	1. Welfare-dependent petty commodity producer. 2. Agricultural petty-commodity producer. 3. Salaried small-scale capitalist. 4. Agricultural small-scale capitalist.	a. Accumulation capacity. b. Degree of agricultural capitalisation.
Cousins (2010)	1. Small to medium-scale capitalist farmers (SSCF). 2. Petty Commodity farmers (PCP) 3. Worker Peasants (WP). 4. Allotment holding wage workers (AHWW). 5. Supplementary food producers (SFP) 6. Capitalists who rely on Non-Farm Income	a. Class analytic typology. b. Scale of production.
Jayne *et al*. (2016)	1. Subsistence / Small scale / small holder (<5ha) 2. Medium-scale farmer (5-100ha) 3. Large scale/ commercial (100ha or more)	a. Land Size
Chipfupa & Wale (2018)	1. Elderly and uneducated 2. Cautious and short-sighted 3. Financial capital and psychologically capital-endowed farmers 4. Social grant-reliant farmers 5. Land endowed dryland farmers	a. Livelihood assets dimensions

Source: Cousins (2010), Aliber *et al*. (2009), Jayne *et al*. (2016), Chipfupa and Wale (2018), NPC (2013), Olofsson (2020) and Yazdan-Bakhsh and Feil (2021).

3. RESEARCH METHODOLOGY

In this section, the main process and steps for achieving the study's objective are detailed. Section 3.1 discusses the conceptual framework for the study; Section 3.2 discusses the empirical framework; Section 3.3. discusses the variables and model selection, and section 3.4 discusses methods of data collection for this study.

3.1. Conceptual Framework

As Carelsen *et al*. (2021) argue that smallholder farmers are not a homogeneous group, but have farming operations that differ, the Principal Components Analysis reduces the factors and groups farmers with more or less similar characteristics together. Chipfupa and Wale (2018) posit that a single farmer's ability to shift towards more commercial agricultural production is influenced by diversity in smallholder farmers' attitudes, goals, decision-making, and resources. As a result, Africa's numerous rural development plans have failed because they have failed to account for farmer heterogeneity, regardless of their source (Chipfupa & Wale, 2018).

A small number of linear combinations of the original variables that best account for the variance of all the variables are known as principal components (Greenacre *et al*., 2022). Greenacre *et al*. (2022) further explain that the overall variance of the original variables serves as a measure of information, and the Principal Components (PCs) best explain most of that variance. Hence, typology construction will involve reducing and simplifying a large number of elements into a small number of elementary types by classifying, describing, comparing, interpreting, and explaining a collection of elements based on predetermined criteria (Alvarez *et al*., 2018). This plays a significant role in guiding policymakers to target a group of farmers with similar characteristics for a specific purpose. This reduction in factors will involve one or more of the methods of classification observed in the literature in TABLE 1.

3.2. Empirical Framework for Identifying Farmer Typologies

The approach to this study begins with a review of the literature and deducing from it what other authors have established about the classification of farmers. TABLE 1 summarises the typologies established in the literature and their characterisation. The variables used by the classification methods in TABLE 2 are also employed in this study to classify farming enterprises on reformed land in KwaZulu-Natal. The variables were selected following the methods in Jayne *et al*. (2016), Olofsson (2020), Aliber *et al*. (2009), Yazdan-Bakhsh and Feil (2021), Pienaar (2013), NPC (2013), Mkuhlani *et al*. (2019), Berre *et al*. (2019) and Chipfupa and Wale (2018). The list of variables derived from these typologies and classification methods is shown in TABLE 2.

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3.3. The Variables and Model Selection

Pienaar and Traub (2015) state that the selected variables should have significant discriminating power, thereby improving individual classification. Those variables should have a clear relationship to the characteristics that the research is interested in (Pienaar & Traub, 2015). Table 2 below provides a list and description of the dependent and independent variables used in the PCA to determine Principal Components. The same variables are used to establish clusters using Hierarchical and K-Means Clustering methods.

TABLE 2: Variables in Principal Components Analysis

Variable	Description of the Variable	Notation in PCA
1. Age	Age of the farmer in years	Age
2. Gender	Gender of the farmer, binary variable (1=male, 0=female).	Gender#
3. Household Size	Number of household persons dependent on farming income, continuous variable.	HH_size#
4. Number in a Legal Entity	Number of individuals in the legal entity, continuous variable	No_entity
5. Management Farming Experience	Farming experience of the farmer in years, continuous variable.	Experience_Mangt
6. Level of Education	Farmer's level of education in years, continuous variable.	Edu_years
7. Farm Size	Size of the farm in hectares, continuous variable.	Size_Ha
8. Credit Access	Access to credit by the farmer, binary variable (1=yes, 0=otherwise).	Credit_access
9. Cost of Labour	Cost of labour input in Rands per annum, continuous variable.	Labour_ZAR
10. Non-Farm Income	Amount of income generated from non-farm activities in Rands, continuous variable.	Non_FI_ZAR
11. Total Value of Assets	Rand value of total assets owned by the farmer, continuous variable.	Total_Assets_ALL

12. Farm Income	Farm income generated through all farm sales in Rands per annum, continuous variable.	Income_ZAR
13. Production Costs	Total costs incurred through farm operations in Rands per annum, continuous variable.	Costs_ZAR
14. Marketing Costs	Total marketing costs incurred per annum in Rands, continuous variable.	Marketing_costs
15. Lease Payment	Annual amount paid for rent in Rands per annum, continuous variable.	Lease_ZAR

3.4. Methods of Data Collection

This section discusses the study area, the population, the sampling of farmers, the data collection instruments, and the data analysis for the study.

3.4.1. Study Area

The study focused on the 10 districts of KwaZulu-Natal. The districts are Amajuba, Harry Gwala, iLembe, King Cetshwayo, uGu, uMkhanyakude, uMgungundlovu, uMzinyathi, uThukela and Zululand. The study area was considered to be the whole province because the land reform programme is implemented across all districts, and its spread is not uniform. Any reduction would have reduced the sample size, thereby preventing proper statistical analysis of the data provided. A smaller sample size would have led to validity challenges (Lakshmi & Mohideen, 2013; Sekaran & Bougie, 2016). As a result, inferences about the entire population would not be made, since the number of assisted land reform enterprises per district varies significantly.

3.4.2. Population

This study considered all land reform farmers in KZN who benefitted from redistribution, tenure reform, and restitution programmes, received government acquisition and post-acquisition support, and were using land for agricultural purposes. The number of farmers meeting was 389.

3.4.3. Sampling of Farmers

The sampling method for this study was purposive sampling. The reason for selecting this sampling method is that the population of land reform beneficiaries in KwaZulu-Natal is held by the Department of Land Reform and Rural Development (DLRRD), and information is not available to the public. Also, this makes the study population well known to the researcher, as the available data on farms transferred to land reform beneficiaries were provided to the researcher on request by DLRRD in KwaZulu-Natal. The farmers were selected to ensure representation from various programmes, i.e., PLAS, LRAD, RLCC, and Other programmes. The other programmes represent farms acquired through joint funding from the state and either a bank loan to the farmer or a farmer's contribution from his or her own capital. The population of 389 is too small to allow for more sampling options, particularly when analysing the data using statistical tests. Leedy and Ormrod (2005) and Patel and Patel (2019) agree that, in purposive sampling, people or other units are selected for a specific purpose, and that the researcher must justify the appropriateness of the chosen sampling method. TABLE 3 shows that all acquisition categories were represented in the sample. The number (N) in the sample and the percentage (%) represent the total number of farmers sampled and the percentage representation of the total (Total N) for the population in that category, respectively.

TABLE 3: Sample Representation by Category [N = 262]

Category	Total N	N Sample	% Sample
Proactive Land Acquisition Strategy	183	155	84,7
Land Redistribution for Agricultural Development	63	21	33,3
Regional Land Claims Commission	87	52	59,8
Other Programmes	56	34	60,7
TOTAL	**389**	**262**	**67,4**

According to Table 3, all farm categories are represented in the sample. The highest category was PLAS (84,7%), followed by Other programmes (60,7%), RLCC (59,8%), and LRAD (33,3%). The study sample comprised 262 land reform farmers from across 10 districts in KwaZulu-Natal. The sample taken was representative of the total population (67,4%), hence inferences can be made about the total population.

3.4.4. Data Collection Instruments

The data were collected at two levels: primary and secondary. The initial list of farmers, including farmer information, was requested from DALRRD. The farmers who met the qualifying criteria were then selected to form the study population, which totalled 389. The structured questionnaire was divided into five sections: social and demographic, training and experience, marketing and production performance, resources (jobs, machinery, and assets), and financial performance information. The variables were formulated within each category and operationalised to ensure measurability and consistency.

As it is challenging to simultaneously optimise internal and external validity, efficacy data from traditional controlled trials are often complemented by evidence from practical trials or observational studies that assess the performance of an intervention under conditions more closely resembling the routine practice of the sampled populations (Kennedy-Martin *et al*., 2015). Hence, the structured questionnaire was piloted to identify shortcomings in the information contained in the form. After piloting and addressing the questionnaire's shortcomings, data were collected from farmers using the revised structured questionnaire. To mitigate bias in self-reported data, the farmers provided information on numbers, production records, and all quantifiable data, referring to previous farm records. In cases where information is provided but cannot be reconciled with the records due to unavailability, industry norms were verified to ensure that the information provided is consistent with them.

In addition, information received from the DALRRD, including farmer information on farm acquisition, sizes, and other historical information, was verified. All information from the structured questionnaire was captured in Microsoft Excel and later transferred to IBM SPSS Statistics 29.0.2.0 (IBM SPSS, 2024) and the DATAtab Online Statistics Calculator (DATAtab Team, 2024) for analysis.

3.4.5. Data Analysis for the Study

The study employed Principal Component Analysis (PCA) to reduce dimensionality into smaller, understandable groups of components for land reform farmers. According to Dossa *et al*. (2011), the primary aim in determining farmer typologies was to reduce data dimensionality by transforming the original set of correlated variables into a smaller, more understandable set of uncorrelated variables. Multivariate methods such as Principal Components Analysis (PCA), Discriminant Analysis (DA), Multidimensional Scaling (MDS), Cluster Analysis (CA), and Factor Analysis (FA) are commonly used in farmer typologies (Dossa *et al*., 2011; Chipfupa & Wale, 2018). A comparison of the Principal Components Analysis (PCA) and Factor Analysis (FA) was conducted to assess conformance with the underlying model assumptions. A test run for each model was conducted, and TABLE 4 shows the output that was obtained:

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TABLE 4: Model Comparison (PCA vs FA)

KMO and Bartlett's Test		**PCA**	**FA**
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0,583	0,584
Bartlett's Test of Sphericity	Approx. Chi-square	831,767	826,431
	Df	105	105
	Sig.	**0,000**	< 0,001
Total variance explained		**63,94%**	63,88%

The Kaiser-Meyer-Olkin Measure [KMO] of Sampling Adequacy and Bartlett's Test of Sphericity were applied to test whether the dataset collected from 262 land reform farmers in KwaZulu-Natal, and whether the 15 variables in TABLE 2 can be used in the Principal Components Analysis model. Goswami *et al*. (2014) confirm that the KMO's criterion is very accurate when the number of variables is less than 30, which is the case for this multivariate reduction.

The results from the KMO in TABLE 4 show 0,583 [KMO > 0,5] while the Bartlett's Test of Sphericity shows that the test was highly significant [P =0,000]. The KMO shows a value greater than 0,5, indicating that the data exhibit sufficient variance that can be partitioned using Principal Components Analysis (Aryadoust, 2020). The communalities in Table 9 were then extracted from the variables, and all values are above 0,3, which indicates that the items would load properly on the factors (Aryadoust, 2020). As a result, the 15 variables selected were then applied in the Principal Components Analysis.

The comparison of the models, Principal Components Analysis (PCA) and Factor Analysis (FA), is presented in TABLE 4. The results from the two models do not differ significantly. However, based on Bartlett's Test of Sphericity and Total Variance Explained, the PCA shows the highest variance explained at 63.94%. The approximate Chi-square for PCA is also higher than that of Factor Analysis, i.e. 831, 767 as opposed to 826, 431 of Factor Analysis. As a result, the PCA provides the best model for reducing multidimensionality in the components. Principal Components Analysis was applied to the model variables to obtain factor scores for each factor. The dominant Principal Components (PCs) with eigenvalues greater than 1 were retained in each dimension as factors. The Hierarchical and K-Means clustering methods were later applied to establish farmer typologies and characterise them among farmers on reformed land.

4. RESULTS AND DISCUSSIONS

4.1. Descriptive Details of the Farmers

TABLE 5: Summary of Descriptive Information of Respondents [N = 262]

Descriptive of Farmers					
		Frequency	**Percent**	**Valid %**	**Cumulative %**
Gender	Female	100	38,2	38,2	38,2
	Male	162	61,8	61,8	100,0
	Total	**262**	**100,0**	**100,0**	
Race	African	229	87,4	87,4	87,4
	Indian	28	10,7	10,7	98,1
	Coloured	5	1,9	1,9	100,0
	Total	**262**	**100,0**	**100,0**	
Marital Status	Married	153	58,4	58,4	58,4
	Single	71	27,1	27,1	85,5
	Separated/divorced	27	10,3	10,3	95,8
	Widowed	11	4,2	4,2	100,0
	Total	**262**	**100,0**	**100,0**	

TABLE 5 shows that the sample comprised of 61.8% males and 38.2% female farmers (N=262). From the total farmers, 87.4% were Africans, 10.7% Indians, and 1.9% were coloured. Regarding marital status, 58.4% were married, 27.1% were single, 10.3% were divorced, and 4.2% were widowed. The mean age of farmers is 46.77 years (SD = 9.91 years). The smallest farm size is 10 hectares, and the largest is 2,247 hectares. The youngest farmer is 24, and the oldest is 72. The average farm size was 351.93 hectares (SD = 246.729 hectares).

TABLE 6: Distribution of Farms by Programme and District

Acquisition of Farms by Programme										
District	**PLAS**		**LRAD**		**RLCC**		**Other**		**Total**	
	n	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**
Amajuba	10	3.8%	0	0%	6	2.3%	3	1.1%	19	7.3%
Harry Gwala	11	4.2%	2	0.8%	3	1.1%	2	0.8%	18	6.9%
iLembe	13	5%	5	1.9%	3	1.1%	2	0.8%	23	8.8%

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King Cetshwayo	26	9.9%	5	1.9%	4	1.5%	4	1.5%	39	14.9%
uGu	15	5.7%	1	0.4%	5	1.9%	5	1.9%	26	9.9%
uMkhanyakude	11	4.2%	2	0.8%	2	0.8%	0	0%	15	5.7%
uMgungundlovu	27	10.3%	2	0.8%	9	3.4%	5	1.9%	43	16.4%
uMzinyathi	13	5%	0	0%	9	3.4%	6	2.3%	28	10.7%
uThukela	11	4.2%	3	1.1%	3	1.1%	2	0.8%	19	7.3%
Zululand	18	6.9%	1	0.4%	8	3.1%	5	1.9%	32	12.2%
Total	**155**	**59.2%**	**21**	**8%**	**52**	**19.8%**	**34**	**13%**	**262**	**100%**

TABLE 6 shows the distribution of land reform farms in KwaZulu-Natal by acquisition programme and district. The highest category is PLAS farms, with 59.2% of the total dataset. The second-highest category is RLCC farms at 19.8%, followed by LRAD at 8% and other programmes such as bank loans and own capital financing at 13%. There are more farms acquired under the uMgungundlovu district, with an overall 16.4%, followed by the King Cetshwayo District with 14.9%. The lowest district in terms of acquisition is uMkhanyakude with 5.7% of the total sample. TABLE 7 shows the Principal Components obtained from PCA.

4.2. Dominant Factors of Land Reform Enterprises

TABLE 7: Extraction Method for Principal Components Analysis

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,545	16,967	16,967	2,545	16,967	16,967	2,422	16,145	16,145
2	1,973	13,152	30,119	1,973	13,152	30,119	1,757	11,714	27,859
3	1,597	10,649	40,768	1,597	10,649	40,768	1,561	10,407	38,266
4	1,273	8,484	49,251	1,273	8,484	49,251	1,364	9,096	47,363
5	1,155	7,702	56,953	1,155	7,702	56,953	1,276	8,507	55,869
6	1,047	6,982	63,935	1,047	6,982	63,935	1,210	8,065	63,935
7	0,984	6,563	70,498						
8	0,905	6,034	76,532						
9	0,788	5,255	81,786						
10	0,715	4,769	86,555						
11	0,659	4,391	90,947						
12	0,494	3,294	94,241						
13	0,386	2,572	96,813						
14	0,328	2,184	98,997						
15	0,150	1,003	100,000						

TABLE 8: Rotated Component Matrix for Principal Components Analysis

Rotated Component Matrix						
	Component					
	1	**2**	**3**	**4**	**5**	**6**
Age	-0,135	0,278	0,049	**0,640**	-0,097	0,164
HH_size#	-0,014	**0,838**	0,020	0,166	-0,134	0,012
No_entity	-0,038	**0,836**	0,039	-0,022	-0,042	0,031
Non_FI_ZAR	0,109	-0,215	-0,014	0,228	-0,109	**0,682**
Experience_Mangt	0,068	-0,059	0,043	**0,836**	0,032	-0,022
Edu_years	0,048	-0,166	0,174	0,097	0,081	**-0,608**
Size_Ha	-0,122	-0,143	**0,714**	-0,239	-0,137	0,045
Marketing_costs	0,129	-0,022	**0,476**	0,221	-0,017	-0,135
Labour_ZAR	**0,818**	-0,106	-0,080	0,084	-0,040	-0,001
Income_ZAR	**0,903**	0,011	0,022	-0,106	0,116	0,049
Costs_ZAR	**0,924**	0,025	0,092	-0,003	0,072	0,042
Total_Assets_ALL	0,000	0,282	**0,792**	0,123	0,168	0,060
Credit_access	-0,103	-0,001	0,198	0,128	**-0,793**	-0,077
Gender#	0,058	0,090	0,230	0,029	0,305	**0,541**
Lease_ZAR	0,013	-0,285	0,232	0,095	**0,662**	-0,138

Source: Extracted through Principal Components Analysis

TABLE 9: Table of Communalities from PCA

Communalities	Initial	Extraction
Age	1	0,544
HH_size#	1	0,749
No_entity	1	0,705
Non_FI_ZAR	1	0,588
Experience_Mangt	1	0,711
Edu_years	1	0,446
Size_Ha	1	0,623
Marketing_costs	1	0,311
Labour_ZAR	1	0,696
Income_ZAR	1	0,843

Costs_ZAR	1	0,869
Total_Assets_ALL	1	0,754
Credit_access	1	0,701
Gender#	1	0,451
Lease_ZAR	1	0,601
Extraction Method: Principal Components Analysis.		

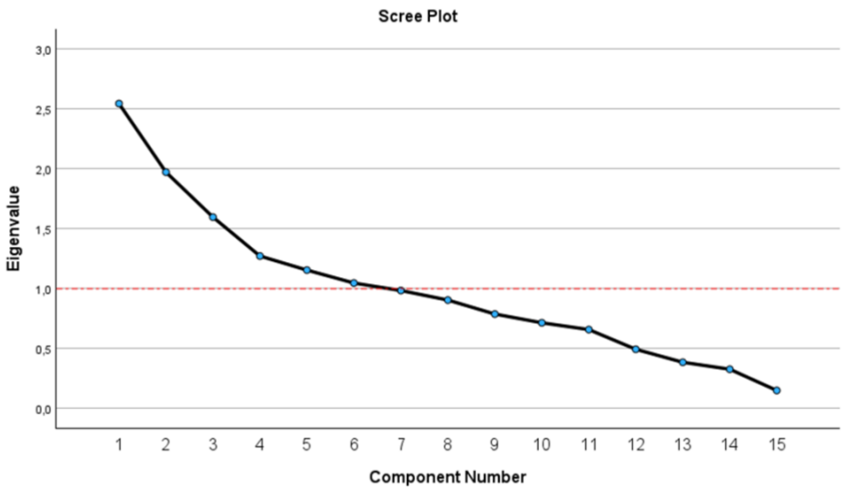

FIGURE 1: Scree Plot from Principal Components Analysis

According to the results in TABLE 7, the components with eigenvalues greater than 1 are retained, and 6 of them explain 63.94% of the variation in the original dataset. The Scree Plot representing the factors in TABLE 8 was extracted and displayed in FIGURE 1. Any determinant greater than 0.00001 can be considered an acceptable indicator of correlation (Aryadoust, 2020). Following Aryadoust (2020), the determinant of 0.038 for the data's correlation matrix can be accepted. According to Christiansen (2018), the general rule is that factors with loadings above 0,4 and below -0,4 can be accepted as key factors of the component. This is also confirmed by Makate *et al*. (2018). The values above 0,4 and below -0,4 are highlighted in bold in the rotated component matrix (Table 8). The results in sections 7 and 8 indicate that 6 components can be extracted from the variables and factors studied.

4.3. Farmer Typology Classifications

In this study, a two-stage classification approach was used to classify land reform farmers in KZN. First, Hierarchical Cluster Analysis was employed to determine the number of clusters in the data.

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Thereafter, the K-Means Clustering Approach was used to classify and interpret the data. This two-stage approach is very useful for determining how close these farmers are to one another and how they differ (Galak, 2020b). Because the variables were measured on different scales, the data were standardised to Z-scores. Standardisation (to Z-scores) is very useful for scaling data to a manageable measurement scale without distorting the data when data are generated from different scales (Galak, 2020a; Marin, 2021).

TABLE 10: Number of Farmers Per Cluster

Number of Cases in each Cluster		
Cluster	1	6
	2	100
	3	34
	4	105
	5	2
	6	15
Valid		**262**
Missing		**0**

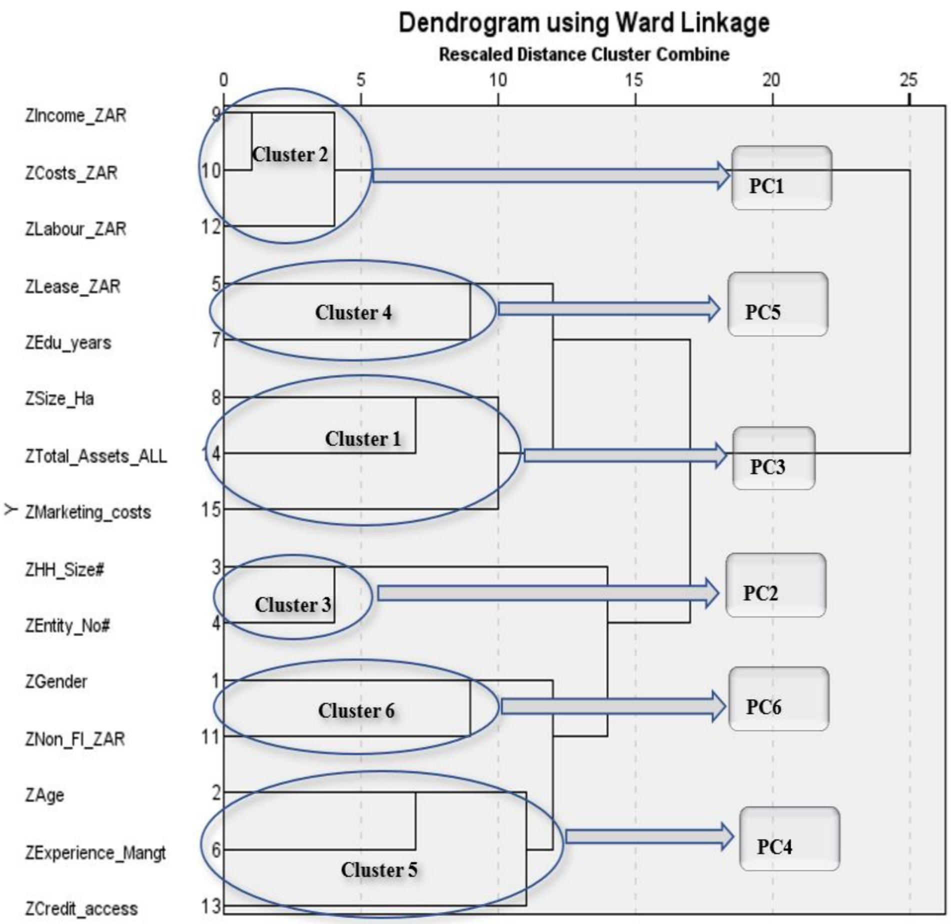

FIGURE 2: Dendrogram with Farmer Clusters

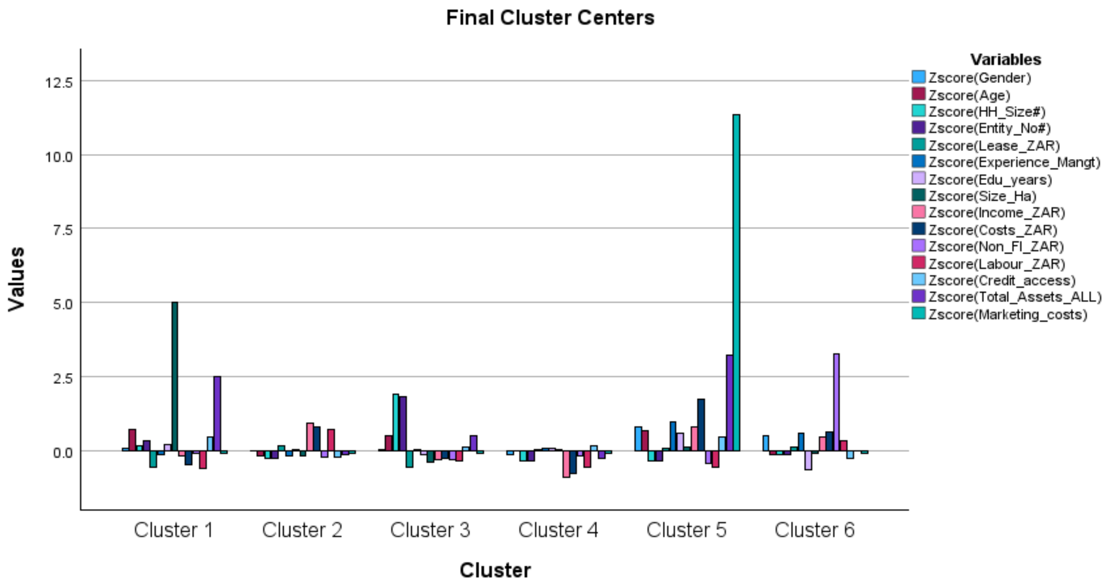

FIGURE 3: Final Cluster Centres

TABLE 11: ANOVA Table for Variables on Clusters

ANOVA						
	Cluster		**Error**		**F**	**Sig.**
	Mean Square	**df**	**Mean Square**	**df**		
Zscore(Gender)	1,345	5	0,993	256	1,354	**0,242**
Zscore(Age)	3,332	5	0,954	256	3,491	0,005
Zscore(HH_Size#)	28,665	5	0,46	256	62,358	<0,001
Zscore(Entity_No#)	26,478	5	0,502	256	52,705	<0,001
Zscore(Lease_ZAR)	3,162	5	0,958	256	3,301	0,007
Zscore(Experience_Mangt)	2,298	5	0,975	256	2,358	0,041
Zscore(Edu_years)	1,735	5	0,986	256	1,760	**0,122**
Zscore(Size_Ha)	32,064	5	0,393	256	81,532	<0,001
Zscore(Income_ZAR)	36,069	5	0,315	256	114,480	<0,001
Zscore(Costs_ZAR)	28,431	5	0,464	256	61,244	<0,001
Zscore(Non_FI_ZAR)	33,755	5	0,36	256	93,700	<0,001
Zscore(Labour_ZAR)	18,182	5	0,664	256	27,365	<0,001
Zscore(Credit_access)	2,002	5	0,98	256	2,042	**0,073**
Zscore(Total_Assets_ALL)	15,273	5	0,721	256	21,176	<0,001
Zscore(Marketing_costs)	52,038	5	0,003	256	16434,992	<0,001
The F tests should be used only for descriptive purposes, as the clusters have been chosen to maximise differences among cases within clusters. The observed significance levels are not corrected for this and thus cannot be interpreted as tests of the hypothesis that the cluster means are equal.						

TABLE 11 presents the Analysis of Variance (ANOVA), which indicates the effects of the variables across the different clusters. The variables and P-values marked in bold in TABLE 11 indicate variables that are not statistically significant and therefore show no difference between the cluster and those variables; i.e., gender, education, and credit access. These variables are discussed under 4.4.

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4.4. Characterisation of Farmer Typologies

TABLE 8 shows the 6 Principal Components, which explain 63,94% of the data set's total variance. The Hierarchical and K-Means Clustering identified 6 clusters of farmers from the dataset, as shown in Figures 2 and. The variables that influence the clusters established correspond to the dominant variables identified in the established factors. Hence, FIGURE 2 matches the established Principal Components with the clusters based on the dominant variables in the PC or the cluster.

Cluster 1 in FIGURE 3 corresponds with the third component retained in the PCA [PC3] and explains 10,6% of the total variance in the data, as displayed in TABLE 7. Cluster 1 represents *High Value Farms*. This cluster is characterised by the farm size (size_Ha), the high value of the farmer's total assets (Total_Assets_ALL), and Marketing Costs (Marketing_costs). Pomp (1994), as cited by Bidogeza *et al*. (2009), confirmed that a relatively small farm size impedes the efficient use and adoption of certain technologies, such as new irrigation types, pumps, and tube wells, that improve production. Tey & Brindal (2015) argue that increased farm size generates high income and profit for the farm, but it may also suppress labour efficiency in production. In addition, large farms can adopt new technologies, thereby increasing the farm's value (Bidogeza *et al*., 2009). This means that when the farmer’s land size increases, their asset base and marketing costs also increase. Regarding marketing costs, Xaba and Masuku (2013) and Kirsten *et al*. (2016) further argue that crop growers rely on adequate transportation facilities, advanced technology, improved infrastructure, and strong communication networks to market their products successfully. The absence of these facilities makes it difficult to market the produce properly and increases marketing costs to reach the desired market (Xaba & Masuku, 2013). Otherwise, farmers end up accepting low-income markets in order to avoid paying transportation costs from income they have not yet generated. Also, in properly regulated markets, once a consignment fails to meet the required quality standard, the owner bears the costs of discarding it, which adds to marketing costs.

Cluster 2 represents *Highly Capitalised Farms.* As shown in FIGURE 2, this cluster corresponds with the first retained component from the PCA [PC1] and explains 17% of the variation in the data. This cluster is characterised by high labour costs (Labour_ZAR), farm income (Income_ZAR), and production costs (Costs_ZAR). As shown in TABLE 8 and FIGURE 3, this finding aligns with the study by Chipfupa and Wale (2018), which found that access to financial resources removes major bottlenecks to small-scale farming and enables farmers to acquire appropriate inputs, conduct farm operations timeously, and hire needed labour. Daloğlu *et al*.

(2014) confirm that operators of large farms tend to invest in new technologies and also engage in conservation practices. This PC represents a class of land reform enterprises that are highly capitalised, with high running costs and income. Well-resourced farmers are entirely dependent on agriculture and less reliant on off-farm income (Sarker *et al*., 2021). Enterprises with higher income also incur higher labour and operational costs. Pienaar and Traub (2015) confirm that this phenomenon is common in the smallholder sector, characterised by labour-intensive small farms that employ conventional production methods. This finding is also in line with Tuyen's (2010) classification, which groups farms by land holdings, income, labour, housing, and machinery or equipment. This further confirms a finding by Khapayi and Celliers (2016), who state that farmers with diverse production skills are more productive and earn higher incomes.

Cluster 3 represents *Family Labour Farms*. In line with FIGURE 2, FIGURE 3 and TABLE 8, cluster 3 corresponds with the second retained component from the PCA [PC2] and explains 13,1% of the variation in the data. This cluster is characterised by high household size (HH_size#) dependent on farm income and a high number of entity directors (No_entity). Hlatshwayo *et al*. (2021) confirm that increased household size reduces the total products sent to the market, as more products are consumed within the household rather than supplied to the market. As a result, larger households would have less produce to sell in the market than smaller households (Kyaw *et al*., 2018). This is cited by Mango *et al*. (2014), who confirm that household food security is affected by household size, with larger households being associated with lower food security. Arguably, little can be done about household size other than improving household education levels, labour participation, and market information (Mango *et al*., 2014). When family farms use family labour for production, labour costs are reduced and farm profitability increases (Hlatshwayo *et al*., 2021). On the other hand, enterprises with a high number of entity directors (No_entity) tend to have a high proportion of people who depend on farm income as well.

Land reform enterprises are failing because the number of people expected to become beneficiaries of a single income that used to support one small family now exceeds what that income can support. For example, under a restitution programme, efforts to limit the number of applicants to a manageable level are impractical because the benefit is rights-based rather than government-initiated redistribution (Aliber & Cousins, 2013). Also, this study argues for training on the separation of roles between administrative and operational personnel (managers and supervisors) and governance and accountability structures (committees, trustees, etc.). Most bloated corporate structures are made up of beneficiaries, not directors, which is an anomaly. It should also be noted that business is not run by the committee, but rather by the skills required to ensure proper decision-making and the appropriate risks associated with the level of investment. Bidogeza *et al*. (2009) argue that when labour markets are functioning properly, farms can hire their own labour. However, where these markets fail, family labour farms are spared because they can generate their own labour (Bidogeza *et al*., 2009). Also, as Davies *et al*. (2020) argue that South Africa's agricultural sector is smaller than those of countries with similar characteristics and is not creating enough employment, these farms are able to create opportunities for their family members. Hence, enhanced food production, food security and higher rural income have been the primary targets of governments in developing countries (Mijena *et al*., 2022; Mokgomo *et al*., 2022). It is for this reason that the agricultural sector is highly recognised for its key role in promoting growth, reducing poverty, and ensuring sustainable food production in the Southern African Development Community (SADC) (Mokgomo *et al*., 2022).

Cluster 4 represents *Resource Constrained Farms*. As shown in Figure 2, this cluster corresponds to the fifth component [PC5] in the PCA and explains 7,7% of the variation in the data set. This cluster is characterised by high lease rental payments (Lease_ZAR) and limited access to credit (Credit_access). This means that when the lease rental amount increases, the farmer's access to credit decreases sharply, and their credit rating is reduced. This aspect of capital requirements for lessees of land reform farms is confirmed by Binswanger-Mkhize (2014), who asserts that a recognisable shift in policy position for state land farms requires smallholder families to have their own resources to make the farms sustainable. This results in selected beneficiaries needing higher incomes to qualify. Khapayi and Celliers (2016) emphasise that the South African government must consider supporting policies and regulations to encourage growth among new farmers, enabling them to survive both domestic and international competition.

Cluster 4 corresponds to typology 4 in Chipfupa and Wale's (2018) study. In their study, typology 4 represented the economically burdened farmers. As a result, even though farmers possess psychological capital, their limited market participation is due to several other obstacles, including distance from the nearest marketplaces, transportation challenges, limited access to financial resources, and a lack of entrepreneurial skills (Chipfupa & Wale, 2018). This is in line with the findings of Tey & Brindal (2015), who found that an increased asset base leads to access to a higher level of financial assistance, such as credit. Lack of access to credit limits the farmer's ability to adopt new technologies that require initial investments (Bidogeza *et al*., 2009). The reduction in farmers' asset base due to increased lease payments reduces their ability to access

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credit, which aligns with cluster 4 in this study. The outcome of cluster 4 suggests that these are the state-owned farms leased to the public, as they are the only properties with lease rental payments.

Cluster 5 represents *Retention Farms* and aligns with the fourth component of the PCA [PC4], which explains 8.5% of the variation in the dataset. This cluster is characterised by the farmer's age (Age) and management experience (Experience_Mgmt). In cluster 5, as farmers grow in age, they also grow in experience and business acumen. Mabuza (2016) emphasises that for a land reform programme to be successful, its beneficiaries must possess the necessary skills and experience in land use and management. However, cluster 5 is associated with stability in production and income, driven by years of production and experience. In this cluster, there is a need to plan to address succession challenges. Experienced older farmers need to introduce their younger children to farming so they can transfer skills and maintain business continuity. However, Baloyi *et al*. (2024) argue that young people with creative, inventive, and problem-solving skills have limited potential to engage in non-primary agribusinesses. Most are inclined to pursue careers in other sectors and are not interested in primary agriculture (Baloyi *et al*., 2024). In support of the argument by Baloyi *et al*. (2024), Kirsten *et al*. (2016) argue that while some land reform farmers would have been part of the project as owners or labourers, most are normally free riders with little interest in farming. As a result, many end up embroiled in conflicts and a lack of cooperation.

Cluster 6 represents *Non-Farm Based Income Farms*. As shown in Figure 2, this cluster corresponds to the sixth and last component [PC6] in the matrix, which explains only 7% of the variance in the data set. This cluster is characterised by non-farm income (Non_FI_ZAR) and the farmer's gender (Gender#). Notably, the ANOVA in Table 11 indicates that gender is not statistically significant for the final cluster centres, suggesting that there is no difference between the clusters and gender. This finding is consistent with the study by Bidogeza *et al*. (2009), who found that off-farm activities positively contribute to the farmer's ability to adopt new technologies. This is motivated by the availability of financial resources required to invest in new technologies. Bidogeza *et al*. (2009) further argue that off-farm income sources may be a viable alternative to overcome cash or credit constraints and enable farmers to invest in new technology. Binswanger-Mkhize (2014) argues that the commercial farmer development model often falls short of the aspirations of many people, who prefer to pursue livelihood strategies that integrate on- and off-farm income. This is due to seasonal agricultural production and income generation.

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As a result, farmers prefer alternative income sources to cover periods when farming is not generating income or is not doing well.

4.5. Summary of Identified Farmer Typologies in KwaZulu-Natal

The six farmer typologies established in this study are summarised in TABLE 12.

TABLE 12: Extracted Principal Components for the Study

Cluster#	PC#	Main Category	Typology Characterisation
Cluster 1	PC 3	High Value Farms	• Size_Ha (+ve) • Total_Assets_ALL (+ve) • Marketing_costs (+ve)
Cluster 2	PC1	Highly Capitalised Farms	• Labour_ZAR (+ve) • Income_ZAR (+ve) • Costs_ZAR (+ve)
Cluster 3	PC 2	Family Labour Farms	• HH_size# (+ve) • No_entity (+ve)
Cluster 4	PC 5	Resource Constrained Farms	• Lease_ZAR (+ve) • Edu_years (+ve)**
Cluster 5	PC 4	Retention Farms	• Age (+ve) • Experience_Mangt (+ve)
Cluster 6	PC 6	Non-Farm Based Income Farms	• Non_FI_ZAR (+ve) • Gender# (+ve) **

**Not statistically significant on final cluster centres.

5. CONCLUSIONS

The objective of this study was to develop farmer typologies and characterise them across land reform farming enterprises, and to use these to inform intervention strategies for improved profitability. Using Principal Components Analysis and Hierarchical and K-Means Clustering, the study confirmed that land reform farmers in KwaZulu-Natal can be categorised into 6 clusters. Typology establishment should be the first assessment before any type of intervention to improve farmer livelihoods is initiated. This will ensure the maximisation of intervention outcomes, as

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every support provided will be appropriately directed to recipients, taking into account their individual or group circumstances.

By following established typologies, the stakeholders in the small-scale farming and land reform sector, government, policy makers, farmers and the market can maximise the efficiency of support provided.

High-value farms capitalise on market linkages, face fewer infrastructure-related challenges, and can invest more of the profits generated into the business to improve efficiency. On the retention farms, guided by the advantage of age and experience, these farmers also possess technical and indigenous knowledge generated over time. Less supervision is required, but support with the necessary inputs and services provided by the government and other stakeholders to farmers. At the same wavelength, information sessions are necessary to improve knowledge and update these farmers on existing and changing practices. The resource-constrained farmers are likely to depend on government inputs and services, such as tractors for planting, seeds and seedling inputs, and fertiliser and chemicals for daily production-season needs. Such farmers need to be prioritised to ensure they remain productive. Their lack of access to services such as credit may limit their production to only subsistence levels and growth potential.

Non-farm-based income farmers can farm on their own without much assistance from external sources. However, this group is usually highly defocused and often engages in farming as a supplement to other business interests or appears as "leisure farmers". Hence, supervision is required to ensure that the services provided are directed towards current needs, as their decision-making is usually driven by their business acumen. Understanding these farmer typologies will help stakeholders determine the appropriate level of supervision and intervention required.

Lastly, the impact of leaseholds is highly detrimental to resource-constrained farmers. While these farmers generally face challenges accessing credit facilities, the responsibility to pay lease rentals may exacerbate their financial circumstances if the government pursues legal action for unpaid leases.

6. RECOMMENDATIONS

From the results of this study, the following recommendations are made:

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- A programme to introduce the transfer of technical and indigenous skills to the next generation of farmers should be considered to ensure smooth succession planning and to guarantee business continuity once the active farmer retires.
- It is recommended that, where family labour is available, farmers be encouraged to prioritise hiring family members at appropriate labour-task rates to reduce the negative effect of high household size on profitability while creating employment opportunities.
- This study recommends a fundamental policy change to proportionally decrease leasing and allow those who succeed in their farming ventures to acquire farms at discounted rates, thereby reducing resource constraints and increasing access to credit with farms as bankable collateral.

7. LIMITATIONS FOR THE STUDY

Some members of land reform enterprises who wished to participate in the study on farms owned by Trusts and Communal Property Associations (CPAs) withdrew due to fear of victimisation. This prevents the researcher from obtaining valuable information to study the real circumstances on the ground in farming communities. Also, farms where beneficiaries have passed on and the government is in the process of allocating a new beneficiary could not be accessed. This is because there is no official person who can provide reliable information about the farming activities. Mostly, such farms are looked after by interim caretakers who need to ensure that no vandalism occurs on the property. Again, farmer availability challenges were observed: a farmer would be busy with farm operations, but preferred that the questionnaire be left so they could fill it out later and submit it. Some of these questionnaires were never returned, which disadvantaged the researcher in eliciting important information that could improve the analysis. However, this cohort was very small and did not affect the analysis or the study's inferences. On farms where entities or enterprise members are in conflict, the information received was sometimes uncoordinated, and when verified, it showed no correlation with the expected norm. In such cases, the information was verified with respondents to ensure it aligned with industry norms. The incoherence would mainly emanate from the farming operation not being run optimally. Hence, these were included in the analysis to give a full picture of the status of land reform farms.

Due to the geographic spread of the farms across areas such as Zululand, Amajuba, and uMzinyathi districts, data collection on some farms would be conveniently conducted based on the proximity of farmers in the same area. In cases where only one farm is located at an outlier site and the farmer does not have an email address or cannot be reached by phone, data were not collected due to the area's spatial dispersion. However, this condition would have no bearing on

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the findings and inferences made, since a good representation of the total population was achieved at 67%.

To address the limitations of the study, future research should consider employing mixed-methods approaches to ensure that a diverse farmer population is reached and that information is collected. This could include digital methods, such as an online questionnaire that respondents can fill out at their convenience using modern technology, such as portable devices like cell phones and tablets. This will ensure that even remote areas are accessible and that respondents will not feel threatened or victimised by their peers because of the commotion caused by the in-and-out movement of data collectors, which draws attention. Electronic reminders, such as short messages to respondents who have not participated in the study, should also be considered to improve questionnaire return rates. These strategies will improve future studies and maximise the impact for the betterment of farming communities.

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