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Risk factors in crop abandonment decisions: Evidence from Zambia

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Abstract

The literature on what drives crop failure and crop abandonment is scant. This paper explores the interplay between risk factors and crop abandonment. We examine the role of risk sources and risk management strategies in crop abandonment by smallholder maize farmers in Zambia. Specifically, we seek to improve the understanding of risk factors in crop abandonment decisions at the subnational level using the Hellwig synthetic risk measure and tobit regression. Based on data for the years 2009 to 2015, we find variability in the Hellwig Risk Index indicating different levels of crop abandonment risk across provinces, with the Laupula, Southern and Western provinces remaining in the high-risk category (Class III) throughout the period. Maize yield, area planted, area harvested, consumer price index (CPI), maize price and climate were the main drivers of crop abandonment risks among farmers across the country. The government should implement targeted interventions and support programmes to address the specific needs of high-risk provinces such as Laupula, Southern and Western. There is also a need for the government to promote efficient land use and provide support for optimal planting and harvesting practices in order to reduce overextension and abandonment risks.

Key words: crop abandonment, Hellwig synthetic risk measure, maize, tobit regression

1. Introduction

In the face of a changing climate, agriculture is one of the hardest hit sectors (Ortiz-Bobea 2021; Chekenya 2023). A warming climate affects agricultural productivity significantly (Ortiz-Bobea *et al*. 2021). One of the direct and immediate effects of climate-induced shocks is on decision-making by smallholder maize farmers in Zambia regarding whether to harvest or abandon a previously planted crop (Chekenya 2023).

Literature documenting the effects of climate change on agricultural productivity is growing. For example, Ortiz-Bobea (2021) employs the Ricardian approach to examine climate change impacts on the United States agricultural sector by using cross-sectional regression of farmland data. Their paper uncovers convergence of empirical evidence suggesting significant estimates of climate change damage. Other studies that have documented similar effects of climate change on the agricultural sector include those by Asafu-Adjaye (2014) on Africa, Iglesias *et al*. (2012) on Europe, Mendelsohn (2014) on Asia, and Malik *et al*. (2022) on Australia.

Meanwhile, the concepts of crop failure and crop abandonment are confusing and have left scholars debating on the exact difference between the two. This unsettled debate has affected the conceptualisation of the concept of crop abandonment by the academic community. Crop failure can be perceived as the total loss of crops on a farm (Mulungu & Tembo 2015). It usually occurs when climate shocks lead to crop destruction by agricultural pests (Haque & Khan 2017). Crop failure is one component of crop abandonment if one looks at its measurement, since a failed crop can still be accounted for as an unharvested area (Mulungu & Tembo 2015). It is instructive to note that crop abandonment does not necessarily imply crop failure (Chekenya 2023). In seasons with good rainfall patterns, holding all other factors constant, unharvested field portions can be a result of crop abandonment and not crop failure.

Crop abandonment is a situation in which a farmer decides not to harvest his/her previously planted crop (Ortiz-Bobea 2021; Chekenya 2023). A study by Obembe *et al*. (2021) contextualise this definition of climate change by arguing that it occurs when adverse climate shocks affect yields negatively, up to a point at which it does not make economic sense to harvest. Other scholars, like Cui (2020), argue that crop abandonment occurs when extremely high temperatures cause yield losses to such an extent that harvesting can no longer economically justify the opportunity cost.

Crop failure is a precondition for crop abandonment if one considers how the latter is statistically measured. A failed crop constitutes one aspect of measuring harvested ratios in crop abandonment (Mulungu & Tembo 2015). Crop abandonment does not necessarily translate into crop failure because, once favourable rains are received at a given location at any time, unharvested ratios for a given crop are a result of crop abandonment and not crop failure. Arguing in terms of a causal relationship, the nature of the link between these two concepts is unidirectional – running from crop failure to crop abandonment (Thurman & Fisher 1988).

Despite the growing body of literature documenting the impacts of climate change on agricultural productivity globally, there is limited empirical evidence of the specific factors influencing crop abandonment decisions in Zambia. Previous studies have focused primarily on the broader impacts of climate change on agriculture, such as those by Asafu-Adjaye (2014) on Africa and Iglesias *et al*. (2012) on Europe, which highlight the significant damages and productivity losses due to climate change. However, these studies do not delve into the nuanced decisions that farmers make regarding crop abandonment.

In Zambia, smallholder farmers face multiple risks, including fluctuating maize prices, inadequate access to index-based insurance programmes, and adverse climate conditions, which collectively influence their decisions to abandon crops (Chekenya 2023). The lack of comprehensive risk management strategies and support systems further exacerbate this issue, leaving farmers with limited options to mitigate the risks associated with crop production (Obembe *et al*. 2021). As a result, understanding the interplay between these risk factors and the propensity for crop abandonment is crucial for developing targeted interventions that can enhance agricultural resilience and productivity in Zambia.

This study therefore aims to fill the gap in the literature by examining the determinants of crop abandonment among smallholder maize farmers in Zambia. Using data from 2009 to 2015, we employed the Hellwig synthetic risk measure and tobit regression analysis to identify key risk factors and their influence on crop abandonment decisions. This research will provide valuable insights into the specific challenges faced by Zambian farmers, and inform policy measures to reduce the incidence of crop abandonment, thereby improving food security and livelihoods. The study will also provide bases for further research in this interesting discipline of crop abandonment, as well as consolidate the literature on this controversial subject.

The rest of the paper is organised as follows: Section 2 provides a literature review on crop abandonment, while Section 3 provides a description of the study area, data sources and types, and empirical methods employed for the analysis. The results are reported and discussed in Section 4, and Section 5 concludes the paper and provides policy recommendations.

2. Review of studies on crop abandonment

Crop abandonment, the decision by farmers to forgo harvesting previously planted crops, has emerged as a significant issue in agriculture, particularly in the context of increasing climate variability and economic instability. This phenomenon not only affects food security, but also has broader implications for rural livelihoods and agricultural sustainability. This literature review examines the key factors influencing crop abandonment, drawing from global studies and making efforts to contextualise the findings within the Zambian agricultural sector.

Climate change is a major driver of agricultural instability, leading to increased risks of crop abandonment. According to Ortiz-Bobea *et al*. (2021), climate change significantly affects agricultural productivity, particularly in regions that are highly dependent on rainfall, such as Sub-Saharan Africa. The increased frequency of extreme weather events, such as droughts and floods, worsens the uncertainty faced by farmers, making crop abandonment a more likely outcome (Chekenya 2023).

Economic instability, including fluctuating crop prices and high costs of agricultural inputs, also plays a critical role in crop abandonment decisions. A study by Chekenya (2023) highlights that smallholder farmers in Zambia often struggle with volatile maize prices, which can make harvesting economically unviable. The lack of access to financial services and insurance further intensifies this risk, thereby exposing farmers to economic shocks (Obembe *et al*. 2021).

The adoption of agricultural practices and the level of technological advancement can influence the likelihood of crop abandonment. Studies by Mulungu and Tembo (2015) suggest that poor agricultural practices, such as inadequate pest control and improper fertiliser application, increase the risk of crop failure and abandonment. Meanwhile, improved agricultural practices and technologies, such as drought-resistant crop varieties and precision agriculture, can mitigate these risks.

The issue of crop abandonment has garnered increasing attention in recent years, particularly in the context of climate change and its impacts on agricultural practices. Several studies have sought to understand the factors driving crop abandonment and the implications for food security and rural livelihoods. For instance, Ortiz-Bobea *et al*. (2021) highlight the broad impacts of climate change on agricultural productivity, noting that climate-induced shocks can lead to significant disruptions in farming activities. Their study emphasises the need to consider how adverse weather conditions affect farmers' decisions to abandon crops, as these decisions are often economically driven. This issue is further explored by Chekenya (2023), who examines the specific case of smallholder maize farmers in Zambia. The findings indicate that unpredictable weather patterns and economic instability are critical factors influencing crop abandonment decisions.

A study by Cui (2020) also provides a detailed analysis of crop abandonment in the context of extreme temperatures, arguing that, when temperatures exceed optimal levels for crop growth, yields are negatively affected, to the point where harvesting is no longer economically viable. This perspective is supported by Obembe *et al*. (2021), who contextualise crop abandonment within the framework of climate change, suggesting that adverse climate shocks can push yields below the threshold that justifies the cost of harvesting.

A statistical approach to understanding crop abandonment is offered by Mulungu and Tembo (2015) through the examination of harvested ratios. Their study posits that crop failure is a significant precursor of crop abandonment, as unharvested areas often reflect broader issues of crop destruction due to pests or climatic events. This view is supported by Haque and Khan (2017), who also identify climate-induced shocks as primary drivers of crop failure and subsequent abandonment.

The relationship between economic factors and crop abandonment is further explored by Asafu-Adjaye (2014) in his study on African agriculture. The author found that market fluctuations, particularly in crop prices and access to risk management tools like insurance, significantly affect farmers' decisions to abandon crops. Similarly, Iglesias *et al*. (2012) documented the effects of economic and climatic variables on crop abandonment across Europe, providing a comparative perspective that underscores the universal challenges faced by farmers in different regions.

To conclude, the literature consistently points to a combination of climatic and economic factors as key determinants of crop abandonment. These studies underscore the importance of developing robust risk management strategies and support systems to mitigate the adverse impacts of climate change on agriculture. Understanding these dynamics is crucial for formulating effective policies that enhance agricultural resilience and sustainability. This study therefore builds on these multidimensional factors to build a synthetic measure of the risk of crop abandonment and to identify the significant factors driving this risk.

3. Methodology of the study

3.1 Study area

Zambia is a landlocked country in Africa, bordered by eight other nations. It covers approximately 752 618 square kilometres and features diverse topography, including plateaus, hills and river valleys (Musambachime 2016; Üllenberg *et al*. 2017; Loryman 2018). Zambia's climate is tropical, with three distinct seasons: a cool dry season (May to August), a hot dry season (September to November), and a rainy season (December to April) (Musambachime 2016; Üllenberg *et al*. 2017; Loryman 2018). The variability in rainfall and temperature across these seasons has significant implications for agricultural activities and crop yields.

The country is divided into ten provinces, each with unique geographical, climatic and socio-economic characteristics that influence agricultural activities and the risk of crop abandonment (Saasa 2003; Mubaya 2010). Understanding these provincial differences is relevant for a comprehensive analysis of crop abandonment risk. Agriculture is a critical sector in Zambia's economy, employing a large proportion of the population and contributing significantly to the country's GDP (Diao *et al*. 2007; Jambo 2017). The agricultural landscape is dominated by smallholder farmers who primarily grow maize, which is a major staple food crop (Sitko & Chamberlin 2015; Pelletier *et al*. 2020). Other important crops include sorghum, millet, groundnuts and various legumes. The sector faces challenges such as limited access to modern farming technologies, inadequate infrastructure, and susceptibility to climate change (Ifejika Speranza 2010; Nyanga *et al*. 2011).

Zambia's diverse climatic, socio-economic and agricultural contexts make it a pertinent study area for examining the risk of crop abandonment. The insights gained from this study therefore could contribute greatly to more effective agricultural policies and practices, ultimately supporting the country's goal of achieving food security and sustainable agricultural development (Nyanga *et al*. 2011; Sitko & Chamberlin 2015; Pelletier *et al*. 2020; Ariom *et al*. 2022).

3.2 Data sources and empirical methods

We examine trends in the risk of crop abandonment in Zambia using annual data covering the period 2009 to 2015. The dataset encompasses data collected from 72 towns across 10 provinces, sourced from the Central Statistical Office (CSO) of Zambia and the Ministry of Agriculture and Livestock. Each year's data is uniformly aggregated from various towns within each province. We employed Hellwig's taxonomic method (Hellwig 1968) to compare the risk of crop abandonment among provinces, which is aligned with the EUROSTAT agri-environmental indicator (Corbelle-Rico & Crecente-Maseda 2014). The synthetic variable, 'risk of abandonment', is generated using diverse indicators combined into a composite index, following Terres *et al*. (2015).

The determination of crop abandonment risk involves conducting statistical analyses on factors affecting crop abandonment, grouping them into a composite index. Factors increasing abandonment risk are considered disincentives, while those decreasing the risk are incentives. Table 1 provides a description of the variables used to construct the synthetic measure of crop abandonment risk. In some instances, rainfall and temperature data were amalgamated into indices and categorised as climate variables. Rainfall and temperature, which are crucial stochastic variables influencing crop yields, contribute significantly to our analysis, marking a substantial knowledge and empirical enhancement to the literature on crop abandonment. Indeed, they play a pivotal role in agricultural production, rural revitalisation and renewal. The diagnostic variables that were used to build the risk indices are presented in Table 1, where we discuss how the variables were measured for the study, and how they are likely to influence the risk of crop abandonment.

Maize yield (R1) was measured in tonnes and represents the annual yield of maize crops. Higher yields are generally associated with lower risks of crop abandonment, ceteris paribus. **Area planted (R2)**, measured in hectares, indicates the total area planted with crops. Larger planted areas can indicate greater agricultural investment and commitment, potentially reducing abandonment risk. **Area harvested (R3)**, also measured in hectares, shows the total area harvested. The ratio of harvested to planted area **(R4)** is a direct measure of crop abandonment risk. **Harvested ratio (R4)**, as a ratio, is a critical indicator of crop abandonment. A lower harvested ratio suggests higher abandonment rates. **Fertiliser use (R5)**, measured in metric tonnes, includes the total quantity of top and basal fertilisers used. Fertiliser usage is a proxy for input investment in agriculture, which could potentially affect crop yields and abandonment decisions. **Consumer price index (CPI) (R6)** is presented as a percentage; it reflects the cost of living. Higher CPI can indicate economic stress, which may influence agricultural decisions, including crop abandonment. The **Maize price (R7)** variable was measured in US dollars per tonne, and represents the market price of maize. Higher maize prices can act as an incentive to continue cultivation, thereby reducing abandonment risk. **Climate variables (R8)** is made up of rainfall and temperature, measured in millimetres and degrees Celsius, respectively, and are crucial for crop growth. Adverse climatic conditions can increase the risk of crop abandonment. **Index-based insurance (R9)** is a dummy variable that indicates the presence (1) or absence (0) of index-based insurance. This variable can provide financial security against crop failure, thereby reducing abandonment risk.

Table 1: Description of variables and data sources

Variable	Measurement	Description	Data source
R1 (Maize yield)	Tonnes	Annual maize crop yield	CSO, Zambia and Ministry of Agriculture and Livestock
R2 (Area planted)	Hectares	Planted area of land	CSO, Zambia and Ministry of Agriculture and Livestock
R3 (Area harvested)	Hectares	Harvested area of land	CSO, Zambia and Ministry of Agriculture and Livestock
R4 (Harvested ratio)	Ratio	Harvested hectares of maize divided by planted hectares	CSO, Zambia and Ministry of Agriculture and Livestock
R5 (Fertiliser use)	Metric tonnes	Sum of the total quantity of top and basal fertiliser used	World Development Indicators
R6 (CPI)	Percentage	Cost of living	World Development Indicators
R7 (Maize price)	US$/tonne	Disaggregated maize price data	CSO, Zambia and Ministry of Agriculture and Livestock
R8 (Climate = Rainfall and temperature)	Millimetres/degrees Celsius	Rainfall and temperature	CSO, Zambia and Ministry of Agriculture and Livestock
R9 (Index-based insurance)	Dummy variable (1 = presence of index-based insurance; 0 = absence of it	Index-based insurance (ibi)	CSO, Zambia and Ministry of Agriculture and Livestock

Understanding the risk factors associated with crop abandonment is crucial for policymakers and agricultural stakeholders in Zambia. By identifying and analysing these factors, interventions could be designed to mitigate risks, improve crop yields, and ensure food security. This study contributes to the literature on agricultural sustainability and rural development by offering insights into effective agricultural policies and practices. The above diagnostic variables used in this study, particularly the integration of climate data and economic indicators, provide a comprehensive framework for assessing crop abandonment risks. This approach does not only enhance our understanding of the phenomenon, but also offers practical solutions for improving agricultural productivity and resilience in Zambia.

3.3 Empirical methods

3.3.1 Construction of the taxonomic measure of risk

We construct a taxonomic synthetic measure to examine the risk of crop abandonment using the Hellwig measurement method. Our choice of the Hellwig model is motivated by its theoretical usefulness as a multi-criteria decision-making approach constructed for ranking alternatives based on their closeness to the ideal solution. The theoretical solution of the Hellwig method calculates distances using the Euclidean norm, premised on the implicit assumption that the criteria being considered are independent. In agricultural economics, the Hellwig approach is useful for assessing the risk of crop abandonment (Hellwig *et al*. 2022; Pawlewicz & Pawlewicz 2023). The synthetic variable is typically formulated by employing an observation matrix, expressed as:

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots\dots\dots\dots x_{1m} \\ x_{21} & x_{22} & \dots\dots\dots\dots x_{2m} \\ x_{n1} & x_{n2} & \dots\dots\dots\dots x_{nm} \end{bmatrix}, \qquad (1)$$

where $x_{ij}(i = 1,2, \dots, n; j = 1,2, \dots, m)$ represents the value of the j^{th} feature (in this case, a variable influencing the risk of crop abandonment) for the i^{th} object.

To address the issue of varying measurement units concerning the diagnostic variables, we normalise them prior to constructing the synthetic risk variable. Thus, the impact of measurement differences is mitigated through normalisation, ensuring comparability among the features. The normalisation process involves standardising the variables using the following formula:

$$W_{ij} = \frac{X_{ij} - \overline{X_J}}{S_j}, \qquad (j = 1,2,3, \dots, n)$$

$$\overline{X_J} = \frac{1}{n}\sum_n^1 X_{ij,} \qquad S_j = \sqrt{\frac{1}{n}\sum_n^1 (X_{ij} - \overline{X_J})^2} \qquad (2)$$

The outcome of the transformation yields a matrix of standardised property values for W, represented as

$$W = \begin{bmatrix} w_{11} & w_{12} & \dots\dots\dots\dots w_{1m} \\ w_{21} & w_{22} & \dots\dots\dots\dots w_{2m} \\ w_{n1} & w_{n2} & \dots\dots\dots\dots w_{nm} \end{bmatrix} \qquad (3)$$

From the matrix obtained, the 'pattern', that is an abstract object (province) with coordinates $P_0 = [w_{01}, w_{02}, \dots, w_{0j}]$, where $w_{0j} = \max\{w_{ij}\}$, when w_j is a stimulant, and $w_{0j} = \min\{w_{ij}\}$, when z_j is a destimulant. We consider that the pattern is a hypothetical province with the most favourable variable values. The next step is to establish the Euclidean distance of each assessed object (province), p_i, from the designated pattern:

$$q_i = \sqrt{\sum_{j=1}^m (w_{ij} - w_{0j})^2} \qquad (4)$$

Based on the values of q_i, the value of the synthetic Hellwig risk measure was calculated and used to evaluate the provinces. To obtain this value, we employed Equation (5).

$$S_i = 1 - \frac{q_i}{q_0}, \qquad (n = 1,2,3, \dots, n)$$

$$q_0 = \overline{q_0} + 2S_{0,}\ \overline{q_0} = \frac{1}{n}\sum_n^1 q_i, \qquad S_0 = \sqrt{\frac{1}{n}\sum_n^1 (q_i - \overline{q_0})^2} \qquad (5)$$

The synthetic Hellwig S_i risk values typically range between 0 and 1, with values closer to 0 suggesting a higher risk of abandonment associated with the province. Higher values indicate a lower risk of abandonment. The presence of negative S_i values signifies a stronger risk of crop abandonment in a given province compared to others.

3.3.2 Characterisation and ranking of provinces into classes of risk of abandonment

We employed the standard deviation and arithmetic mean of the Hellwig synthetic risk measure to classify provinces into distinct levels of crop abandonment risk. Approximately three classes are delineated, representing different risk levels of abandonment (Roszkowska 2024):

Category I (low risk of crop abandonment) $S_i \geq \ S_i + 0.5sS_i$;

Category II (average risk of crop abandonment) $S_i - 0.5sS_i \leq S_i < S_i + 0.5sS_i$; and

Category III (high risk of crop abandonment) $S_i < S_i - 0.5sS_i$.

S_i is the value of the synthetic measure calculated using the Hellwig risk pattern method, and sS_i is the standard deviation of the synthetic meter, S_i.

3.4 Empirical specification of the tobit model

In this paper, we examine the link between risk factors and crop abandonment using the tobit regression approach. This involves regressing the standardised parameters, representing factors influencing decisions to abandon crops, against the measure of risk abandonment (S_i score). The Hellwig synthetic risk measure scores assume values between 0 and 1, thereby categorising the dependent variable as limited dependent and naturally truncated below 0 and 1. Based on this nature of the dependent variable, it is possible to use the tobit model propounded by Tobin (1958). We employed the tobit model for each year under examination to examine the magnitude and direction of the impact of these factors on crop abandonment. The Tobit model is expressed as:

$$Y_i^* = X_i\beta + \varepsilon_i, \tag{6}$$

Where Y_i^* is the latent variable, showing the unobserved true value of the Hellwig synthetic risk measure, β is the vector of coefficients to be estimated, X_i is a vector of independent variables, and ε_i is the white noise or error term. The observed Hellwig synthetic risk measure, Y_i, can then be expressed as:

$$Y_i = \begin{cases} y^*; 0 \leq y^* \leq 1 \\ 0; \quad y^* < 0 \\ 1; \quad y^* > 1 \end{cases}, \tag{7}$$

where the model assumes that ε_i follows a normal distribution with iid properties.

The variables were transformed into a composite index measuring the risk of crop abandonment using an empirical framework for constructing composite indices. The data was standardised at the provincial level in Zambia.

4. Results and discussion

4.1 Summary statistics of variables

The descriptive statistics for the variables used in the analysis are summarised in Table 2. From the table it can be seen that the average maize yield is 1.9 tonnes. The mean planted area is 15 309 hectares. There also is evidence that there is considerable variability in the average harvested area, which has a mean value of 10 915 hectares. Again, the mean harvest ratio is 0.618, indicating that, on average, 61.8% of planted maize is harvested, whilst 39.2% may be lost through abandonment due to extreme weather conditions, such as severe droughts or flooding, or as a result of crop damage from pest infestations and diseases, which render harvesting unprofitable to the farmer. The high level of variability and skewness in maize yield and planted area indicate the need for policies that support consistent agricultural practices and productivity (Amondo *et al*. 2019). Polices that can cushion farmers against huge losses when harvesting costs outweigh benefits could serve as motivation to prevent farmers' decisions to abandoned their crops.

Table 2: Summary statistics of variables used in the study

Variables	Mean	Min	Max	SE (mean)	Skewness	Kurtosis	CV
Maize yield	1.9	0	11.035	0.086	1.418	5.683	1.022
Planted area	15 309.404	0	97 518.227	838.635	1.9	6.447	1.229
Harvested area	10 915.517	0	75 272.982	658.006	2.168	7.597	1.353
Harvest ratio	0.618	0	0.993	0.016	-0.842	2.066	0.593
Fertiliser	5 547.8	0	123 617.16	652.443	4.999	30.422	2.638
CPI	102.975	0	161.465	2.402	-1.207	2.879	0.524
Maize price	191.857	144	357	3.115	1.763	4.535	0.365
Average rainfall	1 020	1 020	1 020	0	.	.	0
Average temperature	150	150	150	0	.	.	0
Index-based insurance	0.286	0	1	0.02	0.949	1.9	1.583
Hellwig risk index	0.576	0.33	0.997	0.008	1.077	2.995	0.307

Notes: SE denotes standard error: CV is coefficient of variation

Table 2 also summarises the level of fertiliser usage across the seven-year period and, from the results, it is clear that fertiliser usage in Zambia is 5 548 metric tonnes on average, with extreme variability. This extreme variability in fertiliser use suggests inefficiencies and potential inequalities in fertiliser distribution in the country (Jorgensen & Loudjeva 2005; Johnson *et al*. 2023). This is worth noting, because fertiliser usage is strongly influenced by availability and accessibility.

The average CPI was estimated at 102.975, and the average maize price was $191.857 per tonne. Rainfall and temperature were constant, at 1 020 mm and 15 degrees Celsius respectively, across all observations.

The mean value of the insurance variables, of 0.286, suggests that only about 28.6% of subscriptions to index-based insurance were recorded within the entire seven-year period. The low uptake of index-based insurance (28.6%) indicates a need for increased awareness and accessibility of insurance programmes (Bogale 2015; Ceballos *et al*. 2017; Isaac *et al*. 2023). The results also show that the average Hellwig Risk Index is 0.576. There is low variability in the Index, which indicates different levels of crop abandonment risk across provinces, as similarly reported in studies by Kurdyś-Kujawska (2021), Ogryzek *et al*. (2021) and Pawlewicz and Pawlewicz (2023). Targeted interventions and support programmes therefore are required to address the specific needs of the high-risk areas that are identified in Table 3.

4.2 Risk of crop abandonment in Zambia

Table 2 reports the results for the Hellwig synthetic risk measure based on data for the years 2009 to 2015. The risk classes are categorised as Class I (low risk), Class II (average risk) and Class III (high risk). The tables reveal temporal variations in risk classes, signifying fluctuations in the risk of crop abandonment. Some of the provinces (like Central in Class I) consistently maintain their risk classification, while others show variations over the years. Lusaka, Northern and Southern provinces fall into Class III, showing a high risk of crop abandonment in these regions. North Western exhibits low risk (Class I), suggesting a low likelihood of crop abandonment.

Central Province also consistently falls into Class I, indicating a low risk of crop abandonment throughout the period. This stability may suggest effective agricultural practices, favourable climatic conditions, or robust support systems that reduce abandonment risk, as suggested by evidence in the literature (Wanzala-Mlobela *et al*. 2013; Amondo *et al*. 2019; Odubote & Ajayi 2020). It could also be attributed partially to stable farming sector growth and high demand for land for both agricultural and non-agricultural activities (Govereh *et al*. 2009). The country could make efforts to understand and replicate the successful strategies used in Central Province in other regions in order to reduce the risk of crop abandonment in these provinces.

The results further indicate that the Copperbelt primarily belongs to Class II (average risk). Following the literature, this implies a moderate risk of crop abandonment, probably due to fluctuating economic conditions or varying levels of agricultural support (Pawlewicz & Pawlewicz 2023; Taoumi & Lahrech, 2023). This is a development that calls for policies aimed at stabilising agricultural productivity and providing consistent support that could help reduce the risk to Class I levels. Addressing specific challenges that contribute to the average risk status is therefore essential.

While provinces such as Central Province remained less likely to abandon crops, the results also show that some provinces, like Laupula, Southern and Western provinces, remained in the high-risk category (Class III) throughout the study period. This indicates probable similar, continuous agricultural challenges across these provinces (Farrington & Saasa 2002). This may reflect unstable agricultural conditions in these provinces that need targeted policy measures (Lekprichakul 2008; Neubert *et al*. 2011).

Table 3: Hellwig measure of risk of crop abandonment in Zambia, 2009 to 2015

Province	2009		2010		2011		2012		2013		2014		2015	
Central	0.9457 ≥ 0.7056	I	0.37647 < 0.5681	III	0.8513 ≥ 0.6548	I	0.9893 ≥ 0.7265	I	0.80284 ≥ 0.61253	I	0.9871 ≥ 0.69280	I	0.9678 ≥ 0.70336	I
Copperbelt	0.51830 ≤ 0.68029 < 0.7056	II	0.5681 ≤ 0.6391 < 0.74433	II	0.7276 ≥ 0.6548	I	0.5226 ≤ 0.5907 < 0.7265	II	0.4758 ≤ 0.5531 < 0.61253	II	0.50146 ≤ 0.5768 < 0.69280	II	0.5337 ≤ 0.6395 < 0.70336	II
Eastern	0.51830 ≤ 0.52350 < 0.7056	II	0.7940 ≥ 0.7056	I	0.4999 ≤ 0.5590 < 0.6548	II	0.5226 ≤ 0.57841 < 0.7265	II	0.4758 ≤ 0.5313 < 0.61253	II	0.50146 ≤ 0.5259 < 0.69280	II	0.5218 < 0.5337	III
Luapula	0.51830 ≤ 0.6553 < 0.7056	II	0.8509 ≥ 0.7056	I	0.4999 ≤ 0.5988 < 0.6548	II	0.5226 ≤ 0.7136 < 0.7265	II	0.653175 ≥ 0.61253	I	0.50146 ≤ 0.6876 < 0.69280	II	0.5337 ≤ 0.62205 < 0.70336	II
Lusaka	0.3741 < 0.51830	III	0.5681 ≤ 0.6047 < 0.74433	II	0.3910 < 0.4999	III	0.38961 < 0.52266	III	0.3303 < 0.47588	III	0.3622 < 0.50146	III	0.3486 < 0.5337	III
Muchinga	0.50100 < 0.51830	III	0.5681 ≤ 0.5816 < 0.74433	II	0.4768 < 0.4999	III	0.5082 < 0.52266	III	0.4758 ≤ 0.492362 < 0.61253	II	0.50146 ≤ 0.5209 < 0.69280	II	0.4927 < 0.5337	III
North Western	0.9457 ≥ 0.7056	I	0.7921 ≥ 0.7056	I	0.7629 ≥ 0.6548	I	0.9965 ≥ 0.7265	I	0.71673 ≥ 0.61253	I	0.8976 ≥ 0.6928	I	0.7634 ≥ 0.70336	I
Northern	0.42208 < 0.51830	III	0.4137 < 0.5681	III	0.3705 < 0.4999	III	0.4018 < 0.52266	III	0.43422 < 0.47588	III	0.4496 < 0.50146	III	0.4038 < 0.5337	III
Southern	0.4800 < 0.51830	III	0.5674 < 0.5681	III	0.43933 < 0.4999	III	0.5226 ≤ 0.5330 < 0.7265	II	0.4163 < 0.47588	III	0.4643 < 0.50146	III	0.4438 < 0.5337	III
Western	0.51830 ≤ 0.60504 < 0.7056	II	0.9420 ≥ 0.7056	I	0.4999 ≤ 0.5960 < 0.6548	II	0.5226 ≤ 0.5447 < 0.7265	II	0.4758 ≤ 0.51159 < 0.61253	II	0.4988 < 0.50146	III	0.5049 < 0.5337	III

Notes: Class I (low risk); Class II (average risk); Class III (high risk)

Provinces such as Copperbelt, Luapula and Western, which are classified under a Class II risk, need to benefit from targeted improvements to push them towards low-risk status. Therefore, policies should focus on strengthening agricultural value chains, improving storage facilities, and ensuring timely access to inputs and credit (Ogryzek *et al*. 2021; Pawlewicz & Pawlewicz 2023; Taoumi & Lahrech 2023; Roszkowska 2024). Some of these policies should focus on improving agricultural extension services, providing better access to quality inputs, enhancing irrigation systems, and developing robust weather insurance schemes to mitigate climatic risks (Neubert *et al*. 2011; Odubote & Ajayi 2020; Kurdyś-Kujawska *et al*. 2021).

The results also show that regular monitoring of agricultural practices and conditions is important in the country. For instance, provinces that show fluctuating risks (Eastern and Muchinga) need adaptive policies that can respond swiftly to emerging challenges, such as changing climatic conditions or market fluctuations. This is especially necessary given the impact of climate on crop abandonment. Therefore, promoting climate-smart agricultural practices is essential. This may include the adoption of resilient crop varieties, implementing efficient water management systems, and integrating agroforestry practices (Lekprichakul 2008; Martey *et al*. 2020; Malik *et al*. 2022).

It is also worth noting that some economic policies that provide incentives for farmers to maintain their crops could also help retain them in the crop production business. In addition, expanding index-based insurance schemes and encouraging farmers to subscribe to these schemes could offer financial protection against crop failures, thereby reducing the economic burden on farmers and discouraging crop abandonment in Zambia (Bogale 2015; Ceballos *et al*. 2017; Odubote & Ajayi 2020). Training programmes aimed at building the capacity of farmers and agricultural officers can enhance productivity and reduce abandonment risks. This may include education on modern farming techniques, pest management and sustainable practices.

4.3 Factors influencing risk of crop abandonment in Zambia

The tobit regression results presented in Table 4 indicate several statistically significant factors influencing the risk of crop abandonment across various years from 2009 to 2015.

The results show that, in 2009, Area planted (R2) was positive and significant ($p < 0.05$). This means that larger planted areas are associated with higher risks of crop abandonment, which might suggest overextension or inefficient resource allocation on farms. Similarly, Fertiliser use (R5) was positive and significant ($p < 0.05$), indicating that higher fertiliser use is correlated with increased abandonment. This is surprising, but could be due to improper application or over-reliance on fertilisers. In contrast, Area harvested (R3) is negative and significant ($p < 0.05$), implying that higher harvested areas are linked to lower abandonment risk, which may indicate successful crop management (Fagbemi *et al*. 2023). This observation means that there is a need to focus on preharvest interventions, such as pest control, climate adaptation strategies, educating farmers on proper fertiliser use and integrating organic practices to ensure sustainability (Asafu-Adjaye 2014; Cui 2020; Chekenya 2023; Taoumi & Lahrech, 2023).

Table 4: Tobit regression results of factors influencing risk of crop abandonment in Zambia

2009				
Risk of abandonment (S_i)	**Coefficient**	**Standard error**	**t-value**	**p-value**
R2	0.285**	0.088	3.24	0.048
R3	-0.201**	0.058	-3.48	0.04
R4	0.442**	0.097	4.58	0.02
R5	0.348**	0.082	4.25	0.024
R6	-0.19	0.113	-1.68	0.192
R7	-0.56	0.292	-1.92	0.151
R8	.0635	0.387	1.64	0.199
Intercept	0.052***	0.047	11.11	0.002
Mean dependent variable	0.612	SD dependent variable		0.197
Pseudo r-squared	-3.371	Number of observations		10
Chi-squared	17.253	Prob > chi^2		0.016
Akaike criterion (AIC)	-4.371	Bayesian criterion (BIC)		-1.648
2010				
Risk of abandonment (S_i)	**Coefficient**	**Standard error**	**t-value**	**p-value**
R4	0.019	0.058	0.32	0.76
R5	0.038**	0.01	3.88	0.012
R6	-0.141**	0.052	-2.69	0.043
R7	0.121	0.078	1.55	0.183
R8	-0.096*	0.04	-2.39	0.063
Intercept	0.678***	0.029	23.25	0.000
Mean dependent variable	0.656	SD dependent variable		0.186
Pseudo r-squared	-2.304	Number of observations		10
Chi-squared	14.612	Prob > chi^2		0.012
Akaike criterion (AIC)	-6.954	Bayesian criterion (BIC)		-4.836
2011				
Risk of abandonment (Si)	**Coefficient**	**Standard error**	**t-value**	**p-value**
R1	0.286**	0.062	4.64	0.019
R2	0.296**	0.086	3.45	0.041
R3	-0.338**	0.086	-3.91	0.03
R5	0.205**	0.054	3.78	0.032
R6	-0.924**	0.171	-5.40	0.012
R7	0.274*	0.093	2.96	0.06
R8	0.132	0.062	2.13	0.123
Intercept	0.692***	0.03	23.24	0.000
Mean dependent variable	0.577	SD dependent variable		0.163
Pseudo r-squared	-1.944	Number of observations		10
Chi-squared	17.353	Prob > chi^2		0.015
Akaike criterion (AIC)	-8.278	Bayesian criterion (BIC)		-5.554
2012				
Risk of abandonment (S_i)	**Coefficient**	**Standard error**	**t-value**	**p-value**
R1	0.196**	0.03	6.64	0.022
R2	-0.215**	0.042	-5.18	0.035
R3	0.156**	0.033	4.77	0.041
R4	-0.85**	0.136	-6.27	0.024
R5	-0.011**	0.017	-0.67	0.57
R6	0.316**	0.044	7.27	0.018
R7	0.01	0.182	0.06	0.96
R8	0.363**	0.079	4.58	0.044
Intercept	0.662***	0.014	45.91	0.000
Mean dependent variable	0.625	SD dependent variable		0.215
Pseudo r-squared	-9.764	Number of observations		10
Chi-squared	33.437	Prob > chi^2		0.000
Akaike criterion (AIC)	-16.862	Bayesian criterion (BIC)		-13.836

2013				
Risk of abandonment (S_i)	**Coefficient**	**Standard error**	**t-value**	**p-value**
R1	0.284**	0.037	7.78	0.016
R2	0.364**	0.064	5.68	0.03
R3	-0.013	0.045	-0.28	0.805
R4	-0.194**	0.04	-4.79	0.041
R5	-2.001***	.173	-11.59	0.007
R6	0.118**	0.013	9.26	0.011
R7	49.009***	3.993	12.27	0.007
R8	-36.565***	2.974	-12.30	0.007
Intercept	-0.121	0.054	-2.22	0.157
Mean dependent variable	0.544	SD dependent variable		0.144
Pseudo r-squared	-3.424	Number of observations		10
Chi-squared	39.129	Prob > chi^2		0.000
Akaike criterion (AIC)	-30.557	Bayesian criterion (BIC)		-27.532
2014				
Risk of abandonment (S_i)	**Coefficient**	**Standard error**	**t-value**	**p-value**
R2	1.814***	0.156	11.63	0.007
R3	-1.968***	0.164	-12.00	0.007
R4	0.147**	0.017	8.60	0.013
R5	-0.156**	0.032	-4.94	0.039
R6	6.828**	0.744	9.17	0.012
R7	131.289**	14.275	9.20	0.012
R8	-0.282*	0.072	-3.91	0.06
R9	-101.224**	11.003	-9.20	0.012
Intercept	-0.393	0.154	-2.56	0.125
Mean dependent variable	0.597	SD dependent variable		0.202
Pseudo r-squared	-8.177	Number of observations		10
Chi-squared	38.394	Prob > chi^2		0.000
Akaike criterion (AIC)	-23.089	Bayesian criterion (BIC)		-20.063
2015				
Risk of abandonment (S_i)	**Coefficient**	**Standard error**	**t-value**	**p-value**
R1	0.126***	0.007	19.30	0.003
R2	-0.044*	0.013	-3.44	0.075
R3	-0.026	0.015	-1.70	0.231
R4	-0.084***	0.008	-10.33	0.009
R5	0.055***	0.003	19.93	0.003
R6	0.044**	0.006	7.11	0.019
R7	0.693***	0.026	26.15	0.001
R8	-0.404***	0.016	-25.71	0.002
Intercept	-0.157***	0.005	-29.37	0.001
Mean dependent variable	-0.262	SD dependent variable		0.132
Pseudo r-squared	-4.069	Number of observations		10
Chi-squared	53.381	Prob > chi^2		0.000
Akaike criterion (AIC)	-46.501	Bayesian criterion (BIC)		-43.476

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. Standard errors are given in parentheses. SD = standard deviation

There is also evidence that, in 2010, Fertiliser use (R5) positively and significantly influenced the risk of crop abandonment ($p < 0.05$). This is consistent with 2009 and indicates a persistent issue with fertiliser practices. However, in 2010, Consumer price index (CPI) (R6) and Climate variables (R8) negatively and significantly affected the risk of crop abandonment. This means that a higher cost of living and adverse climatic conditions increase abandonment, suggesting that economic stability may allow better crop management and reduce abandonment. Efforts to develop climate-resilient agricultural practices and support systems may also enhance farmers' decisions to produce crops in the country (Mulungu & Tembo 2015; Terres *et al*. 2015; Ortiz-Bobea, 2021; Taoumi & Lahrech 2023).

The results reveal that, in the 2011 season, maize yield (R1) and fertiliser use (R5) were positively significant in determining the risk of crop abandonment, while area harvested (R3) and CPI (R6) had negative effects on the risk of crop abandonment. These results are consistent with previous findings on harvest efficiency (Chiona *et al*. 2014; Kalinda *et al*. 2017).

During the 2012 planting season, maize yield (R1) and climate variables (R8) demonstrated a positive impact on the risk of crop abandonment at conventional levels of significance, but area planted (R2) and harvested ratio (R4) consistently revealed a reduction effect on the likelihood of crop abandonment.

In 2013, maize yield (R1), area planted (R2), CPI (R6) and maize price (R7) were significant factors with a positive influence on the risk of crop abandonment, whereas fertiliser use (R5) and climate variables (R8) significantly reduced the risk of crop abandonment.

The results further indicate that about seven variables were statistically significant at various levels of significance in influencing the risk of crop abandonment in Zambia during the 2014 season. Positive factors increasing the odds of crop abandonment include area planted (R2), CPI (R6) and maize price (R7). However, factors such as area harvested (R3), fertiliser use (R5), climate variables (R8) and index-based insurance (R9) are associated with a reduction in the risk of crop abandonment in the country (Bogale 2015).

In 2015, the results imply that the risk of crop abandonment increased significantly with factors such as maize yield (R1), fertiliser use (R5), CPI (R6) and maize price (R7), while area planted (R2) and climate variables (R8) were related to a reduction in the risk of crop abandonment.

The Tobit regression results reveal that crop abandonment in Zambia is influenced by a combination of economic, climatic and agriculture related factors, such as planted area and yield of the crop. Key findings include the significant impact of area planted and harvested, maize yield, fertiliser use, CPI, maize prices and climate variables. These findings are consistent with the findings of other studies, including those of Thurlow *et al*. (2009), Mason *et al*. (2011), Burke *et al*. (2017), Bonilla Cedrez *et al*. (2020) and Zimmer *et al*. (2022).

5. Summary and conclusion

We contribute to the literature by exploring the interplay between risk factors and crop abandonment. Specifically, we examine the role of risk sources and risk management strategies in crop abandonment decisions by smallholder maize farmers in Zambia. By carrying out this empirical exercise, we attempt to improve our understanding of risk factors in crop abandonment decisions at the subnational level, and how they are influenced by other risk sources, such as maize prices, and by risk management strategies, like participation in an index-based insurance programme.

We attempt to achieve our study's objectives by using the Hellwig risk measure and tobit regression. We do so by employing subnational-level data covering the years 2009 to 2015 for 72 towns across 10 provinces in Zambia.

Our main findings are that there is variability in the Hellwig Risk Index, indicating different levels of crop abandonment risk across provinces, with Laupula, Southern and Western provinces remaining in the high-risk category (Class III) throughout the period. Maize yield, area planted, area harvested, CPI, maize price and rainfall are statistically significant in determining the risk of crop abandonment among farmers across the country.

Our empirical strategy is not free from limitations, and we wish to outline these. First, index-based insurance is an emerging development in Zambia, with a relatively low market penetration to date (Van Asseldonk *et al*. 2022). It is possible that it might be too early to start examining its impact on the risk of crop abandonment by farmers. Again, our models may suffer from the omitted variables effect, since other variables such as socioeconomic factors, land degradation and demographic structure were not included in this analysis. The lack of data on certain variables prevented their inclusion in our analysis; for example, without variables such as farmer age, education and farm characteristics, the model may not fully capture the variation in the risk of crop abandonment across provinces.

We therefore suggest that other methods and variables could be applied to understand the same phenomenon under inquiry in our paper, or to modify the current approach (Roszkowska 2024). These include machine learning, neural networks and the Amemiya-MaCurdy random effects component model. We leave this for future inquiry.

Policy recommendations

Based on the findings of this study, we propose the following policy recommendations.

1. The government should implement targeted interventions and support programmes to address the specific needs of high-risk provinces such as Laupula, Southern and Western.
2. There is also a need for the government to promote efficient land use and provide support for optimal planting and harvesting practices in order to reduce overextension and abandonment risks.
3. We also recommend enhanced education and training programmes on proper fertiliser use to ensure sustainable agricultural practices and reduce the risk of crop abandonment.
4. Since the CPI and maize prices are significant determiners of the risk of crop abandonment, it is necessary for the government to strengthen economic policies that enhance farmers' purchasing power and stabilise the cost of living to reduce abandonment risks.

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