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PARAMETRIC INSURANCE BASIS RISK UNDER ACCELERATING CLIMATE AND LAND CHANGES

Kannan Vishwanath* & Lloyd Zulu**
* Fellow, Albert Schweitzer International Foundation, Karl-Löwe-Gasse 22/12, A-1120 Wien, Vienna, Austria
** World Christian University, Lusaka, Zambia

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Abstract:

This analysis evaluates whether accessible climate and land indicators provide stable evidence for agricultural risk assessment relevant to parametric insurance design. A balanced panel of 50 annual observations across five East African countries during 2010 to 2019 combines national agricultural records with selected local climate measurements. Ordinary least squares with country and year effects, country clustered inference and an enumerated wild cluster bootstrap assess conditional associations. A ten-percentage point increase in rainfall deficit is associated with 5.43 percent lower cereal yield, but its confidence interval includes opposing effects. Temperature and forest change associations also remain unresolved, while alternative specifications reverse several coefficient signs. Rwanda's yield declined by 26.58 percent despite remaining above its historical reference throughout, producing no measured shortfall. This benchmark discrepancy reveals how threshold construction can conceal deterioration; causal transmission channels remain unidentified. The contribution distinguishes historical threshold crossing from productivity deterioration and demonstrates specification sensitivity. Agricultural monitoring and insurance development should evaluate benchmark responsiveness and geographical exposure alignment, while actual insurance performance requires matched losses and payments.

Key Words: Agricultural Risk; Climate Exposure; Cereal Productivity; Historical Benchmarks; Panel Data

1. Introduction:

An agricultural insurance index can describe environmental conditions accurately while remaining poorly aligned with the losses experienced by farmers. This distinction makes exposure measurement central to the credibility of parametric insurance. Contracts translate observable conditions into payments, whereas agricultural losses emerge from interactions among weather, land resources, crop composition and management. Clarke (2016) shows theoretically that basis risk can constrain rational demand for index insurance. Carter et al. (2017) identify contract quality and implementation conditions as central to agricultural insurance performance. These contributions establish why index construction matters, but they do not imply that an association between weather and aggregate crop yield measures insurance effectiveness.

Climate exposure presents a measurement challenge because agricultural responses depend on timing, intensity and spatial coverage. Rowhani et al. (2011) demonstrate the relevance of climate variability for crop production in Tanzania. Lobell et al. (2011) identify nonlinear temperature responses in African maize trials, while Ray et al. (2015) document geographical differences in the contribution of climate variability to crop yield variability. Global evidence also distinguishes the production consequences of drought and extreme heat from those of other weather disasters, indicating that different hazards require different representations rather than a single measure of adverse weather (Lesk et al., 2016). Annual precipitation and mean temperature can therefore conceal conditions that matter during sensitive production stages.

Adaptation further complicates the interpretation of climate and productivity relationships. Challinor et al. (2014) show that projected agricultural responses vary with crop, region, warming and adaptation assumptions. Burke and Emerick (2016) find limited evidence that observed adaptation substantially offsets extreme heat damage in United States agriculture. These findings make adaptation a relevant boundary condition, but they do not justify assuming that adaptation explains an imprecise temperature coefficient in another setting. Without direct measures of management responses, the present analysis cannot distinguish adaptation from exposure error, aggregation or omitted agricultural conditions.

Land conditions introduce another source of divergence between measured climate exposure and agricultural outcomes. Lawrence and Vandecar (2015) explain how tropical deforestation can alter temperature and moisture conditions relevant to agriculture. Mueller et al. (2012) demonstrate the importance of nutrient and water management for geographical differences in agricultural productivity. These mechanisms imply that national land statistics may capture several processes simultaneously, including ecological change, agricultural expansion and production adjustment. A national association between forest change and cereal yield consequently cannot identify a

specific ecological pathway without information on the location of land changes and their relationship to cultivated areas.

Insurance research reinforces the need to distinguish environmental proxies from direct evidence of protection. Jensen et al. (2016) examine insurance quality using household livestock outcomes and index insurance information from northern Kenya. Elabed et al. (2013) investigate how insurance design across multiple scales can address basis risk among cotton producers in Mali. Both contributions connect insurance assessment with information relevant to contract performance. The available dataset contains neither insured losses nor insurance payments. The research problem is therefore whether accessible climate and land indicators produce stable productivity associations, rather than whether particular insurance contracts compensate farmers adequately.

This study aims to assess the direction, precision and specification sensitivity of associations between rainfall deficits, temperature anomalies, forest cover changes and national cereal yield. The analysis uses a balanced panel of Ethiopia, Kenya, Rwanda, Tanzania and Uganda over 2010 to 2019. National agricultural indicators are combined with annual climate measures constructed from one selected weather location in each country. The central question is whether estimated productivity relationships remain consistent when exposure definitions, land controls, outcome scales and analytical samples change. Auffhammer et al. (2013) explain why weather measurement and exposure construction can affect economic estimates. Blanc and Schlenker (2017) identify the strengths and limitations of panel models for agricultural climate assessment, while Hsiang (2016) distinguishes the assumptions needed to interpret weather variation as evidence about climate impacts. These considerations support an associational interpretation of the present estimates.

The contribution is a bounded empirical assessment of measurement sensitivity in an accessible East African panel. The baseline estimates leave the proposed relationships unresolved, and several alternative specifications change coefficient direction. The analysis also identifies a consequential benchmark distinction: cereal yield can deteriorate during the observation window while remaining above an earlier reference average. A shortfall indicator based on that average consequently records no shortfall despite deterioration within the observation period. This pattern does not establish insurance underpayment. It demonstrates why historical benchmarks and aggregation choices require scrutiny before accessible productivity indicators inform agricultural risk assessment.

2. Theory, Conceptual Framework and Hypotheses Development:

2.1 Theory, Mechanisms and Hypotheses Development:

This analysis examines how climate variability and land use changes relate to cereal productivity within an agricultural production system constrained by water, temperature and land quality. These relationships matter for parametric insurance because environmental indices provide protection only when their movements correspond sufficiently to insured losses. Clarke in 2016 established that basis risk can limit rational demand for index insurance. Carter and colleagues in 2017 further identified product quality and institutional conditions as central to its effectiveness. The available data support an examination of agricultural production exposure. They do not contain the matched payouts and insured losses required to test insurance basis risk directly.

We define climate and land use changes through three dimensions: rainfall variability, temperature variability and changes in agricultural, forest and arable land shares. Cereal productivity performance concerns output per harvested hectare and its variation over time. The structural mechanism operates through resource constraints. Weather influences the conditions under which crops develop, while land allocation influences productive capacity and ecological support. Farmers can respond through planting decisions, input allocation and land expansion, but these responses depend on resources and institutions. Consequently, the expected relationships remain conditional on adaptation, crop composition and environmental conditions.

Rainfall variability captures changes in water availability relative to crop requirements. Insufficient rainfall can restrict establishment, nutrient uptake and grain development. Concentrated rainfall can also leave damaging dry intervals despite an adequate annual total. Rowhani and colleagues in 2011 demonstrated that seasonal rainfall variability contributed information about cereal yields beyond climatic means in Tanzania. This evidence supports distinguishing rainfall quantity from its temporal distribution.

The expected association is asymmetric. Rainfall deficits should reduce yields where production depends on rainfall and stored soil moisture cannot compensate. Additional rainfall may improve yields under water scarcity, but its benefits can weaken or reverse where drainage becomes limiting. Ray and colleagues in 2015 documented substantial geographical variation in the contribution of climate variability to crop yield variation. We therefore interpret rainfall anomalies relative to local conditions, rather than assuming that identical changes have identical consequences across countries.

Lesk and colleagues in 2016 found that drought reduced national cereal production through changes in both yields and harvested area. Their analysis did not identify an equivalent national effect for every disaster category. This difference cautions against treating all departures from average rainfall as equally harmful. We focus the

directional prediction on rainfall deficits. Annual rainfall and variation across monthly totals provide supporting measures, although neither identifies the timing of stress within a crop season.

H1: Larger Rainfall Deficits Relative to the Historical Baseline are Associated with Lower Cereal Yields Where Production Depends on Rainfall

Temperature variability operates through thermal exposure and crop development. Warming can accelerate development and increase atmospheric demand for water, reducing the time and moisture available for grain formation. Lobell, Bänziger and colleagues in 2011 identified nonlinear heat effects in African maize trials. Their findings support a conditional mechanism in which warming becomes more damaging as crops encounter thermal and moisture constraints.

Temperature effects can diverge across production environments. Moderate warming may benefit crops where low temperatures constrain development, while producing losses in warmer environments. Crop selection and management can also change the observed response. Lobell, Schlenker and colleagues in 2011 linked historical climate trends to changes in global crop production, providing evidence that temperature exposure can influence agricultural performance beyond isolated experimental settings. Such evidence does not establish that every positive annual temperature anomaly reduces yields.

Challinor and colleagues in 2014 showed that projected yield responses depend on warming, crop conditions and adaptation. We therefore formulate a negative expectation for environments already exposed to thermal constraints, while allowing weaker or positive associations elsewhere. Annual mean temperature and temperature anomalies provide feasible exposure measures. Variation across monthly means describes annual seasonality and cannot substitute for daily observations of extreme heat.

H2: Higher Positive Temperature Anomalies are Associated With Lower Cereal Yields in Environments Where Existing Thermal and Moisture Constraints Limit Crop Development

Land use changes influence productivity through resource allocation and ecological buffering. Agricultural and arable land expansion can increase cultivated area, while forest decline can alter local energy and water exchanges. Lawrence and Vandecar in 2015 documented evidence that tropical deforestation can produce warmer and drier conditions, with consequences for agriculture. The proposed mechanism therefore concerns the environmental conditions supporting production, not an assumed direct equivalence between forest area and cereal yield.

Competing incentives make the direction of land expansion uncertain. Farmers may expand cultivation to increase output or compensate for declining productivity. Expansion onto marginal land can reduce average yields even when total production rises. Conversely, improvements on existing cropland can increase yields without expansion. Tilman and colleagues in 2011 demonstrated that alternative combinations of agricultural expansion and intensification produce different production and environmental outcomes. Land share changes therefore cannot be interpreted as productivity improvements by definition.

Mueller and colleagues in 2012 identified nutrient and water management as central determinants of yield gaps. This evidence supports treating management capacity as a boundary condition rather than attributing productivity changes entirely to land allocation. We specify a directional expectation for forest decline where ecological buffering constrains production. Changes in agricultural and arable land shares remain separate explanatory measures with potentially opposing associations. National land shares cannot establish whether forest change occurred near cereal production areas.

2.2 Conceptual Framework:

The framework links observed rainfall, temperature and land measures to observed cereal productivity. Its relationships represent theoretical directions for testing associations. They do not establish causal effects. Auffhammer and colleagues in 2013 emphasized the importance of constructing weather exposure measures that match the economic outcome. Accordingly, the distinction between climate observations at selected locations and national agricultural outcomes remains a central measurement limitation.

We use cereal yield as the primary outcome. Annual yield growth, deviation from the historical baseline, yield shortfall and yield variability provide alternative descriptions of performance. These measures derive from the same yield series and do not constitute five independent indicators of a latent construct. Likewise, annual temperature and its baseline anomaly should not enter the same specification automatically. Hsiang in 2016 showed why exposure definitions and functional form must follow the mechanism and identifying variation. We therefore avoid combining overlapping measures into an unsupported composite index.

Country effects provide a feasible means of accounting for persistent differences in geography and production conditions. Year effects can account for common annual influences. Blanc and Schlenker in 2017 explain that panel models can absorb stable heterogeneity while remaining vulnerable to measurement error and omitted

factors that change over time. With five countries and ten study years, the framework favors parsimonious specifications. It does not support numerous interactions, simultaneous equations or unrestricted nonlinear functions. Adaptation provides a boundary condition, but the available records do not measure its components sufficiently to estimate mediation or moderation. Burke and Emerick in 2016 found limited evidence that observed adaptation eliminated agricultural losses from extreme heat in their setting. We therefore allow adaptation to explain differences in theoretical responses without assigning it an unobserved score or assuming that it neutralizes climatic stress.

Land changes can influence climate exposure, while poor agricultural performance can encourage subsequent land expansion. These possibilities limit causal interpretation of contemporaneous associations. Lobell and Asseng in 2017 demonstrated that statistical and process-based approaches capture different aspects of crop responses and require careful interpretation. We retain H1 through H3 as testable expectations, allow unsupported or inconclusive results, and identify any subsequent changes to outcomes, exposure definitions or hypothesis directions as exploratory. Insurance basis risk remains outside the estimated relationships until matched contract and loss records become available.

3. Data:

This analysis combines climate and agricultural records to construct a balanced panel, document sample coverage and operationalize the proposed relationships. Source reconciliation, transparent transformations and reproducible estimation distinguish observed quantities from calculated measures and unresolved measurement limitations.

3.1 Data Sources, Population, and Sample Construction:

The dataset combines monthly NASA POWER meteorological records with annual agricultural indicators distributed through the World Bank's World Development Indicators. POWER supplies corrected precipitation, identified as PRECTOTCORR, and temperature at two metres, identified as T2M. The recorded service version is API v2.10.0. Its meteorological source is MERRA2, whose assimilation system is described by Gelaro and colleagues in 2017. Molod and colleagues in 2015 document the underlying atmospheric model, while Reichle and colleagues in 2017 explain the precipitation correction methodology. These records represent estimates for spatial grid cells rather than measurements from sampled farms.

The national agricultural series originate from the Food and Agriculture Organization and are accessed through World Development Indicators, source 2, using API v2. They comprise cereal yield, AG.YLD.CREL.KG, agricultural land share, AG.LND.AGRI.ZS, forest land share, AG.LND.FRST.ZS, arable land share, AG.LND.ARBL.ZS, and land under cereal production, AG.LND.CREL.HA. Keenan and colleagues in 2015 and MacDicken in 2015 explain the national reporting and definition issues relevant to interpreting forest statistics. These publications provide methodological context and do not identify the release vintage of the extracted records.
The workbook preserves exact extraction requests, coordinates, access timestamps and source update information.

The records constitute a revised historical snapshot retrieved after the observation window. They do not reconstruct information available at each historical observation date. World Bank data are distributed under CC BY 4.0, subject to indicator specific terms. NASA records are publicly accessible with source acknowledgement. A separate NASA licence identifier and an archived FAO release identifier are not preserved in the workbook. The access routes are the POWER monthly API and the World Bank Indicators API. datacatalog.worldbank.org

The analytical unit is a country paired with one selected climate query location in each year. The five pairs are Kenya and Eldoret, Rwanda and Huye, Tanzania and Dodoma, Uganda and Mbarara, and Ethiopia and Hawassa. The estimation window covers annual reporting years from 2010 to 2019. Climate aggregation covers January through December of each year. Supporting observations from 2000 to 2009 establish historical references and supply earlier values required for growth and rolling variability measures.

The target population comprises cereal producing economies potentially exposed to climate and land changes. The accessible frame contains five purposively selected countries and five climate locations. No comprehensive population list, global eligibility count or probability sampling procedure was constructed. The workbook records the selected countries but does not contain a dated selection protocol. Within this accessible frame, inclusion requires an identifiable country, a reporting year within the specified window and complete inputs for the relevant construction. No selected country was removed.

The annual frequency matches the available national cereal and land indicators. Rainfall is an accumulated annual quantity, while temperature is an annual average. Cereal yield measures output per harvested hectare during the reporting year. Cereal area represents an annual harvested area measure. Land shares describe annual land allocation estimates and are not assumed to represent verified observations on the final day of each year.

Table 1: Sample construction and analytical coverage

Stage	Units	Observations	Reason or rule
Target population	Not enumerated	Not enumerated	No comprehensive population frame was constructed
Accessible source frame	5 countries and 5 climate locations	100 annual agricultural records and 1,200 monthly climate records	Source coverage from 2000 to 2019
Historical reference retained	5 countries	50 annual agricultural records and 600 monthly climate records	Reference coverage from 2000 to 2009
Selected observation window	5 countries	50 annual records and 600 supporting monthly climate records	Reporting years from 2010 to 2019
Exclusions for missing values, duplicate keys or outlier removal	0 countries	0 annual observations	All retained inputs passed the implemented checks
Merged and cleaned annual panel	5 countries	50 country year observations	Complete annual alignment
Baseline and alternative level specifications	5 countries	50 observations per specification	Complete contemporaneous predictors and outcomes
Loss from within window differencing	0 countries	5 observations	First observation removed from each country
First difference specification	5 countries	45 observations	Nine annual changes per country
Each country omission specification	4 countries	40 observations	One country and its ten observations omitted per regression

Monthly and annual records represent different frequencies and must not be added together as independent observations. The annual panel is balanced. Its completeness applies to the selected frame and does not establish population representativeness.

3.2 Data Integration, Cleaning, and Quality Assurance:

National records use ISO3 country identifiers and reporting year as their unique key. Monthly climate records use an analyst assigned country identifier, year and month, linked to the selected query coordinates. Each annual climate aggregate is matched to one national agricultural record. The intended relationship is therefore one annual climate record to one national agricultural record within each selected country and year.

The checks identify 50 unique annual panel keys, 100 unique agricultural source keys and 1,200 unique monthly climate keys. All 50 study window records match their required source observations. No duplicate keys, unmatched study observations or unintended increases in annual records occur. Source input sheets take priority over calculated panel fields. Reconstructed annual values agree with the corresponding workbook fields within numerical tolerance.

The temporal conversion retains POWER month labels and calendar month lengths, including leap years. Monthly mean daily precipitation is multiplied by the number of days before annual summation. Temperature averages are weighted by calendar days. Only the twelve calendar months enter annual aggregation. National crop statistics retain their reported annual labels without adjustment to fiscal years or locally estimated crop seasons. These choices address the exposure construction issues discussed by Auffhammer and colleagues in 2013 and the distinction between weather variation and climatic conditions reviewed by Dell and colleagues in 2014.

No currency conversion, exchange rate adjustment or deflation is required because the measures consist of physical quantities, percentages and ratios. Historical reference calculations use only observations from 2000 to 2009. Growth and rolling variability measures use current and earlier observations. No observation after 2019 enters the analytical constructions. However, the retrospective source snapshot incorporates revisions and does not support claims about real time forecasting information.

Missingness is zero for the retained source inputs across all five countries and every required year or month. No deletion, imputation or interpolation was performed within the analysis. Upstream interpolation and

revision flags are not preserved, so complete annual coverage does not imply that every source value was independently measured. Zero rainfall deficits and zero yield shortfalls indicate that their reference thresholds were not crossed. They do not replace missing observations.

The implemented checks require finite numerical inputs, positive cereal yields and harvested areas, nonnegative rainfall, land shares between zero and 100, and arable shares no greater than agricultural shares. Monthly temperature values are checked against broad plausibility bounds of −90 to 65 degrees Celsius. Calendar lengths, reference denominators and annual arithmetic are also checked. All observations pass these checks. No winsorization, trimming or replacement of valid extremes is applied.

Spatial matching remains the main unresolved integration issue. A query location assigned to a country is not equivalent to a production weighted national exposure. Ray and colleagues in 2015 demonstrate that climate contributions to yield variation differ geographically. Lesk and colleagues in 2016 also distinguish yield responses from changes in harvested area. Consequently, local weather, national yields and national land shares are retained as distinct measurements rather than treated as observations at a common farm scale.

Internal reconciliation verifies numerical construction but does not establish station accuracy, crop season exposure or agreement with independent agricultural measurements. The distinction between statistical relationships and crop processes follows the measurement concerns discussed by Lobell and Asseng in 2017. No cleaning rule was changed to improve coefficient signs or probability values. Because no comprehensive excluded country frame exists, differences between selected and unselected countries cannot be evaluated.

3.3 Variable Measurement, Construction, and Validation:

The framework uses observed and calculated measures rather than latent scores. Rainfall, temperature and land changes provide separate explanatory dimensions. Cereal productivity is represented by yield and four supplementary measures derived from the same yield series. These outcomes are not treated as independent indicators of a latent construct. Exposure definitions and scaling follow the distinction between climatic conditions and economically relevant variation developed by Hsiang in 2016. Equation 1 defines annual climate aggregation.

$$R_{it} = \sum_{m=1}^{12} d_{tm}\, p_{itm}, \qquad T_{it} = \frac{\sum_{m=1}^{12} d_{tm}\, \tau_{itm}}{\sum_{m=1}^{12} d_{tm}}$$

Here, i identifies a country and its selected climate location, t identifies year, and m identifies month. R_{it} is annual rainfall in millimetres, T_{it} is annual mean temperature in degrees Celsius, d_{tm} is calendar days, p_{itm} is monthly mean daily precipitation, and τ_{itm} is monthly mean temperature.

Equation 2 defines rainfall and temperature departures and the rainfall deficit used in the baseline regression.

$$A_{it}^{R} = 100\left[\frac{R_{it}}{\overline{R}_i} - 1\right], \qquad D_{it} = max\{0, -A_{it}^{R}\}, \qquad A_{it}^{T} = T_{it} - \overline{T}_i$$

Here, A_{it}^{R} is rainfall departure in percent, D_{it} is the nonnegative rainfall deficit, and A_{it}^{T} is temperature departure in degrees Celsius. $\overline{R}_i$ is mean annual rainfall during 2000 to 2009. $\overline{T}_i$ is the calendar day weighted temperature across that reference period. The reference is a ten-year benchmark rather than a conventional thirty-year climate normal.

Monthly rainfall variability is the sample standard deviation of twelve-monthly rainfall totals divided by their mean and multiplied by 100. Monthly temperature variability is the sample standard deviation of twelve-monthly temperature means. Rowhani and colleagues in 2011 show why temporal variability matters for cereal production, while Lobell, Bänziger and colleagues in 2011 demonstrate the importance of nonlinear heat exposure. The available monthly measures describe seasonality and cannot identify daily heat thresholds or damaging dry intervals within crop development stages. Equation 3 defines the three land change measures.

$$\Delta L_{it}^{j} = L_{it}^{j} - L_{i,t-1}^{j}$$

Here, L_{it}^{j} is the national percentage of land assigned to category j, comprising agricultural, forest or arable land. ΔL_{it}^{j} is its annual change in percentage points. Positive values indicate expansion of the reported share. Differences use observed source values from the preceding year, including 2009 for the first study observation. Equation 4 defines the supplementary productivity outcomes.

$$g_{it} = 100\left[\frac{Y_{it}}{Y_{i,t-1}} - 1\right], \qquad q_{it} = 100\left[\frac{Y_{it}}{\overline{Y}_i} - 1\right],$$

$$s_{it} = max\{0, -q_{it}\}, \qquad v_{it} = 100\frac{\sigma_{it,3}^{Y}}{\overline{Y}_{it,3}}$$

Here, Y_{it} is cereal yield in kilograms per hectare, g_{it} is annual percentage growth, q_{it} is percentage deviation from the historical reference, and s_{it} is the nonnegative percentage shortfall. $\overline{Y}_i$ is mean yield during 2000 to 2009. v_{it} is trailing yield variability, $\sigma^{Y}_{it,3}$ is the sample standard deviation of current and preceding two annual yields, and $\overline{Y}_{it,3}$ is their mean.

Table 2: Variable dictionary

Variable or indicator	Analytical role	Definition and construction	Source and identifier	Unit and frequency	Transformation and direction	Missing value rule	Coverage and limitation
Annual rainfall	Rainfall indicator	Calendar day adjusted monthly totals summed annually	POWER, PRECTOTCORR	Millimetres, annual	Higher values indicate more rainfall	Retain complete inputs; no imputation	Selected climate location
Rainfall anomaly	Alternative predictor	Percentage departure from historical rainfall reference	POWER, PRECTOTCORR	Percent, annual	Positive values indicate wetter conditions	No imputation	Annual departure does not identify crop season timing
Monthly rainfall variability	Rainfall indicator	Sample standard deviation divided by mean monthly total, multiplied by 100	POWER, PRECTOTCORR	Percent, annual	Higher values indicate greater monthly dispersion	Twelve complete months required	Includes seasonality
Annual mean temperature	Temperature indicator	Calendar day weighted monthly temperature	POWER, T2M	Degrees Celsius, annual	Higher values indicate warmer conditions	No imputation	Selected climate location
Temperature anomaly	Baseline predictor	Annual temperature minus historical reference	POWER, T2M	Degrees Celsius, annual	Positive values indicate warmer conditions relative to reference	No imputation	Does not measure extreme heat exposure
Monthly temperature variability	Temperature indicator	Sample standard deviation of monthly means	POWER, T2M	Degrees Celsius, annual	Higher values indicate greater monthly dispersion	Twelve complete months required	Includes seasonality
Agricultural share change	Additional land predictor	Current agricultural share minus preceding share	WDI, AG.LND. AGRI. ZS	Percentage points, annual	Positive values indicate expansion	Prior year source value required	National allocation estimate
Forest share change	Baseline land predictor	Current forest share minus preceding share	WDI, AG.LND.FRST. ZS	Percentage points, annual	Positive values indicate expansion	Prior year source value required	Does not locate forest change near cereal fields
Arable share change	Additional land predictor	Current arable share minus preceding share	WDI, AG.LND.ARBL. ZS	Percentage points, annual	Positive values indicate expansion	Prior year source value required	Does not identify cultivation intensity
Cereal yield	Primary outcome	National cereal output per harvested hectare	WDI, AG.YLD.CREL.KG	Kilograms per hectare, annual	Natural logarithm in baseline; untransformed in sensitivity analysis	Positive complete values required	Aggregate cereal composition can change
Annual yield growth	Supplementary outcome	Percentage change from preceding annual yield	WDI, AG.YLD.CREL.KG	Percent, annual	Positive values indicate growth	Prior year yield required	Earlier supporting records preserve all study observations
Yield deviation	Supplementary outcome	Percentage departure from historical yield reference	WDI, AG.YLD.CREL.KG	Percent, annual	Positive values indicate yield above reference	Positive reference required	Reference is not detrended
Yield shortfall	Supplementary outcome	Zero or the magnitude of a negative yield deviation	WDI, AG.YLD.CREL.KG	Percent, annual	Higher values indicate larger shortfalls	No imputation; zero is substantive	Not an insured or monetary loss

Variable or indicator	Analytical role	Definition and construction	Source and identifier	Unit and frequency	Transformation and direction	Missing value rule	Coverage and limitation
Yield variability	Supplementary outcome	Trailing three-year coefficient of variation	WDI, AG.YLD.CREL.KG	Percent, annual	Higher values indicate greater relative dispersion	Three complete yields required	Includes current and earlier years
Rainfall deficit	Baseline predictor	Zero or the magnitude of a negative rainfall anomaly	POWER, PRECTOTCORR	Percent below reference, annual	Higher values indicate larger deficits	No imputation; zero is substantive	Benchmark crossing is not an independently verified drought classification
Historical references	Construction inputs	Rainfall, temperature and yield averages during 2000 to 2009	POWER and WDI yield series	Millimetres, degrees Celsius and kilograms per hectare	Fixed within each country	Complete reference observations required	Ten-year reference window
Land shares and cereal area	Construction inputs and descriptive context	Reported agricultural, forest and arable shares and harvested cereal area	WDI land series and AG.LND.CREL. HA	Percent and hectares, annual	Shares remain on the zero to 100 scale	No imputation	Annual source estimates rather than verified final day stocks
Country and year identifiers	Fixed effects and alignment	ISO3 country identifier and reporting year	Source records and query assignment	Categorical identifiers, annual	No numerical index construction	Complete identifiers required	Country assignment does not establish spatial representativeness

Validation consists of source reconciliation, unit checks, denominator checks and reconstruction of the implemented transformations. Management intensity and local ecological conditions remain unmeasured. Mueller and colleagues in 2012 identify nutrient and water management as determinants of yield gaps, while Lawrence and Vandecar in 2015 explain why forest effects depend on climatic processes and spatial context. These limitations prevent interpreting national land changes as direct measurements of farm management or ecological buffering.

Table 3: Descriptive coverage of principal analytical measures

Measure	VO	Mean	SD	Median	Minimum	Maximum
Annual rainfall, millimetres	50	1,356.32	526.04	1,283.44	460.84	2,681.51
Rainfall anomaly, percent	50	21.82	26.25	16.68	−26.64	77.90
Monthly rainfall variability, percent	50	81.20	28.47	74.37	41.95	161.34
Annual temperature, degrees Celsius	50	19.67	2.47	20.33	15.19	23.30
Temperature anomaly, degrees Celsius	50	−0.23	0.39	−0.23	−1.00	0.85
Monthly temperature variability, degrees Celsius	50	1.11	0.39	1.03	0.44	2.17
Agricultural share change, percentage points	50	0.14	0.68	0.24	−2.90	1.29
Forest share change, percentage points	50	−0.05	0.35	−0.10	−0.53	0.59
Arable share change, percentage points	50	0.17	0.73	0.19	−3.17	1.05
Cereal yield, kilograms per hectare	50	1,799.44	343.95	1,727.95	1,314.80	2,711.20
Annual yield growth, percent	50	2.27	13.10	1.20	−33.87	48.41
Yield deviation, percent	50	30.24	31.54	24.17	−18.68	102.34
Yield shortfall, percent	50	1.25	3.89	0.00	0.00	18.68
Trailing yield variability, percent	50	8.19	6.16	6.56	0.95	24.79
Rainfall deficit, percent	50	2.90	6.78	0.00	0.00	26.64

3.4 Analytical Framework, Identification, and Reproducibility:

The analysis estimates conditional associations rather than causal effects or forecasting performance. Equation 5 presents the implemented baseline specification.

$$ln\, Y_{it} = \alpha_i + \lambda_t + \beta_D D_{it} + \beta_T A_{it}^{T} + \beta_F \Delta L_{it}^{F} + \varepsilon_{it}$$

Here, $\ln Y_{it}$ is logarithmic cereal yield, α_i is the country effect, λ_t is the year effect, and ε_{it} is the unexplained component. D_{it} is contemporaneous rainfall deficit, A_{it}^{T} is contemporaneous temperature anomaly, and ΔL_{it}^{F} is

contemporaneous forest share change. The three coefficients describe conditional associations after removing stable country differences and common annual movements.

Ordinary least squares estimate Equation 5 using 50 observations. Country effects account for persistent heterogeneity, while year effects absorb common annual shifts. The specification contains 17 estimated parameters and 33 residual degrees of freedom. Blanc and Schlenker in 2017 explain the strengths of panel models for separating stable heterogeneity from weather variation, while emphasizing their remaining exposure to measurement error and omitted factors.

Inference uses country clustered CR1 covariance estimates. The finite sample multiplier is five divided by four, multiplied by 49 divided by 33. Conventional confidence intervals and probability values use four cluster degrees of freedom. This permits dependence within countries but assumes independence across country clusters. Cameron and Miller in 2015 explain why conventional precision can be overstated when clustered observations are treated as independent.

A restricted wild cluster bootstrap supplements conventional inference by enumerating all 32 Rademacher sign configurations across five countries. The procedure imposes the tested coefficient restriction when constructing bootstrap outcomes. MacKinnon and Webb in 2017 discuss how cluster structure affects bootstrap performance, and their 2018 analysis identifies further difficulties when identifying information is concentrated in few clusters. Full enumeration eliminates simulation randomness but does not guarantee reliable inference with five countries. Common year effects also do not remove every possible form of cross-country dependence.

The sensitivity analyses address defined threats. Replacing logarithmic yield with yield levels evaluates dependence on outcome scaling. Replacing rainfall deficit with the signed rainfall anomaly evaluates the asymmetric deficit construction. Adding agricultural and arable share changes evaluates sensitivity to broader land allocation measures. Five country omission regressions assess dependence on individual countries, using 40 observations each. Equation 6 defines the within window first difference specification.

$$\Delta \ln Y_{it} = \tau_t + \beta_D \Delta D_{it} + \beta_T \Delta A^T_{it} + \beta_F \Delta^2 L^F_{it} + \eta_{it}$$

Here, Δ denotes the change from the preceding year, $\tau_t$is the year effect for annual changes, and $\eta_{it}$is the differenced unexplained component. $\Delta^2 L^F_{it}$ is the change in the annual forest share change. This specification contains 45 observations because differencing is restricted to the study window. It evaluates sensitivity to temporal transformation and does not independently establish stationarity or resolve endogeneity.

The baseline, alternative constructions and sensitivity checks are exploratory. No dated preregistration is supplied. They use consistent observations wherever their construction permits, with losses from differencing and country omission reported explicitly. No observations are removed after examining coefficient signs or statistical significance.

Causal interpretation would require conditional exogeneity and sufficiently accurate exposure measurement. These conditions are not established. Irrigation, fertilizer use, crop composition, agricultural technology and local production conditions can vary alongside the included predictors. Land allocation may also respond to agricultural performance. Conditioning on rainfall and temperature prevents treating the forest coefficient as the full effect operating through those climatic pathways. Burke and Emerick in 2016 further demonstrate why adaptation must be considered when interpreting agricultural responses, although its components are not measured here.

Definitions, reporting years, historical references and transformation rules are held consistent across the implemented models. The unresolved differences concern spatial coverage, source revisions, unmeasured adaptation and the limited number of independent countries. No matched insurance payouts, insured losses, contract triggers or coverage amounts are available. Consequently, the estimand concerns cereal productivity associations and cannot identify actual parametric insurance basis risk.

4. Methods:

4.1 Research Design, Sample and Model Specification:

This analysis uses an exploratory panel design to estimate conditional associations between climate exposure, land changes and cereal productivity. The balanced panel comprises 50 country year observations from Ethiopia, Kenya, Rwanda, Tanzania and Uganda during 2010 to 2019. The five countries constitute a purposive accessible sample rather than a probability sample. The analytical target is therefore restricted to relationships within the observed panel.

The design uses changes within countries after accounting for persistent national differences and common annual movements. Country effects absorb stable characteristics, while year effects absorb influences shared across countries within each year. These adjustments do not eliminate omitted agricultural conditions that change

differently across countries. Blanc and Schlenker (2017) explain that agricultural panel models address stable heterogeneity while remaining vulnerable to measurement error and changing production conditions.

Equation 5 specifies natural logarithmic cereal yield as a function of contemporaneous rainfall deficit, temperature anomaly and annual forest share change, with country and year effects. Rainfall deficit measures the percentage below reference rainfall, temperature anomaly measures departures in degrees Celsius, and forest share change measures annual differences in percentage points. Positive forest change denotes expansion of the reported share. The baseline design matrix has rank 17, comprising an intercept, four country indicators, nine-year indicators and three predictors, leaving 33 residual degrees of freedom.

The rainfall specification distinguishes deficits from years that meet or exceed reference rainfall. It assumes a linear association within the deficit range and does not estimate damage from excess rainfall. The temperature specification estimates a linear association across observed annual anomalies rather than biological heat thresholds. Agricultural and arable share changes enter an expanded sensitivity model. Their inclusion evaluates specification dependence rather than establishing adequate control for confounding.

The predictors enter contemporaneously because the available annual records do not establish crop specific exposure windows or defensible delayed responses. No mediator, moderator, interaction or lagged outcome is estimated. Land allocation may respond to agricultural performance, while land conditions may influence both weather exposure and productivity. Conditioning on rainfall and temperature also prevents interpreting the forest coefficient as a total relationship operating through those climatic pathways.

The estimates remain associational. No treatment assignment mechanism, instrument or external discontinuity provides causal identification. Hsiang (2016) distinguishes weather associations from climate effects identified under defensible assumptions. Direct insurance performance is also outside the estimand because insured losses, contract thresholds and payments are unavailable.

4.2 Measurement, Data Processing, Estimation and Inference:

The sample construction table and variable dictionary document source provenance, eligibility and measurement. Climate observations represent one selected location per country, whereas cereal yield and land shares describe national conditions. This spatial mismatch can distort associations and cannot be assumed to produce attenuation alone. Auffhammer et al. (2013) identify the construction and geographical alignment of weather exposure as consequential choices in economic climate analysis.

Equations 1 through 4 define annual aggregation, historical departures, land changes and supplementary productivity measures. Monthly precipitation rates are multiplied by calendar days and summed annually. Monthly temperature means are weighted by calendar days. Reference conditions use observations during 2000 to 2009, providing fixed ten-year benchmarks rather than conventional thirty-year climate normals. Land changes use preceding source observations, including 2009 values when constructing changes for 2010.

The natural logarithm is applied to positive cereal yields. The retained inputs contain no missing observations requiring deletion, imputation or interpolation. Zero rainfall deficits indicate that reference rainfall was met or exceeded; they do not replace missing values. No winsorization, trimming or removal of valid extreme observations is applied. Revised historical records support retrospective association analysis rather than reconstruction of information available when insurance decisions would have occurred.

All models use unweighted ordinary least squares. Baseline and alternative level specifications retain 50 observations. First differencing retains 45 observations, while each country omission model retains 40. Estimation uses Python with NumPy and SciPy. Exact software and package versions are not recorded in the available documentation, limiting exact reconstruction of the computational environment.

Country clustered covariance estimates allow heteroskedasticity and dependence across years within countries. Equation 7 defines the implemented CR1 covariance estimator.

$$\widehat{V}_{CR1} = \frac{G}{G-1}\frac{N-1}{N-K}(X^{\top}X)^{-1}\left[\sum_{g=1}^{G} X_g^{\top}\,\hat{u}_g\hat{u}_g^{\top}X_g\right](X^{\top}X)^{-1}.$$

Here, $\widehat{V}_{CR1}$ is the estimated coefficient covariance matrix, G is the number of country clusters, N is the observation count, and K is the design matrix rank. X contains all regressors and fixed effect indicators, while X_g and $\hat{u}_g$ contain the regressors and fitted residuals for country g. The superscript $\top$ denotes transposition.

For the baseline model, the correction equals five divided by four multiplied by 49 divided by 33. Conventional confidence intervals and probability values use a student distribution with four degrees of freedom. Cameron and Miller (2015) explain that clustered inference requires particular caution when the number of independent clusters is small.

A restricted wild cluster bootstrap supplements conventional inference. Each coefficient test imposes a zero restriction and enumerates all 32 Rademacher sign configurations across the five countries. Enumeration removes simulation randomness, so no random seed is required. However, the smallest attainable two-sided probability under this implementation is 0.0625. MacKinnon and Webb (2017) show that bootstrap performance depends on cluster structure and the distribution of identifying information. Neither enumeration nor balanced coverage guarantees reliable inference with five clusters.

Country clustering assumes independence across countries. Regional weather systems and economic linkages may violate this assumption, and year effects do not guarantee removal of all shared dependence. Both inference procedures are therefore reported with explicit uncertainty. Equation 8 translates logarithmic coefficients into fitted percentage differences in yield.

$$M_j(h) = 100\left[\exp\left(h\hat{\beta}_j\right) - 1\right].$$

Here, $M_j(h)$ is the fitted percentage difference associated with a change of h units in predictor j, and $\hat{\beta}_j$ is its estimated coefficient. Confidence interval endpoints undergo the same transformation. These contrasts express conditional associations rather than intervention effects.

4.3 Diagnostics, Sensitivity, Reproducibility and Interpretive Limits:

Diagnostic assessment focuses on predictor overlap, remaining variation and dependence on individual countries. Baseline predictors are residualized against country and year indicators before calculating variance inflation factors. This evaluates overlap in the variation used for estimation. Residual variation is considered alongside collinearity because modest predictor overlap does not ensure sufficient identifying information.

The measures are observed quantities or arithmetic transformations rather than latent constructs. Validation therefore concerns numerical consistency, units, denominators and substantive alignment. Factor analysis, composite reliability and average variance extracted are not imposed. Formal normality, unit root and residual dependence tests are not documented as implemented and are not presented as completed procedures.

Sensitivity checks address specific threats. Replacing logarithmic yield with yield in kilograms per hectare assesses dependence on outcome scale. Replacing rainfall deficit with the signed rainfall anomaly examines sensitivity to collapsing nondeficit years to zero. Adding agricultural and arable share changes evaluates sensitivity to broader land allocation measures. These models retain the same 50 observations, separating specification changes from sample changes.

Equation 6 defines the first difference model, which relates annual changes in logarithmic yield to changes in the baseline predictors, with year effects for annual changes. The forest term consequently becomes a second difference of the original forest share. Coefficients are reestimated rather than constrained to equal baseline estimates. Differencing removes the first observation for each country and retains 45 observations. It assesses sensitivity to temporal transformation without establishing stationarity or resolving endogeneity.

Five further regressions omit one country at a time. Interpretation considers changes in coefficient direction, magnitude and uncertainty rather than continued statistical significance alone. Conventional and bootstrap probabilities remain distinct, and nonrejection does not establish that an association is absent.

All specifications and sensitivity checks are exploratory because no dated preregistration is supplied. No cleaning rule was changed to obtain preferred coefficient signs or probability values. Nevertheless, spatial exposure mismatch, unmeasured agricultural management, reverse relationships involving land allocation and dependence across countries remain unresolved.

The replication materials comprise the analytical workbook, construction and estimation script, saved outputs and explanatory documentation. Unrecorded software versions remain a replication limitation. The analysis uses aggregate secondary records without participant recruitment or identifiable household information; no ethics approval or consent procedure is claimed.

The methodological contribution is a transparent application of established estimation and sensitivity procedures. It does not introduce a new estimator or identification strategy. The design clarifies how exposure construction, historical benchmarks, land adjustment, temporal transformation and limited cluster information constrain agricultural risk interpretation.

5. Findings:

This analysis examines the associations of rainfall deficits, temperature anomalies and land changes with cereal productivity across five countries during 2010 to 2019. We present the sample characteristics and main estimates before assessing hypothesis support and specification sensitivity. The results concern agricultural productivity and do not directly measure insurance basis risk.

The balanced panel contains 50 country year observations for Ethiopia, Kenya, Rwanda, Tanzania and Uganda. Each country contributes ten annual observations. The retained variables contain no missing values or

duplicate country year records, and no observations were removed as outliers. Climate measures represent selected locations, while cereal yields and land indicators represent national conditions. The estimates therefore relate local climate exposure to national agricultural outcomes.

Table 1 presents the distributions of the conceptual framework indicators and the additional rainfall deficit measure used in estimation. All indicators have 50 valid observations. Rainfall and temperature anomalies use the historical reference period from 2000 to 2009. Monthly variability measures describe differences across calendar months and therefore include seasonality. Yield variability is the coefficient of variation calculated over the current and preceding two years.

Table 1: Descriptive statistics

Variable	Unit	Mean	SD	Median	Minimum	Maximum
Annual rainfall	Millimetres	1,356.32	526.04	1,283.44	460.84	2,681.51
Rainfall anomaly	Percent of reference	21.82	26.25	16.68	−26.64	77.90
Monthly rainfall variability	Coefficient of variation, percent	81.20	28.47	74.37	41.95	161.34
Annual mean temperature	Degrees Celsius	19.67	2.47	20.33	15.19	23.30
Temperature anomaly	Degrees Celsius	−0.23	0.39	−0.23	−1.00	0.85
Monthly temperature variability	Standard deviation, degrees Celsius	1.11	0.39	1.03	0.44	2.17
Agricultural land share change	Percentage points	0.14	0.68	0.24	−2.90	1.29
Forest land share change	Percentage points	−0.05	0.35	−0.10	−0.53	0.59
Arable land share change	Percentage points	0.17	0.73	0.19	−3.17	1.05
Cereal yield	Kilograms per hectare	1,799.44	343.95	1,727.95	1,314.80	2,711.20
Annual cereal yield growth	Percent	2.27	13.10	1.20	−33.87	48.41
Cereal yield deviation from reference	Percent	30.24	31.54	24.17	−18.68	102.34
Cereal yield shortfall	Percent below reference	1.25	3.89	0.00	0.00	18.68
Cereal yield variability	Trailing three year coefficient of variation, percent	8.19	6.16	6.56	0.95	24.79
Rainfall deficit	Percent below reference	2.90	6.78	0.00	0.00	26.64

The distributions reveal limited coverage of adverse conditions under the selected reference definitions. Rainfall deficits occur in 11 observations, while positive yield shortfalls occur in seven. Moreover, a fixed historical reference can conceal deterioration within the observation window. Rwanda's cereal yield declined by 26.58 percent between 2010 and 2019, yet every annual yield remained above its earlier reference mean. The shortfall indicator therefore measures departures below a historical benchmark rather than all economically relevant productivity losses.

National productivity trajectories also diverge. Cereal yields increased by 54.02 percent in Ethiopia and 14.30 percent in Tanzania between the first and final observation years. They declined by 6.16 percent in Kenya and 29.18 percent in Uganda. These differences support accounting for country heterogeneity but do not attribute the trajectories to climate or land changes.

We estimate an exploratory baseline regression of the natural logarithm of cereal yield on rainfall deficit, temperature anomaly and annual forest share change, with country and year fixed effects. Rainfall deficit is expressed as the percentage below its reference, temperature anomaly in degrees Celsius, and forest change in percentage points. Country clustered standard errors use the CR1 correction, with confidence intervals and conventional probability values based on four degrees of freedom. Cameron and Miller in 2015 explain why clustered observations require dependence aware inference and why a small number of clusters limits precision.

Table 2: Baseline associations with logarithmic cereal yield

Predictor	Coefficient	Clustered Standard Error	95% Confidence Interval	Conventional Probability Value	Wild Bootstrap Probability Value
Rainfall deficit	−0.005586	0.004648	−0.018491 to 0.007319	0.2957	0.3750
Temperature anomaly	0.016433	0.075533	−0.193279 to 0.226145	0.8384	0.8125
Forest land share change	−0.401683	0.315741	−1.278321 to 0.474954	0.2722	0.0625

The rainfall coefficient has the direction anticipated by H1, but its uncertainty prevents a reliable directional conclusion. A ten-percentage point increase in rainfall deficit is associated with 5.43 percent lower cereal yield. The corresponding confidence interval extends from 16.88 percent lower to 7.59 percent higher yield. Rowhani and colleagues in 2011 demonstrated that rainfall variability can influence cereal yields beyond changes in climatic means.

The temperature coefficient is positive, contrary to the negative association anticipated by H2 under thermal and moisture constraints. A temperature anomaly increase of 0.5 degrees Celsius is associated with 0.83 percent higher yield, with a confidence interval ranging from 9.21 percent lower to 11.97 percent higher yield. The estimate accommodates substantial adverse and beneficial associations. Lobell, Bänziger and colleagues in 2011 identified nonlinear heat effects using African maize trials, whereas the available annual temperature measure does not identify exposure above crop specific heat thresholds.

The positive point estimate does not establish a productivity benefit from warming. Challinor and colleagues in 2014 showed that agricultural responses depend on crop conditions and adaptation. The national cereal aggregate and annual temperature anomaly cannot distinguish these mechanisms within the available sample.

The forest coefficient also opposes the direction anticipated by H3. Because positive forest share change denotes expansion, the hypothesis implies a positive coefficient. Instead, an increase of 0.1 percentage points in forest share is associated with 3.94 percent lower yield, with a confidence interval extending from 12.00 percent lower to 4.86 percent higher yield. Lawrence and Vandecar in 2015 identified climatic mechanisms through which tropical deforestation can affect agriculture. The present national land measure does not locate forest changes relative to cereal production areas and cannot isolate those mechanisms. H3 therefore remains unresolved rather than reliably contradicted.

The inference procedures reinforce the need for caution. The wild bootstrap probability values exceed 0.05 for all three predictors. With five clusters, the 32 symmetric sign configurations produce coarse probability values, with a minimum attainable two-sided value of 0.0625 under this implementation. Full enumeration removes simulation randomness but does not establish finite sample validity. MacKinnon and Webb in 2017 demonstrated that wild bootstrap performance depends on cluster structure and the information supporting individual coefficients.

Table 3 assesses sensitivity to outcome scale, rainfall construction, additional land measures and temporal differencing. The level outcome model retains the baseline coefficient directions. Replacing rainfall deficit with the signed rainfall anomaly changes the temperature coefficient’s direction. Adding agricultural and arable land changes also reverses the rainfall and temperature coefficients. First differencing reverses the rainfall and forest coefficients.

Table 3: Specification sensitivity

Specification	Observations	Rainfall Coefficient	Temperature Coefficient	Forest Change Coefficient
Baseline logarithmic yield	50	−0.005586	0.016433	−0.401683
Yield in kilograms per hectare	50	−9.866608	34.696132	−676.564502
Logarithmic yield with signed rainfall anomaly	50	0.001279	−0.010776	−0.462370
Logarithmic yield with additional land changes	50	0.001642	−0.183542	−0.328134
First differences of logarithmic yield and predictors	45	0.003198	−0.088289	0.012401

The expanded land specification produces an exploratory positive association between arable share change and logarithmic yield. Its coefficient is 0.161773, with a conventional confidence interval from 0.086526 to 0.237020 and a conventional probability value of 0.0040. However, its wild bootstrap probability value is 0.1250.

The difference between inference procedures prevents treating this association as established evidence. Agricultural share change has a coefficient of −0.038180 and a conventional probability value of 0.3581. These measures cannot distinguish land conversion from changes in management intensity. Mueller and colleagues in 2012 identified nutrient and water management as important determinants of yield gaps, which remain unmeasured here.

Country omission checks further reveal dependence on sample composition. Across five regressions that each exclude one country, the rainfall coefficient remains negative but ranges from −0.010180 to −0.000438. The temperature coefficient ranges from −0.058991 to 0.077968, while the forest coefficient ranges from −1.017305 to −0.269602. Each regression contains 40 observations and four country clusters. These results show greater directional stability for rainfall than for temperature, but substantial variation in magnitude.

Multicollinearity among the three baseline predictors does not explain the full instability. After removing country and year effects, their variance inflation factors are 1.94 for rainfall deficit, 1.87 for temperature anomaly and 1.06 for forest change. However, the remaining standard deviation of forest share change is only 0.086 percentage points. Limited identifying variation therefore remains consequential even when predictor overlap is modest.

The estimates provide no reliable support for H1, H2 or H3 at the 5 percent level. Rainfall deficits have the expected baseline direction, but uncertainty and specification sensitivity prevent a firm conclusion. Temperature and forest associations are particularly unstable across alternative models. The evidence supports a cautious assessment of agricultural exposure, while the spatial mismatch and absence of matched insurance payouts and insured losses prevent conclusions about parametric insurance basis risk.

6. Discussion:

An environmental indicator can appear economically relevant while providing insufficient evidence for an insurance decision. The baseline associations in Table 2, estimated through Equation 5, illustrate this distinction. Rainfall deficits have the expected negative coefficient, while temperature anomalies and forest share changes have directions inconsistent with their hypotheses. However, their confidence intervals accommodate opposing relationships, leaving all three hypotheses unresolved. The distinctive contribution of this analysis is the joint demonstration of coefficient instability and benchmark sensitivity within the assembled panel. These findings qualify the assumption that accessible climate and land indicators necessarily provide stable measures of agricultural exposure. Jensen and colleagues in 2016 show that insurance quality requires evaluating the risk remaining after coverage. Accordingly, the present productivity coefficients cannot establish the correlation between contractual payouts and insured losses or validate an insurance trigger.

The specification sensitivity results in Table 3 reveal that the apparent climate relationship depends on how land allocation enters the model. Introducing agricultural and arable share changes reverses the rainfall and temperature coefficients. This establishes sensitivity to conditioning variables, but it does not establish partial or full mediation. Equation 5 contains no separately identified mediator equation, and the analysis does not estimate an indirect effect. Imai and colleagues in 2010 explain that causal mediation requires defined pathways and identification assumptions beyond coefficient changes across regressions. The findings therefore sharpen the distinction between a plausible transmission mechanism and an empirically identified pathway. Resource allocation, crop composition and environmental regulation remain competing explanations for the reversals. The theoretical implication is that climate exposure cannot be interpreted independently of the production structure represented in the specification, although the direction of transmission remains unresolved.

The results also prevent assigning dominance to any proposed channel. The larger absolute forest coefficient in Table 2 cannot be interpreted as a larger contribution to productivity because forest change, rainfall deficit and temperature anomaly use different scales. Schielzeth in 2010 demonstrates why coefficient interpretation depends on predictor scaling. Moreover, the forest coefficient changes direction when Equation 6 replaces levels with annual differences, while little forest variation remains after removing country and year effects. No estimated decomposition separates direct and indirect effects, so proportions of a total effect cannot be calculated. Vander Weele in 2016 explains the additional assumptions required for such interpretations. These findings place an empirical boundary on the resource constraint framework: the proposed environmental channels remain plausible, but their relative contributions are not identified by these aggregate measurements.

The clearest structural insight concerns the distinction between historical benchmark crossing and deterioration within the observation window. The descriptive statistics in Table 1 and the construction in Equation 4 classify Rwanda as having no yield shortfall throughout the sample, despite an approximately 27 percent decline between its first and final observations. Thus, complete data and internally correct arithmetic can coexist with a measure that misses a relevant form of deterioration. If such a reference were adopted in contract design, its ability to represent losses would require separate validation. Elabed and colleagues in 2013 examine spatial risk matching through multiscale index insurance. The present evidence adds a complementary design concern: spatial alignment

and reference selection address different dimensions of measurement. Improving geographical resolution alone would not resolve a benchmark that records historical threshold crossings while overlooking subsequent productivity decline.

International comparisons reinforce the importance of matching the exposure definition to the production process. Schauberger and colleagues in 2017 identify adverse responses to high temperatures in US maize and soybean production, with weaker responses under irrigation. The uncertain annual temperature coefficient in Table 2 does not overturn that evidence because Equation 1 averages exposure across months and combines it with national cereal outcomes. The comparison changes the interpretation of apparent geographical disagreement: differences in aggregation and crop conditions must be assessed before attributing coefficient differences to institutional or adaptive capacity. The instability in Table 3 therefore supports a practical requirement for insurers and public agencies to validate locally aligned exposure measures before using these estimates to calibrate triggers or premiums. Future research should combine crop calendars, production area weather, management information and matched payout and loss records. Such data would permit testing whether benchmark choice and spatial aggregation explain variation in protection across settings.

7. **Conclusion and Implications:**

Agricultural deterioration can remain invisible when an indicator answers a different question from the one decision makers need to resolve. This analysis examined the stability of climate and land associations with cereal productivity across five East African countries. The baseline relationships remain unresolved, while alternative specifications change several estimated directions. The contribution is therefore evidence of measurement sensitivity within the available panel, rather than evidence of insurance effectiveness or identified causal mechanisms. Most consequentially, productivity can decline during the observation window while remaining above an earlier reference average. Historical shortfall measures can thus overlook deterioration relevant to agricultural monitoring. This distinction complements research showing that insurance quality depends on the relationship between insured outcomes and contract indices, rather than index availability alone (Carter et al., 2017; Jensen et al., 2016). Insurers and public agencies should evaluate benchmark responsiveness, geographical exposure matching and contract performance separately. Agricultural monitoring should distinguish departures from historical averages from deterioration within the current production period. These are different signals with different operational implications. Consistent with the exposure concerns identified by Auffhammer et al. (2013), the evidence supports improving measurement before translating aggregate associations into protection decisions. Better alignment can strengthen the information used to investigate vulnerability without implying that the available estimates establish compensation needs.

The analysis includes five countries and ten annual observations per country, limiting precision and inference with few independent clusters. One weather location per country cannot represent national agricultural exposure, while national cereal yields combine crops, locations and management conditions. Panel methods do not eliminate these measurement limitations or omitted changes in agricultural conditions (Blanc & Schlenker, 2017; Hsiang, 2016). Future research should combine geographically matched production and weather observations with insurance contracts, losses and payments.

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