

Climate and Vegetation Indicators, Maize Yield, and Basis Risk In Index Insurance Evidence from Three Zambian Provinces, 2000–2023

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Abstract

This thesis examines whether annual climate and vegetation indicators provide stable information about province-level maize yield and whether the same indicators can support credible triggers for index-based insurance in three Zambian provinces. The analysis uses 66 complete province-year observations for Lusaka, Northern, and North-Western provinces over 2000–2019 and 2022–2023. Pooled ordinary least squares is compared with province fixed effects, year fixed effects, two-way fixed effects, and a province-fixed-effects specification with a linear time trend; inference is assessed using HC1 robust standard errors and Driscoll–Kraay sensitivity estimates. Basis risk is evaluated with complete confusion matrices under pooled-mean, province-mean, and province-specific quantile thresholds. The rainfall–yield correlation is modest ($r = 0.174$). Rainfall is positive in pooled OLS, but its coefficient is not significant at the 5% level under either HC1 or Driscoll–Kraay inference. NDVI is negative in pooled and province-fixed-effects models, but this association disappears after common time structure is controlled. No environmental coefficient remains stable across the main specifications. Trigger performance is more consistent: rainfall produces lower mismatch and false-negative rates than annual province-wide NDVI under every threshold family examined. Simple AND and OR combinations do not uniformly improve performance; they redistribute basis risk between missed losses and false payouts. These results separate two empirical questions that are often conflated—whether an indicator is associated with yield and whether it is useful as a payout trigger—and highlight the importance of measurement scale, temporal alignment, and explicit error costs in agricultural risk management.

Keywords

Zambia; Maize Yield; NDVI; Rainfall; Panel Data; Index-Based Insurance; Basis Risk

1. Introduction

In Zambia's rain-fed maize systems, crop risk depends on rainfall timing as well as totals. Prior studies emphasize seasonal variability, location, and management, making Zambia useful for testing coarse environmental indicators under data constraints (Stern & Cooper, 2011; Mulenga et al., 2017; Siatwiinda et al., 2021).

Index insurance replaces farm-level loss assessment with an observable trigger, reducing verification costs but creating basis risk when payouts diverge from losses (Clarke, 2016; Jensen et al., 2016; Carter et al., 2017). Zambia is relevant because remotely sensed rainfall has already been studied for weather-index insurance (Black et al., 2016).

Rainfall is an environmental input; NDVI is a vegetation response. Because NDVI is most informative when aligned with crop areas, phenology, and spatial resolution, annual province-wide NDVI is treated cautiously (Mkhabela et al., 2005; Chivasa et al., 2017; Benami et al., 2021).

Regression fit and insurance performance answer different questions. The analysis therefore tests coefficient stability across panel specifications and, separately, whether transparent triggers reproduce observed loss classifications.

The thesis asks how annual rainfall, NDVI, and temperature relate to maize yield in Lusaka, Northern, and North-Western, and how rainfall- and NDVI-based triggers differ in basis risk. Both questions use the same 66 complete province-year observations, panel regressions, and confusion matrices.

The contribution is methodological rather than causal: it links measurement alignment, specification sensitivity, and trigger validation in a very small panel. The annual indicators are not structural yield determinants and the thresholds are not finalized contracts.

Section 2 reviews the literature; Section 3 presents data and methods; Sections 4-5 report regression and basis-risk results; Section 6 discusses limitations; Section 7 concludes.

2. Literature Review and Analytical Framework

2.1. Climate Variability and Maize Production

Rainfall risk depends on timing as well as totals. Zambia studies emphasize within-season variation and local context, so annual rainfall is treated as a coarse exposure (Stern & Cooper, 2011; Mulenga et al., 2017).

Climate effects also interact with management. Because fertilizer, seed, irrigation, soil, pests, and management are unobserved, annual climate coefficients may absorb omitted agronomic and temporal processes (Siatwiinda et al., 2021).

Annual province averages compress crop-stage and local variation. Coefficients are therefore reduced-form associations, while province and time effects test whether pooled patterns survive basic controls.

2.2. NDVI and Crop Monitoring

NDVI tracks greenness, but its yield meaning depends on crop-cycle alignment. Evidence shows NDVI-yield relationships vary by agro-ecology and seasonal window (Mkhabela et al., 2005; Panek & Gozdowski, 2020).

Spatial alignment also matters. Crop mapping, resolution, validation, and crop masks are important, so province-wide annual NDVI necessarily includes non-crop and off-season vegetation (Chivasa et al., 2017; Benami et al., 2021).

This aggregation can weaken or reverse a yield association without making NDVI intrinsically uninformative; the issue is whether this construction is aligned with maize production.

2.3. Rainfall, NDVI, and Information Content

Rainfall is an input and NDVI a downstream vegetation response. Their relationship varies with rainy-season structure and aggregation, so they are distinct candidate signals (Martiny et al., 2006).

For insurance, local validation and scale matter more than simple correlation; satellite measures must be checked against the loss outcome they are intended to represent (Masiza et al., 2022).

2.4. Index-based agricultural insurance and basis risk

Index insurance reduces loss-verification costs but creates basis risk that affects protection, product value, and demand (Clarke, 2016; Jensen et al., 2016; Carter et al., 2017; Clement et al., 2018).

Basis risk is a contract-design problem. Multiscale and remote-sensing approaches can help, but gains depend on measurement and calibration; Zambia evidence likewise stresses uncertainty and aggregation (Elabed et al., 2013; Black et al., 2016).

Basis risk can reflect spatial or temporal mismatch, measurement error, or trigger design. False negatives leave losses unpaid; false positives pay in non-loss states, so both are reported separately.

2.5. Analytical synthesis, research gap, and expectations

The research gap is the separation of two tasks often conflated in small-data studies: stable indicator-yield association and useful insurance triggering.

Annual climate coefficients are expected to be sensitive to province and time controls, and neither rainfall nor NDVI is assumed to eliminate basis risk. Relative trigger performance must persist across thresholds.

3. Data and Methodology

3.1. Study sample and unit of observation

The unit is the province-year. Lusaka, Northern, and North-Western have environmental data for 2000-2023; missing maize yield in 2020-2021 leaves 66 observations across 22 usable years. Inference is restricted to these provinces because the original selection rule is undocumented.

The three provinces are not treated as nationally representative; without a documented selection rationale and boundary comparability, inference cannot be extended beyond them.

3.2. Variables and data construction

Yield is in tonnes per hectare, but its exact source is unresolved. NDVI is described as MODIS via Climate Engine without a recoverable product rule. Rainfall is attributed to NASA POWER, but its parameter and unit are undocumented; 1.49-4.91 is not an annual millimetre total. Temperature is an annual mean in °C.

Public documentation confirms the stated source families—NASA POWER, Climate Engine/MODIS, and Zambia Statistics Agency materials—but not the exact analytical series.

Because the original POWER query, Climate Engine settings, and yield file are unavailable, supplied values are retained without unsupported units or constructions, and interpretation is restricted accordingly.

Annual matching gives a common frequency but weak agronomic alignment: NDVI includes non-maize/off-season vegetation and rainfall averages across crop stages. Stronger work should reconstruct growing-season rainfall and maize-masked seasonal NDVI.

Table 3.1. Variable definitions and measurement status

Variable	Working definition	Unit / scale	Main limitation
Yield	Provincial maize yield	tonnes/ha	Exact provider/construction unresolved; mixed numerical precision by year
NDVI	Annual mean provincial vegetation index	index, -1 to 1	Exact MODIS product/compositing not documented; no crop mask
Rainfall	NASA POWER-derived rainfall indicator	source scale; exact unit unverified	1.49–4.91 cannot be annual mm total; exact parameter/export required
Temperature	Annual mean temperature	°C	Exact POWER parameter/aggregation should be documented

Note: Four provenance items cannot be verified from the dataset documentation: the exact rainfall parameter/unit, the yield source/construction, the NDVI product/aggregation procedure, and the three-province selection rationale.

3.3. Descriptive and correlation analysis

Descriptive statistics use the 66 complete observations. Correlations are preliminary because shared spatial or temporal patterns can differ from within-province relationships.

3.4. Regression strategy

The baseline specification is a pooled association model:

$$Yield_{it} = \beta_0 + \beta_1 NDVI_{it} + \beta_2 Rainfall_{it} + \beta_3 Temperature_{it} + \varepsilon_{it}. \quad (1)$$

where i indexes province and t year. Pooled OLS is a benchmark; province fixed effects, year fixed effects, and a two-way fixed-effects model test sensitivity to panel structure:

$$Yield_{it} = \beta_1 NDVI_{it} + \beta_2 Rainfall_{it} + \beta_3 Temperature_{it} + \mu_i + \tau_t + \varepsilon_{it}. \quad (2)$$

HC1 robust standard errors are primary. With only three provinces, conventional province clustering is avoided; Driscoll-Kraay with two lags is a sensitivity check, and province fixed effects with a linear trend provide a parsimonious time-control alternative.

The coefficients are interpreted as associations, not causal effects. The purpose of the specification sequence is therefore to test whether the pooled environmental relationships remain qualitatively similar after basic panel structure is introduced.

Province effects remove fixed provincial differences, year effects common shocks, and two-way effects both. Given only three provinces and 22 years, models are compared for qualitative stability rather than treated as definitive estimates.

3.5. Basis-risk evaluation

Basis-risk analysis uses the same 66 observations. A baseline loss is yield below the pooled mean; cutoffs are transparent comparison rules rather than actuarially optimal thresholds.

Triggers are evaluated by TP, TN, FP, and FN. False negatives are missed classified losses and false positives are payouts in non-loss states; AND/OR rules only illustrate how combining rainfall and NDVI redistributes these errors.

Performance is compared across pooled means, province means, and province-specific 30th- and 20th-percentile thresholds. Without welfare weights or pricing, no optimal cutoff is claimed; mismatch and both error rates are considered jointly.

3.6. Diagnostics and sensitivity design

Diagnostics are limited to VIFs, pooled heteroskedasticity tests, Cook's distance, residual persistence over consecutive years, and province-specific/leave-one-out regressions. Unit-root tests are not emphasized with only 22 observations per province and a two-year gap.

3.7 Methodological limitations

The design is limited by three provinces and 66 observations, annual rather than crop-season exposure, incomplete provenance and province selection, omitted

agronomic controls, and the tiny cross-section. Fixed effects and robust covariance are therefore sensitivity tools, not causal identification.

4. Empirical Results

4.1. Descriptive statistics

Table 4.1. Descriptive statistics ($N = 66$)

Variable	Mean	Std. dev.	Min	Max
Yield	2.154	0.603	1.000	3.340
NDVI	0.384	0.097	0.215	0.543
Rainfall indicator	2.748	0.707	1.490	4.910
Temperature	21.504	0.955	19.250	23.390

Note: Statistics are calculated from the 66 complete province-year observations used in the regression models. Across the 66 complete observations, mean maize yield is 2.154 tonnes per hectare, mean NDVI is 0.384, and the rainfall indicator averages 2.748 on its source scale. The descriptive statistics also reinforce the unresolved rainfall-unit issue: values between 1.49 and 4.91 cannot plausibly represent annual precipitation totals in millimetres.

4.2. Correlation structure

Table 4.2. Pearson correlation matrix

Variable	Yield	NDVI	Rainfall	Temperature
Yield	1.000	-0.266	0.174	-0.222
NDVI	-0.266	1.000	0.438	-0.054
Rainfall	0.174	0.438	1.000	-0.522
Temperature	-0.222	-0.054	-0.522	1.000

Note: Correlations are calculated directly from the 66 complete observations; pairwise deletion is not used.

NDVI is moderately negatively correlated with yield ($r=-0.266$), rainfall modestly positively ($r=0.174$), and rainfall negatively with temperature ($r=-0.522$). These pooled correlations do not show whether relationships persist within provinces after common year patterns are removed.

4.3. Panel regression results

In pooled OLS, NDVI is negative ($\beta=-2.533$; HC1 $p=.003$; Driscoll-Kraay $p=.017$). Rainfall is positive but less precise ($\beta=0.264$; HC1 $p=.076$; DK $p=.091$), while temperature is weak. These are benchmark estimates.

Table 4.3. Panel regression estimates

Variable	Pooled OLS	Province FE	Year FE	Two-way FE
NDVI	-2.533 (0.824), $p=.003$	-4.515 (1.652), $p=.008$	-0.908 (0.825), $p=.278$	-0.064 (2.004), $p=.975$
Rainfall	0.264 (0.146), $p=.076$	0.127 (0.188), $p=.503$	-0.028 (0.138), $p=.841$	-0.182 (0.163), $p=.270$
Temperature	-0.052 (0.102), $p=.608$	-0.217 (0.204), $p=.293$	-0.138 (0.060), $p=.026$	-0.488 (0.202), $p=.021$
R^2	0.180	0.203	0.715	0.744
Adjusted R^2	0.140	0.137	0.549	0.573
N	66	66	66	66

Note: Coefficients are followed by HC1 robust standard errors in parentheses; province and year dummy coefficients are omitted. Driscoll–Kraay estimates are reported as a sensitivity check in the text. High R^2 in year-FE models partly reflects the large set of year indicators and is not an out-of-sample performance measure.

After spatial or temporal controls, pooled relationships weaken. Province effects retain negative NDVI but weak rainfall and temperature; year and two-way effects also weaken NDVI and rainfall. No environmental coefficient is stably significant across main time controls and covariance estimators.

A province-FE model with a linear trend gives the same message: NDVI and rainfall are imprecise and temperature only marginal. Time controls therefore suggest that common temporal movement explains an important part of the pooled relationships.

Across specifications, coefficient instability is the most consistent finding. Rainfall loses precision and can change sign after time controls, the pooled negative NDVI association disappears, and temperature's year-effect result weakens under Driscoll–Kraay inference. The annual provincial indicators contain information, but its sign and precision depend materially on how common time variation is handled.

4.4. Province heterogeneity and sensitivity

Province-specific regressions based on 22 observations each show substantial heterogeneity. Lusaka has almost no explanatory power ($R^2 \approx .008$); Northern has $R^2 \approx .317$ with a positive rainfall association; and North-Western has $R^2 \approx .466$ with a strong negative NDVI association. These contrasts argue against reading the pooled coefficient as a national response function.

Leave-one-province-out estimates are also sensitive. Excluding Lusaka makes the pooled rainfall coefficient more precise, whereas excluding Northern or North-Western leaves it weak. The present sample cannot distinguish whether these differences reflect agro-ecology, crop calendars, land cover, data quality, or omitted management, but they show that the same annual indicator behaves differently across provinces.

4.5. Empirical diagnostics

The diagnostics show no severe multicollinearity or strong evidence of pooled heteroskedasticity, but they do indicate serial persistence in parts of the panel and

sensitivity to influential observations. These features support the use of robust inference and caution against placing too much weight on individual p-values.

Table 4.4. Regression diagnostics

Diagnostic	Result	Interpretation
VIF	NDVI 1.31; rainfall 1.79; temperature 1.45	No severe multicollinearity
Breusch-Pagan	$p = .676$	No strong pooled heteroskedasticity evidence
White test	$p = .365$	No strong pooled heteroskedasticity evidence
Province-FE residual persistence	North-Western $\approx .56$; Northern $\approx .78$	Serial dependence may remain in two provinces
Cook's D > 4/N	Lusaka 2005, Lusaka 2008, Northern 2011, Lusaka 2023	Source records should be checked; do not delete automatically
Random effects	Not retained	Only three groups; singular/boundary variance component

5. Basis Risk and Index Design

5.1. Threshold sensitivity

Rainfall's relative advantage persists under province-specific means and province-specific 30th- and 20th-percentile thresholds: it has lower mismatch and lower false-negative rates than annual NDVI in every threshold family tested. This indicates better trigger alignment within the observed sample, not an actuarially optimal or fully calibrated insurance index.

A fuller insurance design would use crop-season indicators, a documented loss benchmark, and an explicit loss function. Weighted or probabilistic combinations could then be tested against a rainfall-only benchmark, but added complexity should be retained only if validation shows a better protection-cost trade-off.

5.2. Hybrid-rule trade-offs

The hybrid rules do not consistently improve on rainfall alone. At the province-specific 20th percentile, for example, the AND rule matches rainfall on overall mismatch but misses about 87% of classified loss events. Simple hybrids therefore shift basis risk between farmer-side and insurer-side errors rather than eliminate it.

Table 5.1. Threshold sensitivity for NDVI and rainfall triggers

Threshold family	NDVI mismatch	Rainfall mismatch	NDVI FNR	Rainfall FNR
Global mean	.545	.409	.710	.419
Province mean	.682	.394	.563	.344
Province 30th percentile	.455	.303	.714	.476
Province 20th percentile	.364	.212	.800	.467

Table 5.2. Baseline pooled-mean confusion-matrix results

Trigger rule	TP	TN	FP	FN	Accuracy	FNR	FPR
NDVI	9	21	14	22	0.455	0.710	0.400
Rainfall	18	21	14	13	0.591	0.419	0.400
Hybrid AND	8	24	11	23	0.485	0.742	0.314
Hybrid OR	19	18	17	12	0.561	0.387	0.486

Regression and trigger analyses answer different questions. Panel models test whether indicators have stable yield associations after spatial and temporal controls; threshold rules test whether an indicator coincides with a defined loss state. Here the former mainly shows specification sensitivity, while the latter shows a more consistent relative advantage for rainfall over annual NDVI.

Under the pooled-mean rule, rainfall achieves higher accuracy and misses fewer classified loss observations than NDVI. NDVI fails to trigger for about 71% of yield-loss observations, compared with about 42% for rainfall, while both rules have a 40% false-positive rate under this cutoff.

This better classification performance does not validate a causal rainfall–yield model. The narrower conclusion is that, under the current data and loss definitions, rainfall thresholds align more closely with classified low-yield states than annual province-wide NDVI thresholds do.

5.3. Implications for index construction

The insurance-design implication is methodological: a payout rule should not be chosen because its indicator is significant in one yield regression. Trigger quality depends on alignment with the loss definition, spatial and temporal representativeness, and the relative costs of missed losses and false payouts.

A stronger analysis would compare multiple thresholds, report sensitivity and specificity with mismatch, and repeat the rules using crop-season measures. Weighted or probabilistic indices could then be judged against simple rainfall by whether they improve the false-negative/false-positive trade-off.

6. Discussion

6.1. What the panel models do—and do not—show

The panel estimates do not support a stable climate coefficient: NDVI and rainfall

weaken under year effects and the linear trend. The main empirical result is therefore specification sensitivity rather than dominance of any environmental variable.

That sensitivity is plausible in a three-province annual panel with unobserved changes in technology, inputs, markets, and policy. The time controls are diagnostic, not causal; coefficients that change sign or precision under them should be interpreted cautiously.

Spatial diagnostics point the same way. Province-specific and leave-one-province-out estimates vary, and some observations are influential. The current data cannot separate agro-ecological heterogeneity, measurement error, land-cover differences, or omitted management, so the pooled coefficient is an average for the observed province-years rather than a national response function.

For insurance, association and decision usefulness are distinct. A statistically precise yield coefficient is neither necessary nor sufficient for a good payout trigger, so basis-risk results complement rather than duplicate the regression analysis.

6.2. Measurement Alignment: Scale, Season, and Crop Specificity

The NDVI result is best read as a measurement-alignment problem. Successful yield studies align NDVI with crop areas and crop-relevant seasonal windows (Mkhabela et al., 2005; Panek & Gozdowski, 2020; Chivasa et al., 2017; Benami et al., 2021). The annual province-wide measure used here lacks that alignment, so its negative or unstable coefficient is not an agronomic effect.

Rainfall has a related alignment problem because annual province averages can hide onset, dry spells, and stage-specific stress. Its stronger classification performance is therefore a relative result within these data, not proof that the current rainfall construction is already an appropriate insurance index.

Four alignment dimensions matter: variable definition, spatial support, temporal window, and connection to the target outcome. Rainfall lacks a stable structural yield coefficient but classifies low-yield states better than current NDVI; stronger claims require crop- and season-aligned reconstruction of both.

6.3. Basis Risk, Product Quality, and Trigger Choice

Trigger results are more stable than regression coefficients, but they show relative performance rather than product adequacy. Confusion matrices are useful because they separate missed losses from false payouts.

Simple AND/OR hybrids do not automatically improve the contract: AND reduces false payouts but can miss losses, while OR improves recall at the cost of more non-loss payouts. They are sensitivity exercises, not optimal contract designs.

For Zambia, rainfall's better loss classification supports its use as a benchmark, not as a finished product. Crop-season calibration, local validation, and an explicit loss function remain necessary before product use.

The thesis therefore separates two validation layers: stability of the indicator-yield relationship and alignment of a payout rule with intended loss states. This prevents a regression coefficient from being treated directly as a product recommendation. A rainfall-only rule is the natural benchmark because it is interpretable and outperforms annual NDVI here. Additional remote-sensing information should be retained only if it improves out-of-sample protection without an unacceptable rise in false payouts; payout functions should reflect explicit error costs, not in-sample accuracy alone.

6.4. Scope, limitations, and next empirical steps

The conclusions are bounded by four data limitations: three provinces and 66 observations; annual, non-crop-masked indicators; missing agronomic controls; and unresolved provenance for rainfall, yield, NDVI construction, and province selection. These are limitations of the evidence base, not presentation issues.

The next priority is better alignment: reconstruct growing-season rainfall, calculate NDVI over maize areas and relevant phenological windows, trace yield provenance, and expand or justify the geographic sample. More flexible triggers should follow only after these measurement issues are addressed.

7. Conclusion

Annual rainfall, NDVI, and temperature do not provide stable maize-yield coefficients across the specifications examined. Rainfall is modestly positively correlated with yield, NDVI is negative in pooled OLS, and temperature becomes more negative under year controls, but these patterns change with time structure and inference. None supports a structural or causal interpretation.

Rainfall performs more consistently as an insurance trigger: it has lower mismatch and fewer missed losses than annual province-wide NDVI across all tested thresholds. Neither measure is a finalized payout rule, and simple hybrids mainly redistribute false-negative and false-positive risk. Yield association and trigger suitability therefore require separate validation.

The contribution is disciplined validation. Small agricultural panels require attention to spatial scale, crop-season alignment, specification sensitivity, and trigger errors. Better provenance, maize-specific NDVI, and broader or justified geographic coverage would make the framework more credible for Zambian crop-risk and index-insurance analysis.

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