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Impact-Based Forecasting Prototype for Agriculture in Machakos and Makueni Counties, Kenya

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Abstract

Recent advances in weather and climate forecasting have improved the ability of early warning systems (EWSs) to deliver tailored, accurate, and timely warnings. Effective EWSs must communicate not only the occurrence of hazards but also their implications for people, livelihoods, and sectors. Impact information is often too general or insufficient, and adapting impact-based forecasting (IBF) to specific sectors in rural communities remains a significant challenge. Rural communities are particularly vulnerable to extreme weather, as agricultural outcomes are closely linked to seasonal variability. This study presents an IBF prototype for beans in subsistence farming communities, integrating impact estimation with a crop yield model that incorporates weather, farm management, and socio-economic data to determine sub-county impact risk levels and yield changes in Machakos and Makueni. Yield data is obtained from the Ministry of Agriculture in Kenya, and stakeholder engagements provide feedback on the model's performance. The prototype delivers sector-specific information for agricultural stakeholders, including hazard data, the proportion of cropland exposed to extreme drought or rainfall, potential yield impacts, priority areas for anticipatory action, and population exposure. Analysis of October-December 2025 forecast data indicates that precise sub-county impact information can improve agricultural risk management and decision-making.

1.0 Introduction

Traditional weather and climate forecasts have emphasized on meteorological variables such as rainfall, temperature, and wind speed, often without explicitly linking these hazards to their potential consequences for livelihoods and socio-economic systems[1]. Climate services aim to address this limitation by translating forecast information into formats that facilitate decision-making[2]. However, many initiatives do not quantify hazard implications for specific sectors or populations. Impact-based forecasting (IBF) addresses this gap by integrating forecast data with vulnerability and exposure information to estimate potential impacts and support anticipatory action[1,3]. This approach is particularly valuable in contexts where livelihoods are directly exposed to climate variability, such as the rainfed smallholder farming systems prevalent in semi-arid East Africa, where nearly 60% of the population depends on rainfed agriculture [3]. Climate variability influences both short-term farm management decisions and seasonal choices, such as crop selection and planting dates[4]. In these settings, seasonal rainfall anomalies rapidly translate into yield losses, yet forecast products rarely communicate risk in terms relevant to farmers and county agricultural officers, such as expected yield, planting date viability, or crop loss. Kenya's semi-arid lands exemplify this gap: agriculture is almost entirely rainfed, seasonal rainfall is highly variable, and existing advisories remain predominantly hazard-based.

An IBF system uses climatological and seasonal forecast data to assess hazard likelihood, agricultural yield data to estimate potential impacts, and socio-economic data to evaluate exposure and vulnerability. Collectively, these inputs generate sector-specific risk information that enables decision-makers to act

prior to an event [5]. Agricultural IBF extends conventional forecasting by integrating weather information with farming calendars, crop sensitivity, market dynamics, and socio-economic vulnerability to produce targeted advisories. These advisories can guide planting, harvesting, insurance activation, and climate-smart interventions[6]. In semiarid regions such as Machakos and Makueni Counties in Kenya, where bimodal rainfall is highly variable and where recurrent droughts threaten smallholder livelihoods, impact-oriented forecasts are particularly valuable for enhancing resilience [7]. However, implementation remains constrained by the limited availability of localized vulnerability datasets and by rapidly evolving farming systems, including shifting cropping patterns and land-use changes[8,9]. Participatory approaches that engage farmers and extension officers in coproducing forecast products have demonstrated considerable potential to address these constraints and improve uptake [5].

Recent advances in machine learning have increased the opportunities for agricultural IBF. Tree ensemble methods, such as XGBoost, random forest, and gradient boosting, have demonstrated robust predictive performance for early warning of drought, yield forecasting, vegetation health assessment, and crop failure classification[10]. However, the dynamic nature of farming systems and structural heterogeneity across sub-counties indicate that predictive accuracy alone is insufficient for operational IBF. This heterogeneity extends beyond agroclimatic factors: sub-counties systematically differ in poverty incidence, the proportion of female-headed households, education levels, credit access, and market proximity. Consequently, an identical rainfall deficit may produce varying yield outcomes and distinct welfare consequences. Effective targeting of anticipatory action therefore requires understanding both the mechanisms through which, and the populations for whom, weather shocks translate into yield loss.

While tree-based models capture nonlinear relationships and process heterogeneous datasets, they offer limited interpretability of individual coefficient estimates and do not distinguish between within-unit and between-unit variation. Differentiating these sources of variation is essential for understanding the effects of weather shocks across structurally diverse sub-counties [11,12]. This distinction is particularly important for socio-economic indicators, which change slowly at the sub-county level and are absorbed by unit intercepts in conventional fixed-effects models, even though their cross-sectional variation is key to identifying structurally disadvantaged populations. The Mundlak correlated random effects specification addresses this by jointly estimating the within-sub-county weather response and the structural yield advantage associated with baseline agroclimatic and socio-economic conditions[13]. Incorporating socio-economic indicators directly into the yield response function departs from the conventional two-stage IBF architecture, where they are included only as a post hoc vulnerability multiplier, and instead makes their contribution to the predicted loss explicit at the coefficient level. This is significant because existing agricultural IBF applications typically conclude with generalized risk classifications, such as regional hazard maps, aggregate yield anomalies, or ordinal severity categories, which indicate that a season is likely to be poor without specifying what actions should be taken, by whom, or when.

In response, this study develops an agricultural IBF framework for Machakos and Makueni Counties, Kenya, focusing on beans. The framework attributes seasonal, managerial, and structural contributions to predicted yield loss at the coefficient level and translates these losses into decision-referenced outputs. We will utilise the October to December (OND) 2025 seasonal forecasts as a case study year to develop a prototype IBF product for the counties in Kenya

2.0 Results

2.1 OND 2025 Weather Forecast and Impacts Outputs

According to the OND 2025 seasonal forecast, rainfall across Machakos and Makueni Counties is expected to range from 300 mm to over 650 mm (Fig. 1a). The standardized precipitation index over three months (SPI-3) was applied to the forecast rainfall data to provide actionable agricultural information. The results indicate that most sub-counties are expected to fall within the near-normal range (SPI-3 between − 0.43 and + 0.84). The northwestern and northeastern areas are forecast to be wetter than average (SPI-3 values of + 1.0 to + 2.0), whereas the central areas are projected to experience mild to localized moderate drought conditions. Minimal or no severe or extreme drought conditions are anticipated in either county during the OND 2025 season (Fig. 1b). This forecast classification allows farmers and extension officers to prioritize anticipatory drought preparedness measures in central areas. This study also supports the implementation of suitable water management and drainage strategies in wetter northern sub-counties before the onset of the season.

2.2 Cropland exposure and drought categories

The IBF prototype tool provides projections regarding the extent of cropland potentially exposed to various drought categories. For example, according to the OND 2025 seasonal forecast for Machakos and Makueni counties, the tool projected that most cropland will experience near-normal moisture conditions (SPI-3: −0.43 to + 0.84), with over 50% of agricultural land in most sub-counties expected to fall within this range (Fig. 2a). One central subcounty is projected to experience mild dry conditions (SPI-3: −0.44 to − 0.84), potentially affecting 60–80% of the cropland (Fig. 2b). The forecast also indicates that few to no regions will experience moderate, severe, or extremely dry conditions, implying a low probability of widespread drought stress during the season (Fig. 2c, d, e). Additionally, no cropland is expected to be exposed to extremely wet conditions, indicating a minimal risk of flooding. In contrast, 20–40% of agricultural land in northern Machakos is forecast to experience mild wet conditions, which may require anticipatory agronomic interventions such as enhanced drainage or disease management planning. The predominance of near-normal conditions in the forecast suggests a favourable rainfall outlook for rainfed agriculture, with a limited necessity for large-scale prepositioning for drought or flood emergencies during the OND 2025 season.

We conducted pixel-level analysis to quantify the proportion of agricultural land projected to be affected by each SPI-3 hazard class within sub-county boundaries, thereby providing advanced warning of

cropland exposure to drought and wetness at the sub-county level (Fig. 3). This information allows stakeholders to identify areas that require preventative interventions before conditions deteriorate. The forecast indicates substantial heterogeneity in projected hazard exposure among sub-counties in Machakos and Makueni during OND 2025. Near-normal conditions (SPI-3: −0.43 to + 0.84) are expected to predominate in most sub-counties. Kathiani and Kangundo are projected to have 100% cropland under near-normal moisture. Kibwezi West (97%), Kibwezi East (91%), Kilome (70%), Mbooni (72%), and Machakos Town (65%) are also forecast to experience predominantly normal conditions, which is consistent with the spatial patterns. In contrast, Kaiti is projected to have 67% cropland under mild dry conditions, representing the most severe forecasted moisture deficit in the region. Mbooni is expected to face 26% severe dry exposure, and Makueni is expected to face 11% extreme dry exposure, indicating that localized but significant moisture stress necessitates an early drought response.

In the northern sub-counties, the forecast projects significantly wetter-than-normal conditions. Mavoko is expected to have 55% of the cropland with above-normal moisture (21% very wet, 34% moderately wet), Masinga 50% moderately wet, and Yatta 71% above normal (29% very wet, 42% moderately wet). These projections raise anticipatory concerns regarding waterlogging, increased disease pressure, and potential delays in field access. This pixel-level forecast breakdown informs anticipatory action planning. Drought mitigation measures, such as water harvesting and drought-tolerant seed distribution, can be prepositioned for Kaiti, Mbooni, and Makueni. In contrast, drainage and moisture management interventions should be prioritized for Mavoko, Masinga, and Yatta prior to the onset of the season.

The agricultural IBF tool is designed to provide hierarchical summary information on hazard exposure, enabling decision-makers to assess conditions from regional to sub-county levels for effective resource allocation. The prototype system generates automated forecast reports at the regional, county, and sub-county scales, highlighting key drought and flooding risks according to seasonal outlook classifications (Fig. 4). According to the OND 2025 seasonal forecast, a combined total of 682,440 hectares in Machakos and Makueni are projected to experience near-normal conditions, representing more than 70% of agricultural land with generally favourable moisture conditions (Fig. 4a). In contrast, significant moisture deficits are expected in certain areas: approximately 66,634 hectares (6.9%) are forecast as Mildly Dry, 5,078 hectares (0.5%) as Moderately Dry, 743 hectares (0.1%) as Severely Dry, and 124 hectares (< 0.01%) as Extremely Dry (Fig. 4a). These forecast results underscore the necessity for anticipatory interventions tailored to the projected severity and specific locations of deficits within sub-counties.

The forecast summary information extends beyond regional aggregates by providing sub-county-specific breakdowns that facilitate targeted anticipatory action (Fig. 4b). Each sub-county forecast summary details the total cropland area, hectares projected to be exposed to each standardized precipitation index (SPI) class, key drought or wetness thresholds likely to be exceeded, and recommended early actions in accordance with IBF protocols. This approach links recommendations directly to local forecast conditions (Fig. 4b). For wetness, the sub-county forecast summary identifies areas at risk of excess moisture, explains the rationale for anticipatory actions, and presents detailed cropland exposure

projections across the extremely wet, very wet, moderately wet, and mildly wet categories. Recommended anticipatory actions, including enhanced waterlogging monitoring, drainage inspections, strategic fungicide application for moisture-related diseases, and mapping of flood-prone areas, are directly tied to these local forecast exposure thresholds, thereby clarifying the justification for each pre-emptive measure.

2.3 Gender Information Inclusion and Impacts on IBF for Agriculture

The proportion of female-headed farming households (FHH) has a highly significant negative coefficient ($\beta = -0.030$, SE = 0.008, $p < 0.001$), indicating that sub-counties with higher shares of female-headed households consistently experience lower yields after accounting for weather, management, and other socioeconomic variables. Quantitatively, a 10-percentage-point increase in the FHH share, which is roughly equivalent to moving from the 25th percentile of the FHH distribution (Kangundo, ~ 32%) to the median (Mwala, ~ 42%), corresponds to a 3.0% decrease in the predicted yield. This translates to a reduction of approximately 0.04–0.07 t/ha at mean yield levels. The persistence of this association after adjusting for weather and management factors suggests the presence of deep structural constraints on the productivity of female-managed farms, rather than differences attributable solely to seasonal management.

2.4 Yield change and impact forecasts

Spatial analysis of predicted bean yield impacts during the OND 2025 short rains demonstrates substantial heterogeneity across Machakos and Makueni Counties, with no clear north–south gradient (Fig. 5a). Projected yield gains of 40–60% in the northernmost sub-counties underscore the need to maintain optimal moisture levels and pest management practices to achieve these gains. The most significant losses are concentrated in the north-central belt, where one sub-county is projected to experience a 50–60% reduction and adjacent areas fall within the 20–40% loss range, designating this region as a priority for anticipatory action. Central sub-counties display variable performance, with losses up to 20% and isolated areas of gain, indicating the need for flexible, locally tailored interventions. In the southern region, impacts are more moderate: south-central sub-counties remain near neutral (approximately − 10% to + 10%), while the far southern and south-eastern sub-counties are projected to experience losses of 20–30%.

The categorical classification (Fig. 5b) organizes these spatial differences into four distinct classes. Moderate Gain is limited to the far northern sub-counties, which are optimally positioned for production scaling. Slight Gain extends across the adjacent northern margin. Moderate Loss predominates in the north-central belt and also appears in the far south and south-east, identifying two spatially distinct clusters that require focused agricultural support. Slight Loss is characteristic of the intervening south-central sub-counties, where standard advisory support is likely adequate.

Yield change predictions were produced at the sub-county administrative level, matching the spatial resolution of historical yield records and the predictor variables used for model calibration. Consequently, each sub-county polygon is assigned a single uniform value, and intra-sub-county variation in yield response is not captured, reflecting the modifiable areal unit problem in spatial analysis. To prevent overestimation of the spatial extent of impact, both panels are masked to cropland; white areas within county boundaries denote urban centres, rangeland, and other non-cropland. This masking delineates agricultural land in Machakos and Makueni, restricting displayed impacts to cultivated zones and giving stakeholders clear boundaries for targeting insurance, seed distribution, and extension services exclusively to agricultural land.

2.4.1 Stakeholder Engagements to validate and define thresholds

Sub-counties are classified as yield gains or yield losses based on the predicted proportional change in yield relative to their historical mean. The classification thresholds are specific to each subcounty. In Kibwezi East and Kibwezi West, slight losses are 0–30%, and moderate losses are 30–50%. In the Machakos County sub-counties, a narrower slight-loss band of 5–25% reflects lower baseline yield variability. The predictions include subcounty-level prediction intervals from the residual distribution, ensuring that the confidence level is communicated with each classification. Both the category and magnitude of deviation guide the type and urgency of recommended responses, such as deploying drought-tolerant seeds, providing targeted irrigation support, activating crop insurance, or increasing input investment when seasonal outlooks are favourable [6].

2.5 Areas for priority anticipatory actions

The IBF prototype tool assesses the severity of agricultural impacts using a composite scoring system that incorporates affected cropland area, yield change magnitude, and population exposure density (Table 1). Each sub-county is assigned a severity score (0–3 scale) based on the yield change category, and an impact score (0–100 scale) that integrates severity, cropland area, and exposed population. The impact score determines the action-level classification. This section presents two complementary prioritization layers: the first identifies the most affected sub-counties based on severity and impact, and the second translates these scores into recommended anticipatory action levels, specifying the urgency of the required response.

Makueni exhibits the highest composite impact (142,014 ha affected, severity 3, impact score 100.0) and is the only sub-county classified as "Extreme – Immediate Action," which necessitates emergency response activation. Mwala (96,835 ha, severity 3, impact 68.2) and Kibwezi East (118,742 ha, severity 2, impact 55.7) are classified as "Severe – Activate Action," requiring resource prepositioning and intervention deployment. Mbooni (93,755 ha, severity 2, impact 44.0), Yatta (60,120 ha, severity 2, impact 28.2), and Kibwezi West (117,447 ha, severity 1, impact 27.6) are categorized as "Moderate: Be Alert and Ready." The remaining eight sub-counties are classified as "Low: Keep Monitoring," indicating the need

for routine surveillance protocols. These include Kilome (45,986 ha, impact 21.6), Machakos (44,075 ha, impact 20.7), Kathiani (20,543 ha, impact 14.5), Mavoko (26,887 ha, impact 12.6), and Kangundo (16,255 ha, impact 7.6), as well as Kaiti (30,492 ha), Matungulu (45,195 ha), and Masinga (107,676 ha), which record Moderate Gain and therefore have zero severity and impact scores.

Two aspects of this ranking warrant attention. First, the action level is determined by the composite impact score rather than yield category alone. For example, Kibwezi West is classified as "Moderate – Be Alert and Ready" despite a projected Slight Gain, due to its extensive cropland area and high population exposure, which increase the composite score. In contrast, Kathiani receives the same severity score as Makueni and Mwala but is classified as "Low: Keep Monitoring" because of its limited cropland area (20,543 ha). Second, the ranking reflects aggregate consequence rather than yield loss alone, which is the metric most relevant for resource allocation and anticipatory action planning.

Table 1
Summary of impact-based forecasts for bean yield change, severity scores, cropland exposure, and recommended action levels in the Machakos and Makueni sub-counties for the OND 2025 seasonal forecast.

Sub-county	Yield category	Area (ha)	Severity score	Impact score	Action level
Makueni	Moderate Loss	142,014	3	100.0	**Extreme: Immediate action**
Mwala	Moderate Loss	96,835	3	68.2	**Severe: Activate action**
Kibwezi East	Slight Loss	118,742	2	55.7	**Severe: Activate action**
Mbooni	Slight Loss	93,755	2	44.0	**Moderate: Be alert and ready**
Yatta	Slight Loss	60,120	2	28.2	**Moderate: Be alert and ready**
Kibwezi West	Slight Gain	117,447	1	27.6	**Moderate: Be alert and ready**
Kilome	Slight Loss	45,986	2	21.6	**Low: Keep monitoring**
Machakos	Slight Loss	44,075	2	20.7	**Low: Keep monitoring**
Kathiani	Moderate Loss	20,543	3	14.5	**Low: Keep monitoring**
Mavoko	Slight Loss	26,887	2	12.6	**Low: Keep monitoring**
Kangundo	Slight Loss	16,255	2	7.6	**Low: Keep monitoring**
Kaiti	Moderate Gain	30,492	0	0.0	**Low: Keep monitoring**
Matungulu	Moderate Gain	45,195	0	0.0	**Low: Keep monitoring**
Masinga	Moderate Gain	107,676	0	0.0	**Low: Keep monitoring**

The tool provides a priority action framework that delineates critical intervention zones requiring resource mobilization based on impact severity thresholds (Table 2). Each severity class corresponds to anticipatory actions, lead times, and responsible actors. The analysis identifies three sub-counties as priority areas for anticipatory action, divided into one critical and two high-priority zones.

Makueni (impact score 100.0, 142,014 ha of affected cropland) is the only critical-priority sub-county, designated for an extreme-level response. This classification triggers the prepositioning of certified drought-tolerant seeds at ward-level agrovet points and the activation of cash-transfer beneficiary lists. The County Department of Agriculture, in coordination with the NDMA, must initiate these actions six to

eight weeks before the start of the season to ensure feasibility within the lead time. Mwala (impact score 68.2, 96,835 ha affected) and Kibwezi East (impact score 55.7, 118,742 ha affected) are high-priority areas requiring a severe-level response. For these sub-counties, the framework triggers targeted extension messaging on planting window adjustments and deploys scouting teams to address forecast pest risk. County extension services deliver these at a four- to six-week lead time. Kibwezi East is included despite being in the Slight Loss yield category because its large cropland area and exposed population raise its composite impact score above the severe threshold. Moderate-impact sub-counties remain under enhanced monitoring, with reassessment scheduled for the next forecast update rather than indefinite monitoring.

By linking each severity class to a specific action, responsible actor, and lead time, the framework differs from a simple severity ranking. This approach enables county governments to allocate limited emergency resources in proportion to the severity. Its focus on impact ensures the most critically affected populations receive timely support while preserving emergency response capacity and avoiding unnecessary dispersion of interventions across regions.

Table 2
Priority sub-counties for anticipatory action based on forecast bean yield loss, cropland exposure, and impact scores for the OND 2025 season.

Priority	Sub-county	Yield category	Area (ha)	Impact score	Action required
CRITICAL	Makueni	Moderate Loss	142,014	100.0	**Extreme: Immediate action**
HIGH	Mwala	Moderate Loss	96,835	68.2	**Severe: Activate action**
HIGH	Kibwezi East	Slight Loss	118,742	55.7	**Severe: Activate action**

Note: Sub-counties are ranked according to impact score and are included only if their score exceeds the threshold for anticipatory action. The priority classes are Critical (dark red) and High (red). The colour coding aligns with that used in Table 1.

3.0 Discussion

The OND 2025 Impact-Based Forecasting (IBF) prototype for Machakos and Makueni Counties highlights both the operational potential and the challenges of translating seasonal climate forecasts into actionable agricultural risk information for smallholder systems in semi-arid East Africa. The prototype applies the World Meteorological Organization's impact-based forecasting framework, expanding its use from general hazard warnings to crop-specific seasonal advisories.

The SPI-3 classification of the ECMWF SEAS5 OND 2025 forecast [16] showed a clear north–south rainfall gradient, with over 650 mm in the far north and less than 300 mm in the south. Regionally, 70.3% of cropland (682,440 ha) experienced near-normal conditions, and critical drought exposure was minimal

(867 ha, 0.1%), indicating OND 2025 was not a crisis-level drought year. Sub-county analysis, however, revealed localized dry areas, especially in Kaiti (67% of cropland mildly dry), Mbooni (26%), Makueni (11%), and Machakos Town (8%). The dominant regional signal was wet: critical wet exposure reached 76,047 ha (7.8%), mainly in the north, where Mavoko and Yatta each had over 28% of cropland in moderate-to-extreme wet classes and were assigned enhanced monitoring. This spatial variability highlights a key challenge for agricultural early warning systems: county-level averages can obscure local conditions affecting vulnerable households and mask the simultaneous occurrence of dry and wet hazards within a single season.

The composite impact-scoring framework combines hazard intensity, cropland exposure, yield-change magnitude, and population density to prioritize anticipatory action. Makueni scored highest (100.0; 142,014 ha; Moderate Loss) and was the only sub-county classified for extreme-level immediate action. Mwala (68.2) and Kibwezi East (55.7) were categorized as severe and required anticipatory measures. Mbooni (44.0), Yatta (28.2), and Kibwezi West (27.6) were assigned to enhanced monitoring. The other eight sub-counties, including Kilome (21.6) and Kangundo (7.6), were designated for routine monitoring. The ranking reflects multiple factors. Kibwezi West is in the moderate tier despite a projected Slight Gain due to its large cropland area and exposed population. Kathiani, although sharing Makueni's severity score, is assigned to routine monitoring because of limited cropland. This approach demonstrates the advantage of a composite score over a simple severity ranking for resource allocation. It aligns the prototype with forecast-based financing models, where pre-agreed thresholds trigger action before an event [17]. Lead times for the severe and extreme tiers are intended to cover the period from forecast issuance to season onset, depending on when the seasonal forecast is released.

The significant negative association between the proportion of female-headed households ($\beta = -0.030$, SE = 0.008, $p < 0.001$) and predicted yield is a critical consideration for IBF design. A 10-percentage-point increase in this proportion, such as the difference between the 25th percentile (Kangundo, ~ 32%) and the median (Mwala, ~ 42%), reduces predicted yield by 3.0%, or about 0.04–0.07 t/ha at mean yield levels. This difference is comparable to that caused by seasonal weather variation. Gender vulnerability is therefore a measurable determinant of yield, not just a contextual factor. Its persistence after accounting for weather and management variables suggests structural constraints on female-managed farms rather than differences in seasonal management practices. Decomposition studies support this view: Kilic et al.[18] found female-managed plots in Malawi to be 25% less productive, with 82% of the gap due to observable endowments and the rest to differences in returns to these endowments. Similar evidence exists for Nigeria[19] and Uganda [20]. These findings align with Doss[21] (2021) and FAO[22] estimates of a 13–30% gender yield gap in sub-Saharan Africa, and with evidence that women account for over 60% of common bean producers in the region, yet face persistent structural barriers. For IBF targeting, identical weather shocks will have more severe food security impacts in sub-counties with higher proportions of female-headed households, where coping assets and recovery credit are more limited and uptake of early warning communications is lower[7,23]. IBF systems should include a gender vulnerability index in impact assessments to ensure that similar hazards prompt differentiated response

intensities. The three priority sub-counties in Table 2 should be targeted for gender-sensitive anticipatory actions, such as female-focused cash transfers, seed vouchers, and awareness campaigns delivered through women's groups.

Several factors limit the prototype's operational precision. Vulnerability inputs rely on census data aggregated at the sub-county level over multi-year intervals, which masks important variations within sub-counties, especially in semi-arid areas. In these regions, factors such as water access, soil type, and market proximity create distinct risk profiles within a single administrative area. To accurately reflect adaptive capacity, more frequent and spatially detailed data, such as mobile phone-based livelihood surveys and community resilience assessments, are needed. Relying solely on the SPI as the agricultural drought trigger does not capture the transition from meteorological to agricultural drought, which is influenced by soil and land cover [24]. This method also overlooks the impact of rising temperatures on evaporative demand, as measured by the SPEI, which is expected to increase drought risk under warming conditions [25].

Further structural limitations affect the prototype. The ECMWF input data, with a native resolution of about 9 km interpolated to 1 km, cannot capture the sub-kilometre microclimatic variability needed for farm-level decisions in complex terrain. Prioritizing machine learning-based downscaling to 250 meters is essential for future improvements. The absence of standardized, spatially detailed impact data for validation and calibration remains a significant challenge. Creating a longitudinal sub-county impact database that combines county production reports, insurance claims, agro-dealer records, and citizen science data is necessary to establish empirically based trigger thresholds. These thresholds, which activate pre-agreed anticipatory actions across agroecological zones, crop types, and seasons, have not yet been formally calibrated. Stakeholder workshops with county agricultural officers, humanitarian agencies, and farmer organizations are recommended to develop transparent, evidence-based trigger mechanisms[17]. While sub-county resolution across 14 units supports extension and county planning, it does not reach the farm level where planting and input decisions are made. The 2010–2024 October–November–December (OND) panel is too short for robust climate–yield analysis, excludes the long rains, and covers few extreme years relevant to IBF. Advisories are issued with seasonal lead times, but many decisions occur within the season, and annual yield reporting prevents mid-season updates.

These constraints define the prototype's current operational scope but do not represent fundamental limitations of the overall approach. Currently, outputs are most effective for pre-season decisions at sub-county and county levels, such as prioritizing extension messaging, positioning inputs, and scheduling anticipatory actions. IBF should be viewed as a progressive capability, with its main limitation being the resolution and frequency of available impact data rather than the modelling framework. As sub-county yield reporting improves, farm practice data become more detailed, and within-season impact observations are standardized, advisories can be further localized. Farmer adoption of IBF outputs is not yet well understood. Integrating these outputs into existing advisory platforms, such as mobile services and farmer field schools, and including indigenous and traditional knowledge as parallel inputs, would improve community ownership, contextual relevance, and last-mile effectiveness.

4.0 Conclusion

This study demonstrates the value of customizing impact-based forecasts for specific crops and sectors, exemplified by beans in the rural sub-counties of Machakos and Makueni, Kenya. By integrating seasonal weather forecasts with sub-county socio-economic data and farm management practices into a unified yield prediction function, the prototype translates hazard information into crop-specific impact estimates. The outputs include seasonal yield change categories, the proportion of cropland exposed to dry and wet extremes, the population affected by yield impacts, a composite impact score, and an associated tier of recommended anticipatory action. When applied to the OND 2025 season, the framework identified one sub-county requiring immediate action, two requiring activation, and three warranting enhanced monitoring, out of fifteen assessed. This tiering represents a practical contribution by converting an undifferentiated regional signal, where 70.3% of cropland was within the near-normal range, into a ranked and proportionate allocation of limited response capacity. Because the ranking is composite rather than solely hazard-based, it identifies sub-counties with high aggregate consequences despite modest yield changes and deprioritizes those where severe yield signals affect minimal cropland.

The framework also differentiates between weather-driven and structurally driven losses. This distinction is operationally important, as it clarifies where seasonal relief is suitable and where long-term investment in adaptive capacity is needed. The finding that the proportion of female-headed households is as significant a yield determinant as seasonal weather variation indicates that impact-based forecasting should include social vulnerability as a forecast input, not just as context. Sub-county resolution aligns with the administrative level where county agricultural offices allocate extension resources. This enables meteorological services and extension officers to provide advisories tailored to specific management decisions rather than to broad severity classes. Realizing this potential at the farm level will require higher-resolution forecasts, more comprehensive yield records, and a standardized impact database to calibrate trigger thresholds. Therefore, the main limitation for impact-based agricultural forecasting is the availability of detailed impact data, not the modelling approach.

5.0 Data and Methods

5.1 Study Area.

Machakos and Makueni Counties are located in southeastern Kenya, spanning approximately 36.9°E to 38.5°E longitude and 0.8°S to 3.0°S latitude. This region is part of the arid and semiarid land (ASAL) zone, which is characterized by a bimodal rainfall pattern (long rains: March-May; short rains: October-December), with a mean annual precipitation between 400 and 1300 mm and varying agro-ecological zones (Fig. 6) The agricultural sector consists mainly of smallholder rain-fed farming, with maize (*Zea mays*) and beans (Phaseolus vulgaris) as the primary food crops, which are typically intercropped and occasionally rotated across seasons. Irrigation coverage remains limited, accounting for less than 5% of the cultivated area[26], which renders crop production highly sensitive to seasonal rainfall variability. The

region has experienced several severe droughts (2010–2122 failed OND followed by failed MAM in 2011, OND 2020, MAM and OND 2021 and OND 2022) alongside flash flood events[27,28]. The prolonged drought of 2020–2022 led to substantial crop losses and heightened food insecurity[29]. This underscores the relevance of these areas for IBF for agricultural studies.

5.2 Data.

This study integrates climatological, seasonal forecast, agricultural yield, and socio-economic datasets to develop an IBF prototype for Machakos and Makueni Counties, Kenya (Table 3). Climatological records establish the baseline for defining anomalies; seasonal forecasts provide predictive signals at actionable lead times; yield records serve as the impact variable for system training; and socioeconomic indicators describe the structural conditions that influence how climate anomalies result in production losses. All datasets were harmonized to a unified spatial and temporal framework to enable composite risk analysis at the sub-county level.

Table 3
Summaries of the datasets and information sources used in the study, detailing their coverage, resolution, variables and purpose.

Data and Source	Coverage/resolution	Variables	Purpose in study	Notes and limitations
Climate Data: CHIRPS v2.0	1981–present; 0.05° (~ 5 km)	Rainfall totals	Climatology, OND seasonal rainfall profiles, SPI-3, rainfall variability	Validated for Kenya and the Greater Horn of Africa
Seasonal forecast: C3S multimodel archive / ECMWF SEAS5	1981–2024 hindcasts; downscaled to 0.01° (~ 1 km)	Precipitation, Tmax, Tmin, agro-meteorological indices	Forecast skill assessment, tercile probabilities, bias correction, seasonal impact modelling	Ensemble mean used to reduce stochastic noise and improve stability
Agricultural Data: Kenya State Department for Agriculture	Sub-county: Machakos and Makueni; OND seasons	Common bean yield (t ha^{-1})	Fine-scale crop productivity analysis and rainfall–yield relationships	Outliers screened for reporting inconsistencies; yield anomalies classified into five ordinal impact classes
Socioeconomic: KNBS 2019 Population and Housing Census	National to sub-county	Population, household demographics, education, livelihoods, poverty indicators	Integration of socioeconomic variables into the model function	Temporal lag relative to the OND 2025 forecast period may affect representativeness
Exposure Data: derived from census and agricultural land-use data	Sub-county	Cropland distribution, farming communities, agricultural assets	Identification of populations and assets at risk from climate hazards	Exposure linked to cropland extent and smallholder farming concentration
Farm management data: compiled binary indicators	Sub-county	Fertiliser use, irrigation, early planting, pest management	Adoption of key agricultural practices affecting production	Practices linked to enhanced cropland productivity

5.3 Detecting and approximating bean croplands

Identifying key crop types and crop areas is essential for estimating potential farming regions and determining the predominant crop type. Acquiring reliable crop area data for previous and upcoming farming seasons is vital to avoid incorporating non-cropland areas, such as grasslands, forests, valleys, hills, and riverbanks. Remote sensing data, including those from Machakos and Makueni, were used to

identify crop types and crop areas across different counties in Kenya. Previous studies have demonstrated that remote sensing data are suitable for estimating crop areas and classifying crop types with very high accuracy[30,31]. Remote sensing provides timely information on crop type classification and crop area in contexts where traditional methods are insufficient. This study focused on beans within Machakos and Makueni Counties; beans are typically grown in maize croplands, a hypothesis confirmed during the Machakos and Makueni Consultations workshop. Therefore, only pixels containing maize croplands were extracted, excluding other crops.

5.4 Agricultural IBF Systems: Architecture, inputs and outputs

The agricultural IBF prototype is structured as a three-stage system (Fig. 2). The first stage, coproduction, involves defining forecast requirements, decision timelines, and action thresholds in collaboration with farmers, extension officers, and county agricultural staff. The second stage, the modelling core, incorporates three input classes: seasonal weather forecasts, on-farm management practices, and localized socio-economic conditions. These inputs are processed through two advisory streams. This study focuses on and reports on the second stage, which uses a yield response function, f(weather, management, socioeconomic conditions), to produce a seasonal yield forecast, which is subsequently categorized by yield change (Fig. 2). The third stage, validation and uptake, includes stakeholder feedback to inform coproduction in the subsequent season.

Each input variable is linked to a specific advisory output and a defined decision type. Table 4 presents these relationships, along with the spatial scale and temporal frequency associated with each variable. Table 2 describes each input class via a consistent framework: the variable, the mechanism by which it influences agricultural outcomes, its spatial and temporal resolution, and the corresponding IBF output.

Table 4
Correspondence between the IBF input variables, impact mechanism, decision type, and system output.

Input variable	Spatial scale	Temporal frequency	Impact mechanism	IBF output	Decision supported
Seasonal rainfall forecast	Sub-County	monthly (1–3)	Moisture deficit during critical growth stages reduces grain filling	drought trigger, exposed cropland,	Anticipatory input distribution; destocking advisories
Farm management practices	Sub-County	Seasonal	Modifies the yield response to a given weather anomaly	Yield risk category	Extension messaging targeting
Socio-economic indicators	Sub-County	Census data (periodic)	Determines capacity to absorb a production shortfall	Yield risk category weighting	Prioritization of target populations
Rural population and cropland extent	Sub-County	Periodic	Defines the exposed population and area	All outputs (exposure layer)	Scale of response required

5.5 Crop yield impact forecasting as a function of weather, management, and socioeconomic factors

Conventional agricultural IBF typically involves two stages: first, biophysical or statistical yield models estimate hazard impacts via weather data, and the resulting loss estimates are then combined with exposure and vulnerability data to generate a risk score. In this approach, socioeconomic information is incorporated solely as a scaling factor, implicitly assuming uniform producer responses to weather conditions. In contrast, this study incorporates farm management practices and socio-economic information directly into the yield response function, enabling predicted yields for a given seasonal forecast to reflect the productive and adaptive capacities of each subcounty. Consequently, two sub-counties experiencing identical rainfall deficits may show different yield outcomes because of variation in irrigation, input use, and farm structure. While weather-only models treat such variation as unexplained error, this formulation attributes it to measurable and potentially actionable factors. The impact signal is thus conditioned on the socio-economic context during estimation rather than being adjusted post hoc.

The crop yield in subcounty i during season t is modelled as a function of seasonal weather conditions (W), farm management practices (M), time-invariant socioeconomic characteristics (S), and a stochastic error term:

$Y_{it} = f(W_{it}, M_{it}, S_i, \varepsilon_{it})$ (1)

This approach follows the production function framework established by Schlenker and Roberts[32] for smallholder crop systems and is extended to panel data by Lobell and Burke[33]. This framework enables yield to be explained simultaneously by seasonal climate signals, on-farm management decisions, and the structural socio-economic context, a distinction that is critical for effective targeting in IBF.

Yield anomalies, which are calculated relative to subcounty historical means, are derived from model predictions under three weather scenarios: below-normal, near-normal, and above-normal. These scenarios correspond to the tercile categories used in operational seasonal forecasts[2,34]. This alignment ensures that results are directly interpretable by farmers, extension officers, and humanitarian planners. Sub-counties are classified as experiencing either yield gains or losses relative to their baseline, with the magnitude of deviation informing the type and urgency of recommended responses, such as drought-tolerant seed deployment, targeted irrigation support, crop insurance activation, or increased input investment under favourable outlooks [35].

5.6 Representing Weather Variability for the IBF Model

Substantial multicollinearity among meteorological variables, indicated by variance inflation factors exceeding 100 for temperature variables in preliminary analyses, makes direct inclusion in regression models unreliable [36]. In accordance with Schlenker and Roberts[32], principal component analysis (PCA) was used to reduce dimensionality within two theoretically defined variable groups: the water group (total rainfall, soil moisture, dry days) and the temperature group (Tmax, Tmin, dewpoint, soil temperature). Solar radiation was included as a standalone predictor due to its low collinearity (VIF < 5). The first principal component for the water group explained 78.4% of the variance, whereas the first and second principal components for the temperature group explained 86.3% and 8.9%, respectively.

A primary methodological challenge involves addressing unobserved subcounty heterogeneity, which includes stable agroecological, infrastructural, and institutional characteristics that influence yields but are not directly observable[37]. The Mundlak (1978) within-between estimator addresses the limitations of both fixed and random effects by incorporating subcounty means of all time-varying regressors into the model. The model is specified as follows:

$$y_i = \alpha + \beta(w_{ui} - \bar{w}_{ui}) + \gamma\bar{w}_{ui} + \beta m_i + \delta S_i + \varphi t + u_i \quad (2)$$

In this specification, w_i denotes the vector of time-varying weather principal component analysis (PCA) scores, and $\bar{w}_i$ represents the subcounty long-run mean, which serves as the Mundlak correction term. The term $(w_i - \bar{w}_i)$ captures within-subcounty deviations that reflect year-to-year weather anomalies. The vector m_i includes farm management practices, S_i comprises time-invariant socioeconomic indicators, and φt denotes a linear year trend. The coefficients β quantify the within-unit weather response, whereas γ measures the structural yield advantage associated with wetter or warmer subcounty baselines, a distinction that is only estimable through the Mundlak decomposition[38].

5.7 Yield Forecast Scenario and Yield Change Classification

Yield anomalies, which are calculated relative to subcounty historical means, are derived from model predictions under three weather scenarios: below-normal, near-normal, and above-normal seasonal conditions. These scenarios match the tercile categories used in operational seasonal climate forecasts [2,34] allowing model outputs to be directly interpreted within the communication framework familiar to farmers, extension officers, and humanitarian planners. Three weather scenarios represent plausible October–December 2025 outcomes: (i) the operational seasonal forecast, which is the tercile with the most likely outcome; (ii) a dry scenario with forecasts adjusted toward drier conditions; and (iii) a wet scenario with forecasts adjusted toward wetter conditions. Adjustments use sub-county-specific tercile boundaries rather than a uniform regional approach. The inclusion of management in the yield function enables the model to capture an additional scenario dimension beyond weather-only models.

5.8 Gender Information in the IBF Context

Gender information was incorporated as part of the broader socioeconomic predictor set within the yield model. The gender-related variables included the proportion of female-headed farming households (% of female-headed households) and the proportion of women with disabilities in the farming population (% Disability_Female), both of which were measured at the subcounty level[39].

These variables are essential for three primary reasons. First, they capture structural differences in farming capacity and agency across sub-counties that weather and management variables alone do not explain. Sub-counties with higher proportions of female-headed households systematically face greater labor, asset, and credit constraints, as well as reduced autonomy over key farming decisions such as planting timing, input use, and hired labor. These factors directly reduce yield capacity regardless of seasonal weather conditions. Second, within the IBF context, gender indicators shift the forecast output from a hazard-based assessment to an impact-based assessment. A subcounty with a high proportion of female-headed households is predicted to experience greater yield losses from the same weather shock than a sub-county with lower female-headed households. This enables anticipatory action to be targeted where impacts will be most severe rather than where rainfall deficits are greatest[40,41]. Third, female-headed households often have limited access to timely agricultural and early warning information due to cultural norms and time burdens that restrict their engagement with extension services and advisory networks[42]. This limitation compounds the capacity and impact-based vulnerabilities described above. Collectively, these dimensions ensure that gender vulnerability is quantitatively embedded in the forecast model rather than treated as an afterthought in humanitarian response planning. This approach provides decision-makers with an evidence-based and reproducible foundation for gender-responsive early action.

Declarations

Funding Declaration

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Author Contribution Statement

Alex Ogelo developed the methodology, conducted the analysis, and drafted the original manuscript. **Masilin Gudoshava** conceived the study, contributed to its methodological development and conceptualization, supervised the project, and reviewed and edited the manuscript. **Joyce Jelagat** and **Linda Ogallo** contributed to the study's conceptualization. All authors reviewed the manuscript.

Data Availability Statement

Data will be made available upon request, subject to ethical approval and authorization from the data provider.

Additional information
Correspondence and requests for materials should be addressed to A.O.

Consent to Participate Declaration

Stakeholders such as county agricultural officers, extension officers, county officers, agro-dealers, farmer representatives from Machakos and Makueni Counties, and representatives from research institutions and the private sector attended a validation and consultation workshop in Nairobi to provide feedback on the model and IBF prototype outputs. At the beginning of the workshop, participants were informed of the objectives, reminded that participation was voluntary, and assured that no personal information would be recorded or published. All participants gave verbal informed consent before sharing feedback.

Consent for publication
Not applicable. The manuscript does not contain individual data or identifiable information.

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Figures

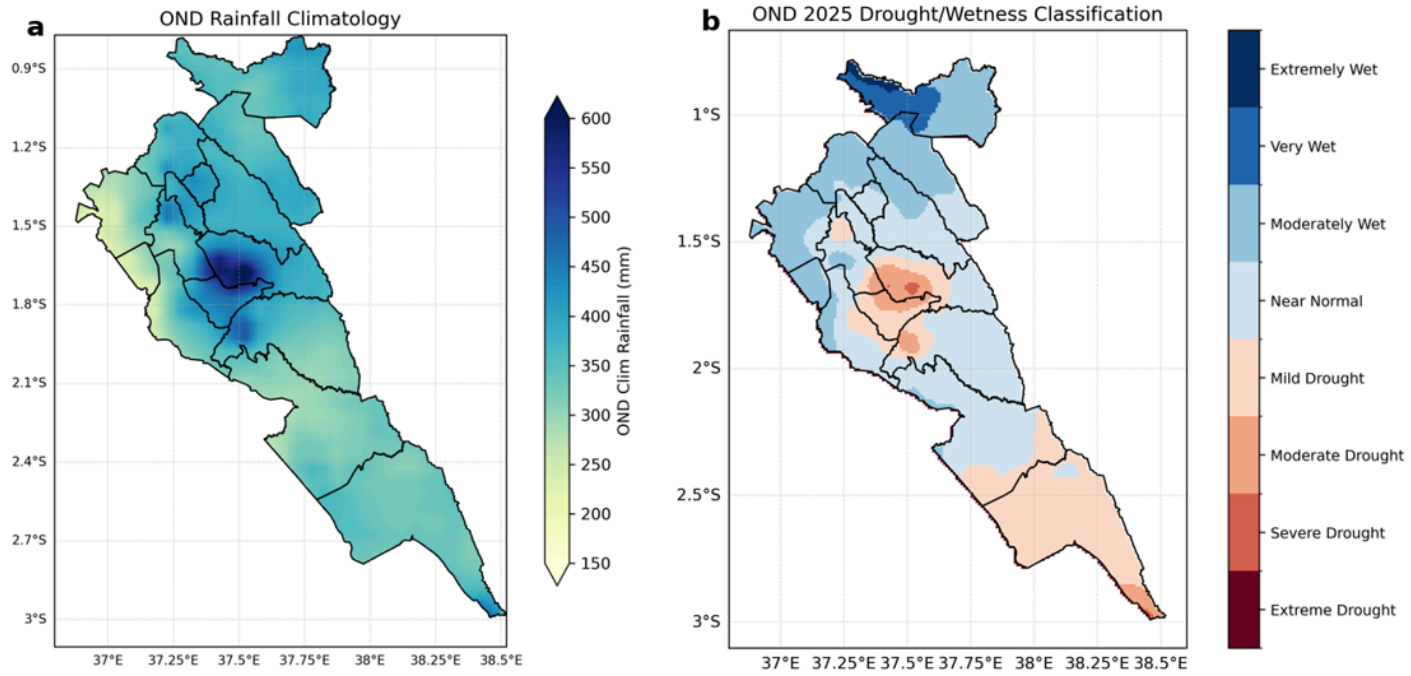


Figure 1

OND climatology and 2025 weather forecast information for Machakos and Makueni counties. Panel (a) presents the Climatological rainfall (1981 to 2020) for the OND season based on the CHIRPS dataset, whereas Panel (b) illustrates the SPI-3 classifications, ranging from extremely wet to extremely dry.

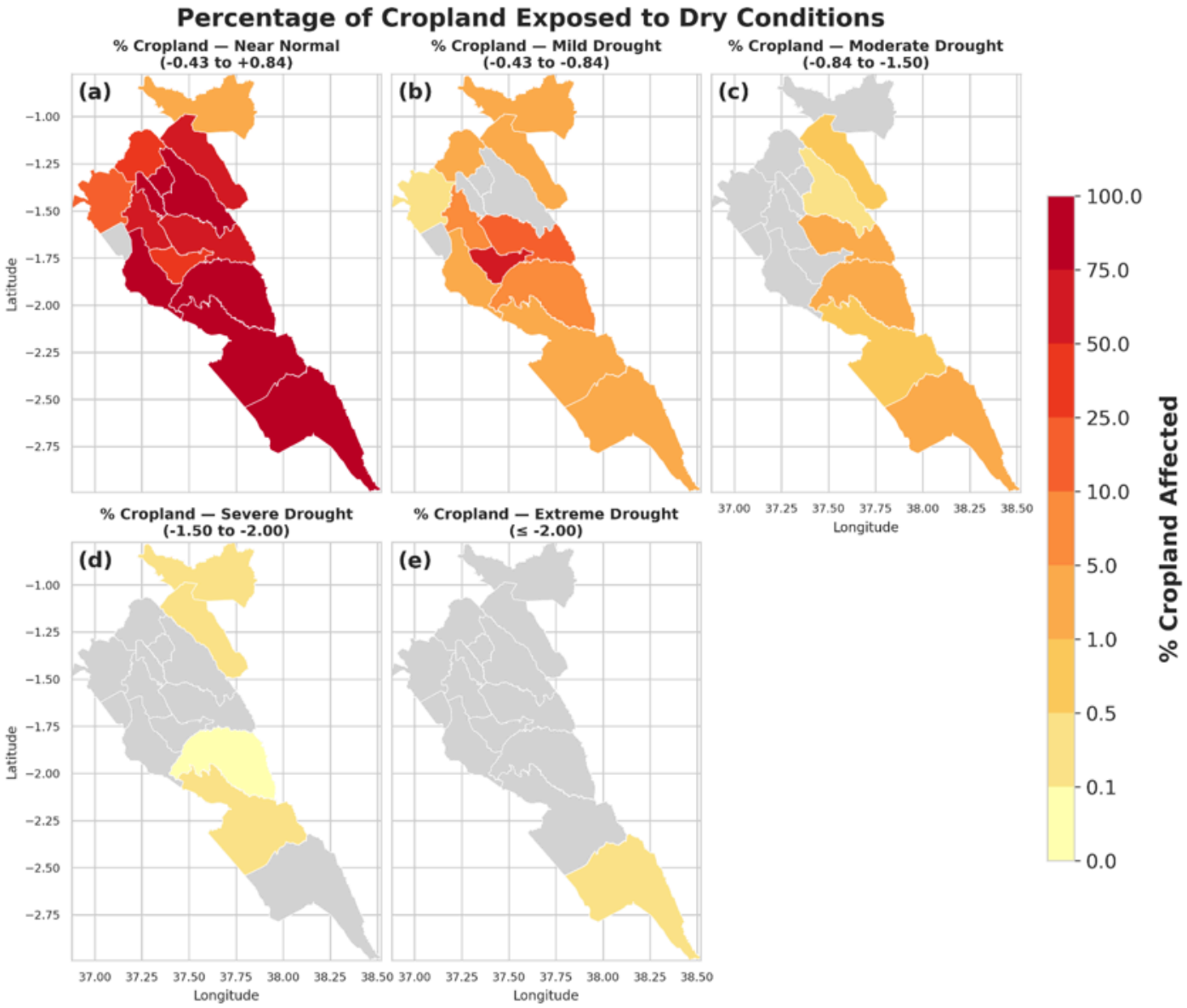


Figure 2

Anticipated percentage of cropland exposed to dry conditions during October–November–December (OND) 2025. (a) Croplands with near-normal conditions (SPI -0.43 to 0.84). (b) Croplands experiencing mild dryness (SPI -0.44 to -0.84). (c) Croplands experiencing moderate dryness (SPI –0.84 to -1.50). (d) Croplands experiencing severe dryness (SPI -1.50 to -2.00). (e) Croplands experiencing extreme dryness (SPI < -2). Grey indicates no exposure in that category.

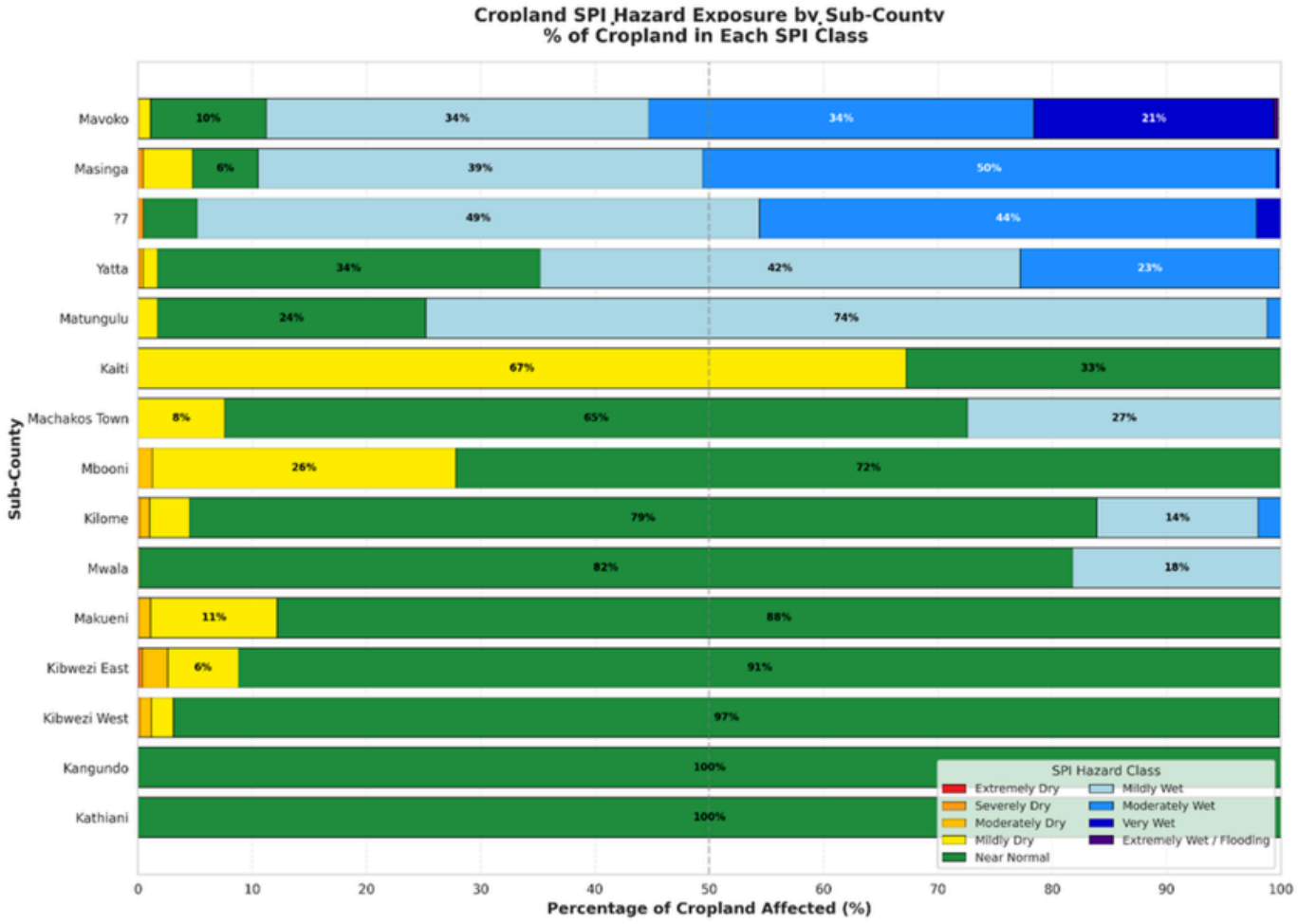


Figure 3

Pixel-based percentage of cropland exposed to various hazard classes per subcounty in Machakos and Makueni Counties. The figure indicates the dominant hazard class, either drought or flooding, within the cropland areas.

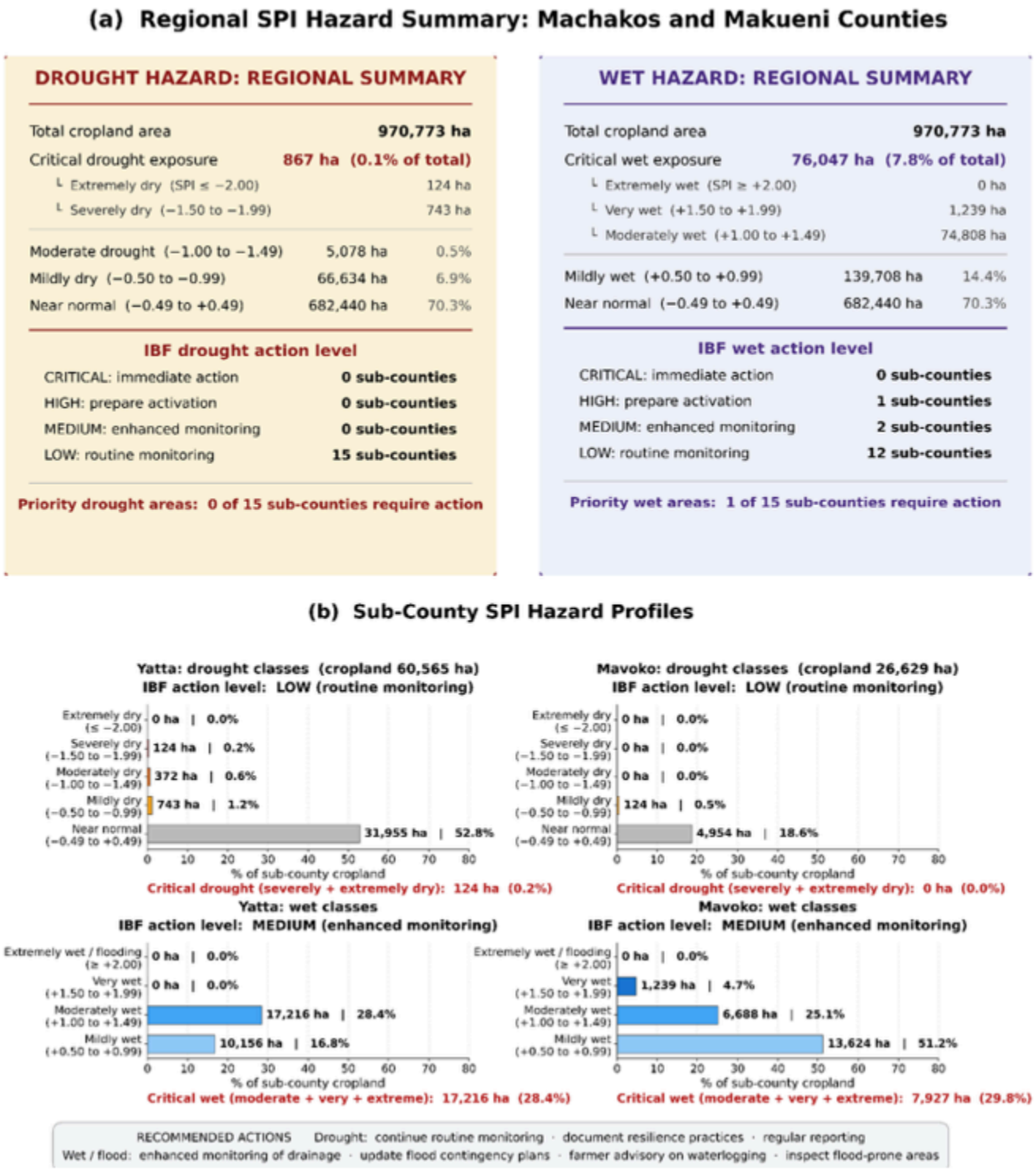


Figure 4

Summary of hazard class impacts. (a) Regional impact-based forecast information. Subcounty impact-based forecasting (IBF) information highlighting drought and flood risks and identifying priority areas.

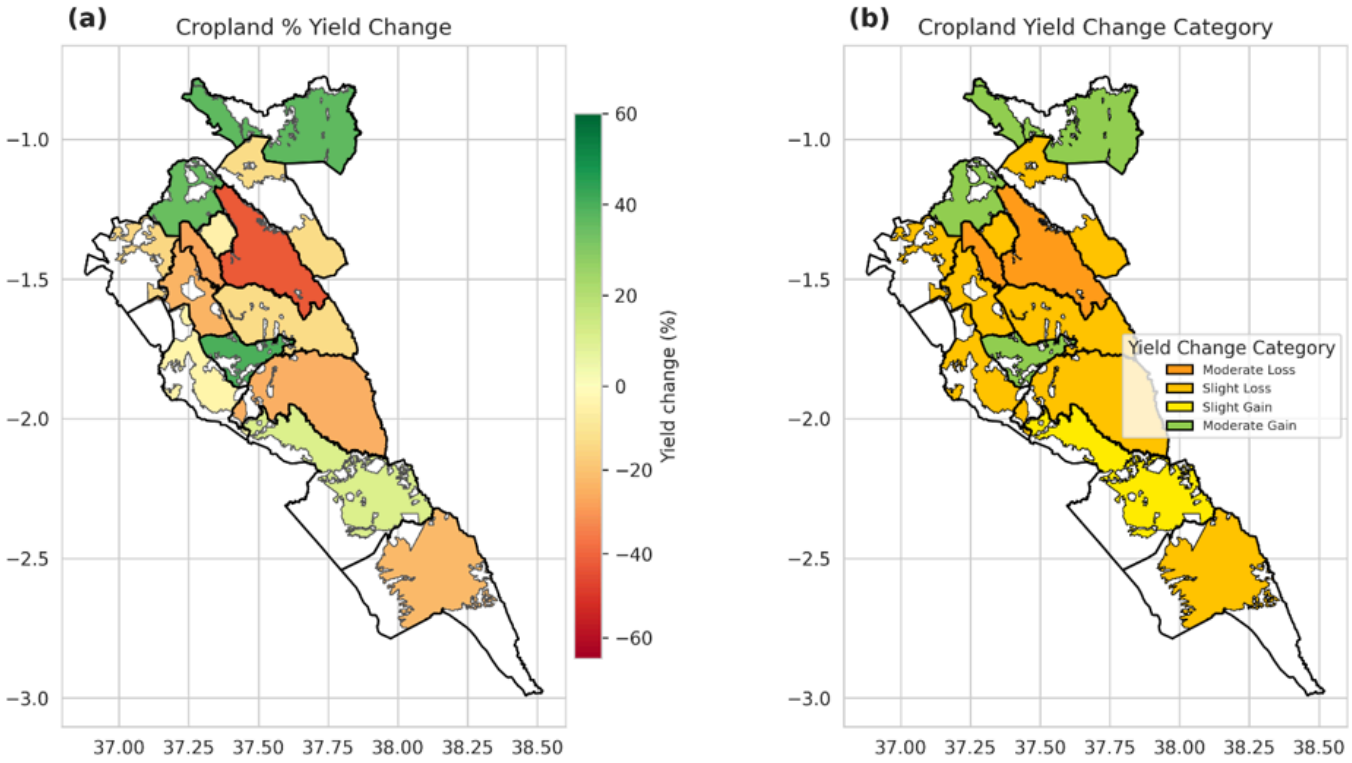


Figure 5

Projected category and changes in bean yield across the Machakos and Makueni sub-counties for the OND 2025 season within croplands. (a) Continuous percentage yield changes relative to the historical mean. (b) Yield change categorized by subcounty.

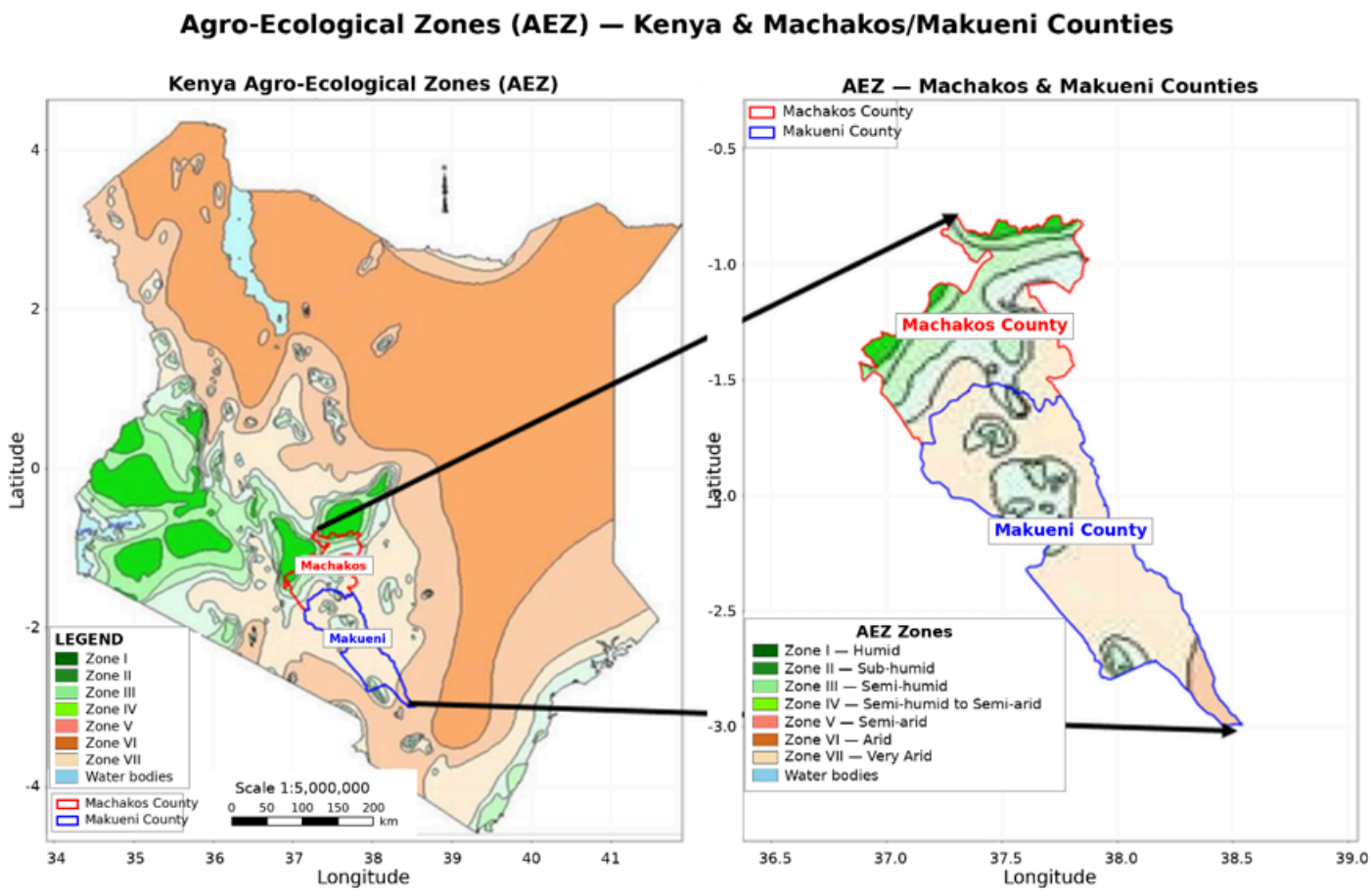


Figure 6

Agro-ecological zones (AEZs) of Machakos and Makueni Counties (source: Kenya Soil Survey). The left panel displays the national AEZ distribution, with Machakos and Makueni Counties outlined in red and blue, respectively. The right panel provides a detailed view of these counties, illustrating the spatial distribution of the AEZ zones.

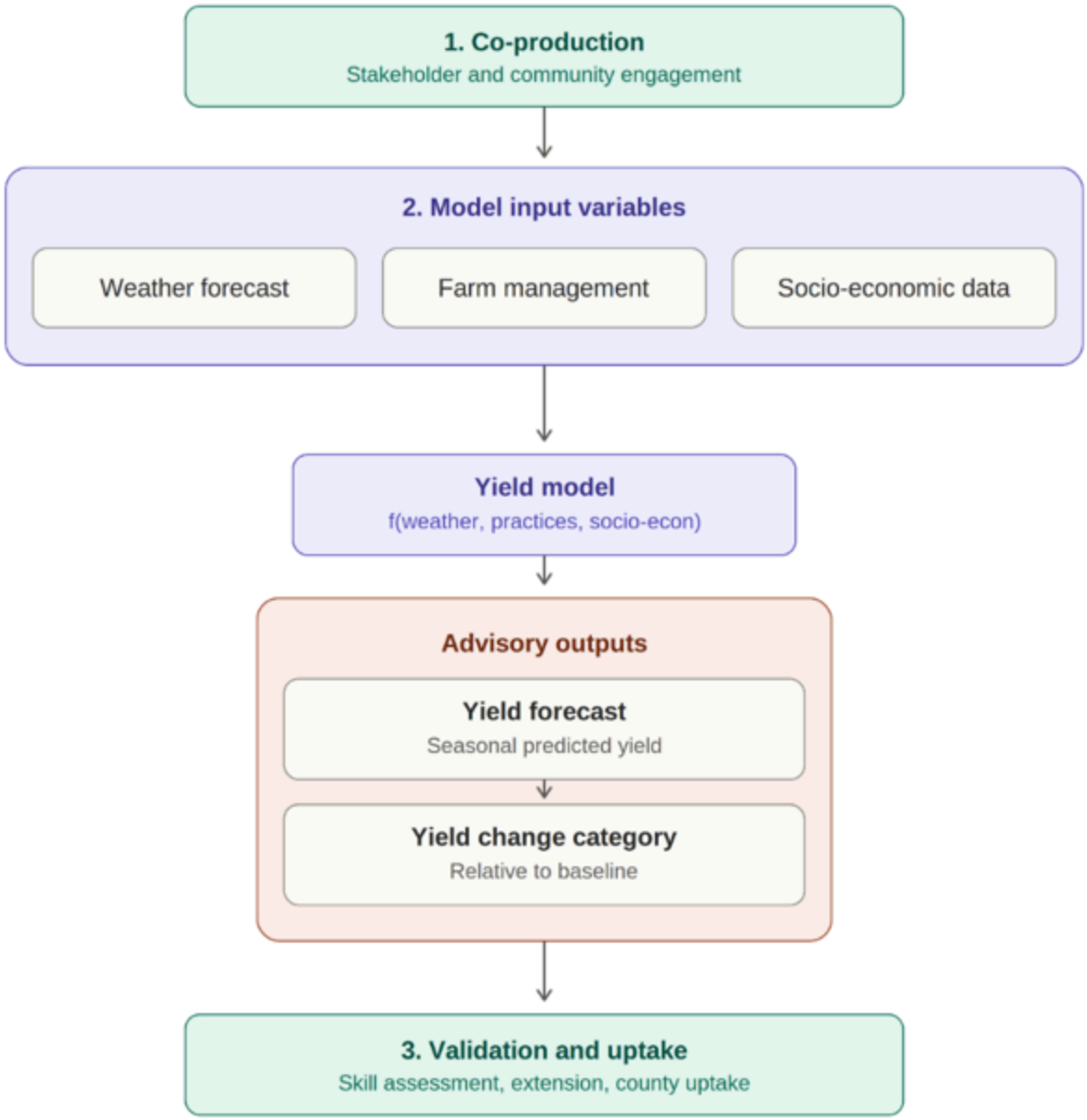


Figure 7

A schematic diagram illustrating the agricultural IBF development process from the coproduction level to validation and update