



Integrating Meteorological Forecasts and Scenario Simulation to Support Smallholder Maize Farming Decisions in Kakamega County, Kenya

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Abstract

Seasonal rainfall outlooks can support advance planning in rainfed maize systems, but farm operations depend not only on seasonal rainfall totals but also on rainfall timing, continuity and short dry periods. This study examined Kenya Meteorological Department (KMD) March-May seasonal outlooks for Kakamega County from 2021 to 2025 and used a transparent stochastic scenario model to explore rainfall indicators relevant to farm decision-making. Official outlook messages were reviewed separately from retrospective observations. Three illustrative rainfall scenarios, each comprising 10,000 synthetic 92-day sequences, represented sparse, intermediate and frequent rainfall conditions. A candidate planting trigger was defined as at least 20 mm of rainfall accumulated over three consecutive days and completed by day 30. Among sequences reaching the trigger, a subsequent seven-day dry spell within 21 days occurred in 54.6%, 11.0% and 0.7% of the sparse-, intermediate- and frequent-rain scenarios, respectively. A separate three-day dry run within 30 days occurred in 100.0%, 95.3% and 58.5% of the same scenarios. Sensitivity analysis showed that rainfall occurrence and persistence could substantially alter post-trigger dry-spell exposure even when expected seasonal rainfall was held constant. The results demonstrate that seasonal rainfall totals alone do not capture decision-relevant rainfall sequences. A practical climate-service approach should therefore combine seasonal contingency planning with short-range updates and field verification. The simulated proportions are illustrative and should not be interpreted as calibrated probabilities of crop failure, yield loss or other farm outcomes in Kakamega.

Keywords: Agro-meteorology; climate services; dry spells; maize; rainfall scenarios; seasonal forecasts; smallholder farming

Introduction

Rainfed maize production requires decisions at different time scales. Seasonal rainfall outlooks can inform advance preparation, whereas planting, weeding, harvesting and postharvest handling depend on weather over shorter periods, crop development and field conditions. Seasonal climate forecasting has considerable potential to support agricultural risk management in sub-Saharan Africa, but translating forecast information into practical farm decisions remains a persistent challenge (Hansen et al., 2011).

The usefulness of climate information depends on more than scientific quality. Farmers and extension services also require information that is relevant to specific decisions, available at the appropriate time and understandable within the local production context (Dilling and Lemos, 2011; Lemos et al., 2012). In semi-arid Kenya, previous research linked seasonal climate forecasts with crop simulation to address the mismatch between broad climate information and the scale at which crop-management decisions are made (Hansen et al., 2004). That work provides a methodological precedent, but it does not by itself validate a decision model for Kakamega County, where local rainfall patterns, soils and farming practices differ.

Kakamega provides a useful setting for examining how seasonal information might be translated into operational guidance. The County Government of Kakamega used participatory

scenario planning in communicating the 2023 seasonal outlook (County Government of Kakamega, 2023) while KMD provides agrometeorological services and ten-day bulletins that can update information as the season progresses (Kenya Meteorological Department, 2023). Kenya Meteorological Department also publishes seasonal outlooks describing expected rainfall categories, onset and continuation (Kenya Meteorological Department, 2021; 2022; 2023; 2024; 2025).

This study therefore examines how categorical seasonal outlooks can be complemented by simple rainfall-sequence indicators. It combines a structured review of KMD March-May outlooks for 2021-2025 with controlled stochastic rainfall scenarios. The objectives were to (i) summarize the forecast messages issued for Kakamega, (ii) examine how rainfall occurrence affects a candidate planting trigger and subsequent dry-spell exposure, and (iii) test whether different rainfall occurrence and persistence patterns can produce different operational conditions even when expected seasonal rainfall is unchanged. The analysis was intended as a transparent decision-support framework rather than a calibrated local forecast model or an evaluation of farm-level impacts.

Materials and Methods

Review of seasonal outlooks

Kenya Meteorological Department (KMD) March–May seasonal outlooks for the five completed

years from 2021 to 2025 were reviewed from the public archive (Kenya Meteorological Department, 2021; 2022; 2023; 2024; 2025). For each year, the analysis retained the issue date, the rainfall outlook referring to Kakamega, and statements on expected onset or continuation. Retrospective weather reviews were examined separately (Kenya Meteorological Department, 2021; 2022; 2023; 2024; 2025). The conventional Kakamega meteorological station is identified by KMD as WIGOS 0-20000-0-63687, located at 0.2775° N, 34.7642° E and 1,559.6 m above sea level. Forecast categories were retained as issued and were not converted into deterministic rainfall amounts.

Rainfall scenario model

Three illustrative rainfall scenarios were generated to examine how rainfall sequences

influence simple operational indicators. Stochastic weather generation provides a transparent way to separate rainfall occurrence from rainfall amount and to test the consequences of alternative rainfall sequences (Richardson, (1981). Each scenario consisted of 10,000 synthetic seasons of 92 days. Daily rainfall occurrence, W , followed a Bernoulli distribution with wet-day probability q . Daily rainfall amount was represented as $R = W \times (1 + G)$, where G followed a gamma distribution with shape 2 and scale $(A/(92q) - 1)/2$. Under this specification, the expected 92-day rainfall total is A , wet days exceed 1 mm and dry days have zero rainfall. NumPy's default random-number generator was used with seed 20251003. The baseline scenarios assume independent daily rainfall occurrence and seasonally constant parameters (Table 1).

Table 1. Assumptions used in the three synthetic rainfall scenarios.

Scenario	Daily wet-day probability (q)	Expected 92-day rainfall (A)
Sparse rain	0.25	450 mm
Intermediate rain	0.45	650 mm
Frequent rain	0.65	850 mm

Operational indicators

A candidate planting trigger was defined as the first completed three-day period accumulating at least 20 mm of rainfall and ending by day 30. Among sequences that met this trigger, post-trigger exposure was defined as the occurrence of at least one seven-day dry spell during the following 21 days. Sequences without a trigger were excluded from this conditional denominator, and no future rainfall was used to

identify the trigger. A separate independent 30-day block was used to determine whether at least one three-day dry run occurred. This indicator represents the availability of short rain-free periods in the synthetic sequence; it is not evidence that maize would necessarily be ready for harvest or safe storage. Postharvest suitability also depends on grain moisture and appropriate drying and storage practices.

Sensitivity analysis

Sensitivity analysis held expected seasonal rainfall at $A = 650$ mm while varying the daily wet-day probability q from 0.15 to 0.75. A second analysis held $q = 0.45$ and varied rainfall persistence using $\rho = 0, 0.3$ and 0.6 , where the probability of a wet day depended partly on the previous day's wet/dry state. Each experiment contained 10,000 sequences and used the same generator seed at the start of the experiment series. These tests were designed to examine structural sensitivity of the indicators and do not reproduce observed seasonal peaks, local soil-water processes or farm hydrology.

Results

Seasonal outlooks and reported rainfall

The five KMD outlooks described contrasting rainfall expectations for Kakamega (Table 2). The 2021 and 2024 outlooks favoured above-average rainfall, the 2022 and 2025 outlooks indicated near- to above-average rainfall, and the 2023 outlook indicated below-average rainfall ((Kenya Meteorological Department, 2021; 2022; 2023; 2024; 2025). All five outlooks indicated that rainfall could continue into June. This is important because the March- May reporting period should not automatically be interpreted as the end of the rainy season. In the 2022 outlook, the county table described rainfall distribution as good whereas the general narrative described it as fair.

Table 2. Summary of KMD March–May seasonal outlook information for Kakamega, 2021-2025.

Year / issue date	Rainfall outlook	Expected onset or continuation	Continuation
2021 / 19 Feb	Above average	Second to third week of March	Into June
2022 / 22 Feb	Near to above average	Second to third week of March	Into June
2023 / 1 Mar	Below average	Third to fourth week of March	Into June
2024 / 29 Feb	Above average	Continues from February	To June
2025 / 31 Jan	Near to above average	Continues from February, with dry spells	To June

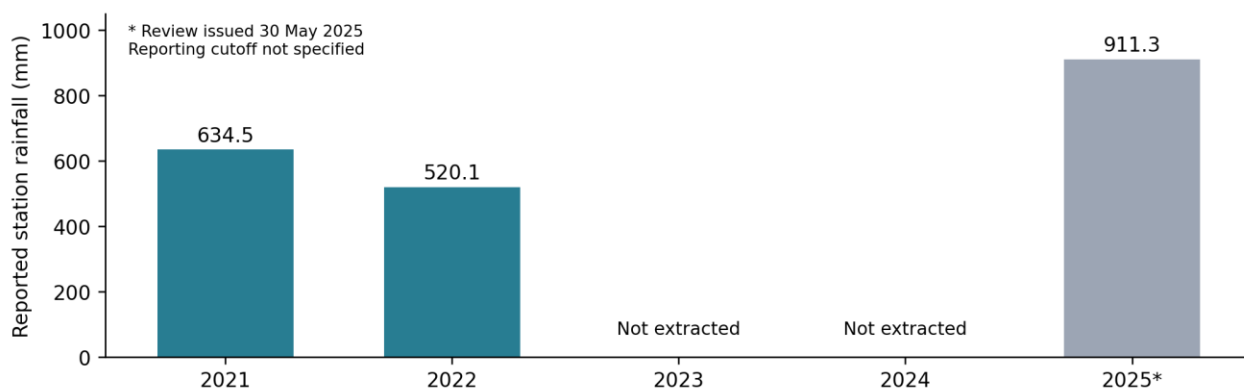


Figure 1. The March-May seasonal rainfall totals reported for Kakamega meteorological station in 2021-2025 KMD reviews.

Seasonal forecast categories should not be treated as realized rainfall observations. Relatively wet outlooks in 2021 and 2022 were followed by station classifications of near-average and below-average rainfall, respectively. This comparison is descriptive rather than a formal forecast verification. Proper verification requires forecast probabilities and observations to be matched in space, time, category definition and climatological baseline, and evaluated using appropriate probabilistic scoring methods.

Scenario Results and Sensitivity Analysis

The simulated rainfall totals closely reproduced the intended scenario means. Across 10,000 sequences per scenario, mean cumulative rainfall was 451.0 mm for sparse rain, 647.2 mm for intermediate rain and 849.7 mm for frequent rain, compared with specified expectations of 450, 650 and 850 mm, respectively (Figure 2A).

The candidate planting trigger was reached by day 30 in 98.1% of sparse-rain sequences, 99.9% of intermediate-rain sequences and 100.0% of frequent-rain sequences (Table 3; Figure 2B). Because trigger attainment was high in all three scenarios, this indicator alone provided little separation between favourable and less favourable rainfall sequences.

Differences became much clearer after the trigger. A seven-day dry spell within the following 21 days occurred in 54.6% of sparse-rain sequences, 11.0% of intermediate-rain sequences and only 0.7% of frequent-rain sequences. Thus, reaching the initial rainfall trigger did not guarantee rainfall continuity during the subsequent establishment period. Shorter dry periods were common across all scenarios: at least one three-day dry run in an independent 30-day block occurred in 100.0%, 95.3% and 58.5% of the sparse-, intermediate- and frequent-rain scenarios, respectively.

Table 3. Simulated operational indicators across 10,000 sequences per scenario.

Scenario	Trigger by day 30 (%)	Post-trigger dry run (%)	seven-day dry run	Three-day dry run in 30 days (%)
Sparse rain	98.1	54.6		100.0
Intermediate rain	99.9	11.0		95.3
Frequent rain	100.0	0.7		58.5

The sensitivity analysis showed that dry-spell exposure depended strongly on rainfall occurrence and persistence, even when expected seasonal rainfall was unchanged. With A fixed at 650 mm, increasing q from 0.15 to 0.75 reduced post-trigger exposure from 83.4% to 0.1%. At $q = 0.45$, increasing persistence from $\rho = 0$ to 0.3 and 0.6 increased exposure from 11.0% to 28.4% and 52.3%, respectively. Therefore, rainfall sequences with the same expected seasonal total

can have very different post-trigger dry-spell characteristics.

Monte Carlo standard errors for the proportions in the three primary scenarios were no greater than approximately 0.51 percentage points. This indicates high numerical precision for the simulated proportions, but it does not address uncertainty in the assumed parameter values, the chosen probability distributions or the applicability of the scenarios to observed local rainfall.

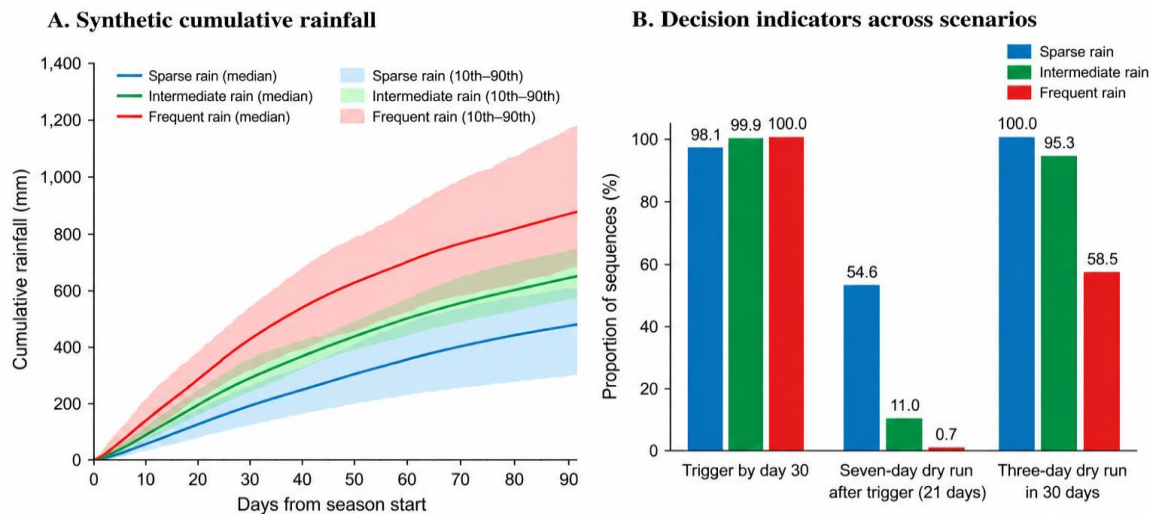


Figure 2. Simulated synthetic rainfall and decision indicators. (A) median cumulative rainfall and the 10th–90th percentile envelope. (B) Proportion of sequences reaching the planting trigger and experiencing post-trigger and short dry spell.

Discussion

The main finding is that seasonal rainfall amount and the sequence in which rainfall occurs provide different types of information for maize-management decisions. The sensitivity analysis demonstrated that post-trigger dry-spell exposure can change substantially even when expected seasonal rainfall remains constant. This is consistent with stochastic weather-generation approaches that model rainfall occurrence and intensity as distinct processes (Richardson, 1981) and with previous Kenyan work linking seasonal climate information to crop simulation (Hansen and Indeje, 2004). However, the present scenarios diagnose decision mechanisms rather than estimate realized farm benefits.

The results also clarify why a seasonal outlook should be used for contingency planning rather than as a stand-alone operational instruction. Seasonal forecasts can indicate whether farmers and extension services should prepare for relatively dry or wet conditions, but shorter-term decisions require updated weather information and field observations. Effective climate services depend not only on scientific credibility but also on salience, legitimacy and the ability to connect knowledge with users' decisions (Cash et al., 2003).

For planting decisions, the candidate rainfall trigger used in this study should therefore be interpreted as a prompt for further checking rather than as an automatic planting rule. In the

sparse-rain scenario, almost all sequences reached the trigger, yet more than half subsequently experienced a seven-day dry spell. The agronomic consequences of such a dry period cannot be inferred from rainfall alone because crop establishment depends on soil water availability, evaporation, crop development and cultivar response. Process-based crop models such as DSSAT and APSIM illustrate the additional soil, crop and management information required to translate weather sequences into crop outcomes (Jones et al., 2003; Holzworth et al., 2014).

The three-day dry-run indicator illustrates a different operational consideration. Short dry periods became less frequent as rainfall occurrence increased, suggesting a possible trade-off between moisture continuity and opportunities for field or postharvest operations that benefit from rain-free weather. Nevertheless, a dry window does not establish that maize is mature or sufficiently dry for safe storage. FAO guidance emphasizes adequate drying and appropriate grain moisture for maize storage, while Kenyan evidence from hermetic storage systems demonstrates the importance of pre-storage drying and moisture management in reducing mould and aflatoxin risks (Ng'anga et al., 2016).

The framework is most useful as an extension architecture that combines information at several time scales. Seasonal outlooks can support

advance contingency planning; subsequent KMD updates can refine timing; and field observations can determine whether a particular action is appropriate. This approach is consistent with climate-information usability research and with knowledge-system principles that emphasize credibility, salience, legitimacy and sustained interaction between information producers and users (Cash et al., 2003). Advisories should therefore record the forecast issue date, uncertainty and relevant field conditions rather than present a seasonal category as a fixed operational instruction.

The study has important limitations. The rainfall scenarios are synthetic and were not calibrated to Kakamega daily observations. The baseline model assumes stationary parameters and independent wet-day occurrence, while the persistence analysis is deliberately simplified. The analysis also does not represent soil water balance, crop phenology, disease processes, grain moisture or market prices. Crop-response modelling would require locally appropriate soil, cultivar and management inputs and careful calibration and evaluation (Jones et al., 2003; Lobell et al., 2010). Gridded rainfall products such as CHIRPS could supplement station observations, but their local performance and product version would need to be evaluated before use (Funk et al., 2015). Likewise, any future assessment of KMD forecast skill should match forecasts with observations and apply

proper probabilistic verification measures rather than rely on descriptive category comparisons (Gnetiting and Raftery, 2007).

Conclusion

The combined review of KMD seasonal outlooks and controlled rainfall scenarios provides a transparent way to translate broad seasonal information into decision-relevant questions for smallholder maize production in Kakamega County. The analysis shows that rainfall occurrence and persistence can strongly influence post-trigger dry-spell exposure even when expected seasonal rainfall is similar. Seasonal rainfall totals and outlook categories should therefore be complemented by shorter-term updates and field verification when guiding operational decisions. The proposed framework supports adaptive climate-service delivery, but local calibration and prospective evaluation are required before the simulated indicators can be interpreted as probabilities of crop, livelihood or economic outcomes.

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