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THE IMPORTANCE OF FORECASTING CROP YIELDS AND REGIONAL CROP DISTRIBUTION BASED ON AGRO-CLIMATIC CHARACTERISTICS AND MARKET DYNAMICS

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KEYWORDS

crop yield forecasting, agroclimatic suitability, regional crop allocation, market uncertainty, water constraints, agricultural decision support

ABSTRACT

Crop planning requires forecasts of production and market conditions. This paper examines the integration of crop yield forecasting and regional crop distribution through a narrative synthesis and a conceptual decision model. The framework combines agroclimatic suitability, timely yield forecasts and market scenarios to allocate cultivated area under land, water and production constraints. Its mathematical formulation links uncertain yields and prices to operating margins. The analysis highlights the importance of forecast timing, resource availability and joint yield–market uncertainty in comparing regional cropping alternatives. The contribution is methodological, with predictive accuracy and economic benefits requiring empirical validation.

1. Introduction

Agricultural planning requires decisions under uncertainty about weather, yields and harvest prices. Regional differences in climate, soils and irrigation availability influence crop suitability and production outcomes. Hultgren et al. [1] show that adaptation affects estimated climate impacts, while climate-related losses and adaptation costs remain relevant to planning. Crop yield forecasting estimates expected output for a particular crop, location and season. Van Klompenburg et al. [2] identify weather and soil information as common inputs to machine learning models. Anderson et al. [3] demonstrate the potential for useful preseason maize and wheat forecasts in some regions. Forecasts available before planting can inform crop selection, while later updates support management and harvest preparation. Market conditions also influence crop choices. The OECD-FAO Agricultural Outlook [6] links commodity prospects to production, consumption, trade and prices, while Sable et al. [7] examine historical prices and seasonality in agricultural marketing. Since high yields or favourable prices alone cannot establish profitability, this paper proposes a decision framework linking timely yield forecasts, agroclimatic suitability and market scenarios to feasible regional crop allocations.

2. Materials and Methods

The study uses a narrative synthesis of peer-reviewed research and institutional documentation covering agroclimatic suitability, crop forecasting, crop allocation and agricultural markets. The selected sources span 2017–2025 and were chosen for their direct relevance to at least one of these components. The synthesis supports a conceptual model rather than a systematic meta-analysis or a field experiment. The five methodological stages are described below; Figure 1 summarizes how their inputs connect to crop allocation. Forecasts and economic assumptions are combined only after their spatial units, decision dates and measurement conventions have been aligned.

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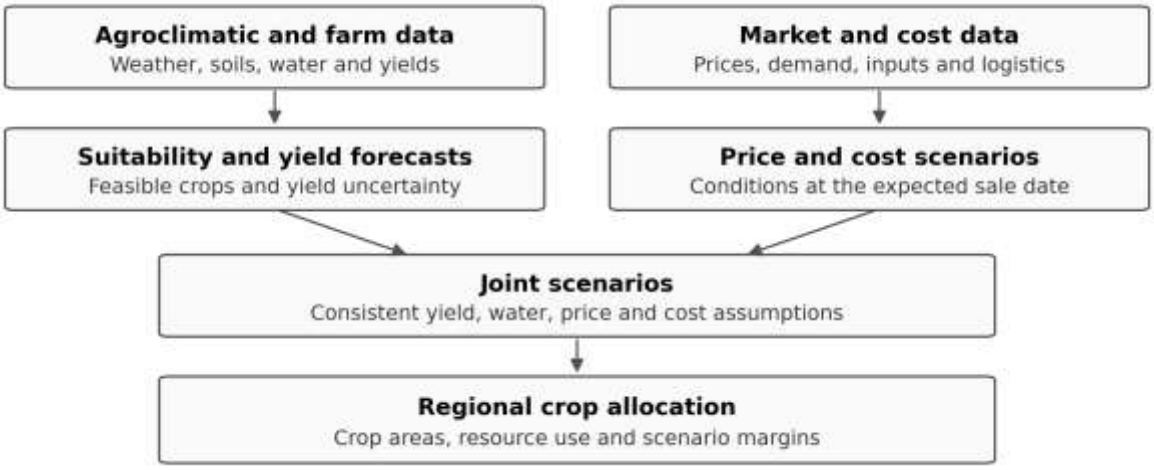


Figure 1. Conceptual workflow linking crop yield forecasts, market scenarios and regional crop allocation.

2.1. Agroclimatic Characterization and Data Preparation

Agroclimatic characterization identifies feasible crops and management practices using temperature, rainfall, soil moisture, irrigation reliability and soil constraints. The FAO Global Agro-Ecological Zones framework assesses crop suitability and attainable production from climatic and soil conditions [8]. These conditions should guide crop-specific eligibility rules supported by agronomic evidence.

Historical weather data can be supplemented by ERA5-Land reanalysis [9], which reconstructs past conditions rather than predicting future weather. Additional inputs include production records, crop calendars, soil observations and market data, summarized in Table 1.

Table 1.

Information required to connect forecasting with regional crop planning.

Information group	Representative variables	Role in planning
Agroclimatic conditions	Growth-stage temperature, rainfall, soil moisture, irrigation supply	Screen feasible crops and describe seasonal production risks
Land and production	Soils, cultivated area, crop history, yields, management	Define regional capacity and estimate crop-specific output
Market conditions	Local prices, seasonal demand, contracts, market access	Estimate sale-period revenue and assess market capacity
Costs and infrastructure	Seed, fertilizer, labour, energy, transport, storage	Estimate operating margins and implementation limits

All records should be matched to a common crop, region and season definition. Monetary values require a consistent currency and price basis. Missing observations, revisions and changes in administrative boundaries should be documented. Information that becomes available after a forecast issue date must be excluded from that forecast, including later price observations and full-season vegetation measurements.

2.2. Crop Yield Forecasting

The forecasting stage estimates yield conditional on the information available at a stated issue date. A general crop-specific model is written in Equation (1). The same formulation

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can represent regression, tree ensembles or a crop model combined with statistical correction; the algorithm should be selected through validation appropriate to the intended decision.

$$\hat{y}_{rct|\tau} = f_c(X_{rc,\leq\tau}, \widetilde{W}_{rt|\tau}, M_{rct}) \quad (1)$$

Here, r denotes a region, c a crop, t the target season and τ the forecast issue date. The forecast yield is measured in tonnes per allocated hectare. X contains observations available by τ, including soils, historical yields and weather already observed. W̃ represents uncertain weather for the remaining period, and M specifies the assumed management. For a fixed target season, a denotes the planned area matrix and the production of crop c in a scenario is defined by Equation (2).

$$Q_c^s(a) = \sum_r a_{rc}\, y_{rc}^s \quad (2)$$

The area assigned to a crop is measured in hectares and scenario production in tonnes. Yield must use the same area convention as allocation. If source statistics report tonnes per harvested hectare, crop failure and the difference between planted and harvested area must be incorporated before using those yields with planned cultivated area. Scenario yields should also remain consistent with the irrigation and management assumptions used by the allocation model.

2.3. Market Dynamics and Economic Feasibility

The market component estimates conditions at the expected sale date. Seasonal price models should be compared with simple benchmarks, such as the previous corresponding season, before their forecasts guide crop selection. Equation (3) converts joint yield and market scenarios into an operating margin for the planned areas.

$$\Pi_s(a) = \sum_r \sum_c a_{rc}(p_{rc}^s\, y_{rc}^s - k_{rc}^s - l_{rc}^s) \quad (3)$$

In this expression, p is the sale price in currency units per tonne, k is production cost per hectare and l is marketing cost per hectare, including transport and storage where applicable. The resulting margin is measured in currency units. This margin is a modelled economic comparison and should not be interpreted as a complete farm account unless all relevant costs are included.

2.4. Regional Crop Allocation under Resource Constraints

The allocation stage chooses crop areas using scenario margins while limiting exposure to adverse outcomes. One transparent formulation balances the expected margin against the worst margin among the scenarios, as shown in Equation (4). The risk preference is explicit so decision makers can compare allocations under different levels of conservatism.

$$max_{a,z}\, [(1-\lambda)\sum_s \omega_s\, \Pi_s(a) + \lambda z], \quad z \leq \Pi_s(a)\ \forall s \quad (4)$$

The scenario weights ω are non-negative and sum to one. The parameter λ lies between zero and one and controls the emphasis placed on the worst scenario. The auxiliary variable z is bounded by every scenario margin. Increasing λ gives greater weight to adverse outcomes; it does not guarantee protection against events outside the scenario set. The basic land and water restrictions are given in Equation (5).

$$\sum_c a_{rc} \leq A_r, \quad \sum_c a_{rc}\, w_{rc}^s \leq W_r^s \quad \forall r,s \quad (5)$$

A is the allocable land area in hectares. The water requirement w is expressed in cubic metres per hectare and W is the available irrigation water in cubic metres. Requirements and availability use the same accounting boundary, including delivery efficiency where relevant. The inequality permits fallow land. Crop suitability and agreed production bounds can be represented by Equation (6).

$$0 \leq a_{rc} \leq e_{rc}\, B_{rc}, \quad D_c^{min} \leq Q_c^s(a) \leq D_c^{max} \quad (6)$$

The eligibility indicator e is one for an agronomically feasible crop–region combination and zero otherwise; B is its area ceiling in hectares. The lower production bound Dmin may represent a staple supply commitment, while

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Dmax represents a justified market or handling limit, both in tonnes.

2.5. Validation and Scenario Assessment

Evaluation must distinguish forecast quality from allocation quality. Yield and price models should be tested on future seasons that were unavailable during training. Where transfer to new regions is intended, a separate spatial holdout is needed. This follows the broader principle that validation should reflect temporal and spatial dependence [10].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (7)$$

Here, n is the number of held-out observations, y is observed yield and ŷ is its forecast; RMSE has the same unit as yield. Prediction interval coverage should be assessed together with interval width.

3. Results

Agroclimatic characterization separates physically feasible options from options that are attractive only under an assumed price or historical average yield. The suitability framework in [8] supports distinguishing climatic and soil limitations. In the proposed allocation model, this distinction becomes explicit through crop eligibility and resource constraints. For example, a crop can remain thermally suitable while becoming infeasible under the available irrigation supply. A suitability map alone would therefore be insufficient to determine its cultivated area. Market analysis changes the criterion used to compare suitable crops. Equation (3) shows that an increase in expected yield raises the operating margin only in relation to the sale price and associated costs. The central outcome is a consistent connection between forecast information and a constrained area decision.

4. Conclusion

Forecasting crop yields and planning regional crop distribution are closely related tasks because expected output determines the consequences of allocating land to a crop. Their practical value depends on combining agroclimatic feasibility with the prices, costs and resource conditions expected during production and sale. This paper has organized those relationships into a conceptual workflow and a mathematical allocation model that makes uncertainty and constraints explicit.The analysis supports using forecasts at stated decision dates, matching yield and area definitions, evaluating joint climate and market scenarios, and testing allocation outcomes separately from prediction accuracy.

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