

Article

Spatially Explicit Crop Planning for Water–GHG–Profit Trade-Offs in Northeast China’s Black Soil Region: An End-to-End Land Use Optimization Framework

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Abstract

Land use planning in the Black Soil Region of Northeast China must be sustainable, taking into account food security, water use, GHG emissions, and economic returns. Current crop suitability mapping and single-objective optimization studies tend to analyze crop occurrence, crop structure, and spatial allocation independently, which is of little value in spatial planning. In this study, a three-stage integrated approach is proposed, involving deep learning crop occurrence mapping, multi-objective crop structure optimization, and suitability-guided spatial allocation. During Stage I, a lightweight U-Net semantic segmentation model, BlackSoilCropNet, is developed to provide per-pixel occurrence probabilities of rice, maize, soybean, and other types of crops based on Sentinel-2 time series and auxiliary environmental predictors. In stage II, NSGA II will optimize the area structure of the crops and reduce water consumption and GHG emissions with the maximum profit under the constraints of the cropland, water, and production. Selected Pareto optimal solutions are transformed to crop allocation maps and transition hotspot outputs in Stage III. The framework resulted in three viable planning options. The economic priority scenario resulted in the highest profit (USD 27.9 billion), with higher water consumption and emissions. The environmental-priority scenario resulted in a reduction in water use to $118.2 \times 10^9 \text{ m}^3$ and emissions to 50.9 MtCO_{2e}, but at the cost of lower production and profits. There was a balance between economic stability and an improved environment in the balanced scenario. The framework provides a reproducible, geospatial decision support approach for sustainable farming planning and black soil conservation overall.

Keywords: agricultural land use planning; multi-objective optimization; Northeast China Black Soil Region; NSGA-II; remote sensing

Academic Editor: Dong Jiang

Received: 30 March 2026

Revised: 11 June 2026

Accepted: 16 June 2026

Published: 26 June 2026

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1. Introduction

Heilongjiang, Jilin, Liaoning, and the eastern part of Inner Mongolia (NBSR) are among the grain production bases of China. It has good productive capacity in the form of its fertile Mollisols and has been crucial to national food security, as it hosts large-scale

cultivation of staple crops such as rice, maize, and soybeans [1]. But the soil quality, water resources, ecosystem stability, and greenhouse gas (GHG) emissions are under pressure due to long-term intensive cultivation. To this end, China has implemented the Black Soil Protection Law and related implementing rules to enhance the institutional and legal mechanisms for black soil protection [2]. The changes in policy are a sign that a decision on crop planning in the NBSR should be made not only on the basis of yield or the area used for cultivation but also with regard to the efficiency of the use of resources, environmental performance, and the ecological sustainability of the crop [3,4].

The planting of crops is tightly coupled with various resource and environmental processes in the NBSR. The spatial distribution and area structure of crops influence irrigation quantity requirements, land use intensity, agricultural energy use, fertilizer-associated emissions, and stability of ecosystem services [5]. In this regard, crop planning should be considered as a multi-objective problem of water, land, energy, environment, and ecological footprint, not only as a production adjustment problem [6]. The water-energy-food-ecosystem nexus may be a useful framework for assessing such interactions, as improvement in one dimension could create stress in another [7–9]. For instance, the quest for economic profit can lead to higher water consumption or GHG emissions, and the protection of the environment can lead to lower production or incomes. Crop planning studies under the nexus have thus been increasingly promoted in recent years, with a special focus on multi-objective optimization under explicit constraints of water availability, food security, and environmental protection.

Black soils are also ecologically vulnerable, highlighting the significance of the integrated planning perspective. Black soils are a world-rare resource of immense value with regard to stable grain production. Soil organic carbon has decreased, soil erosion risk has increased, and the capacity of cultivated land systems has lowered in Northeast China due to intensive farming [10]. Adopting reduced tillage and residue return can lead to an increase in SOC and crop yields; however, the potential of these effects depends on the climate, soil characteristics, and duration of conservation [11]. Meanwhile, cultivated land in the NBSR offers significant ecosystem services, and recent research has highlighted the importance of taking into account the value of ecosystem services, ecological security, and landscape vulnerability in land use interventions [10,12,13]. These results demonstrate that the design of the crop structure and its location need to be considered as a whole when balancing agricultural productivity, economic benefit, and ecological protection.

New opportunities for spatially explicit crop planning by remote sensing and deep learning. Sentinel-2 also offers multispectral data with appropriate spatial resolution and revisit period, which is widely used to monitor agriculture [14]. The time series of Sentinel-2 data can be used as input in dense data streams to provide information on crop phenology, and deep learning models can be trained using the spectral and temporal patterns to classify major crop types at a large spatial scale [15]. The previous studies indicated the feasibility of mapping rice, maize, and soybean and other crops using Sentinel-2 through deep learning approaches, particularly temporal reconstruction, attention mechanisms, or convolutional architectures [16,17]. Fully convolutional networks, 3D convolutional models, and recent temporal learning methods have also given improvements in dynamic and in-season crop mapping [18–20]. Benchmark datasets and resources for crop mapping can be made open, which also helps to build reproducible models and comparative analyses [21,22].

However, there are a number of methodological deficiencies. First, the majority of crop-mapping studies are only interested in the accuracy of the classification and do not relate the crop probability map to land use optimization in downstream areas [16,17,19]. Second, many crop structure optimization studies determine aggregate crop areas but do

not use spatially explicit, data-driven crop occurrence information to guide where the optimized areas should be placed [23]. Third, however, spatial allocation studies may be based on the correlation-based suitability indicator or the heuristic allocation rule, which might not fully represent crop-specific patterns learned from remote sensing and environmental predictors [9,24]. Also, in geospatial applications, the neighborhood where samples are being trained and tested may be similar, so a random strategy may overestimate the performance of the model. Spatial block validation is thus recommended to mitigate spatial leakage and thereby to obtain a better estimate of generalization [25,26].

To overcome these drawbacks, a deep learning-based crop occurrence mapping approach is developed and integrated with a multi-objective crop structure optimization algorithm in one reproducible crop planning framework to achieve spatial allocation. First, a lightweight semantic segmentation model called BlackSoilCropNet is employed to compute per-pixel probabilities of the occurrence of each class (rice, maize, soybean, etc.) for a Sentinel-2 time series and a set of environmental auxiliary data. Such probabilities are not agronomic suitability measures but rather suitability proxies based on data. The second stage is optimizing the water use efficiency and GHG emissions of the crop area structure using a non-dominated sorting genetic algorithm II (NSGA II) with the objective of maximizing profit within the constraints of cropland, water, and production. The third step is the spatial allocation of the optimized crop area targets within the cropland grid to create a crop layout map for each scenario, as well as to identify the transition hotspots.

This study has four key contributions. Firstly, it builds BSCNet as a lightweight crop occurrence mapping model for rice, maize, and soybean, and other classes in the NBSR, which is evaluated using a spatial block-level validation method. Secondly, it contains a clear optimization module based on the NSGA II approach, which contains explicit constraints on water, GHG, profit, cropland, production, and water cap. Third, it suggests an allocation procedure guided by suitability, which transforms optimized targets of crop area into maps of the scenarios while minimizing suitability loss. Fourth, it enables the integration of these elements into a reproducible end-to-end workflow that can produce scenario results that are easily understood from an economic, environmental, and balanced crop planning perspective.

While the various tools and technologies of deep learning crop mapping, NSGA II optimization, and suitability-guided crop allocation have all been employed in past research, they are typically used individually. The proposed framework, on the other hand, links these components in a sequential decision pipeline, in which the output of each stage is directly fed into the next stage. Crop occurrence probabilities from BSCNet are used to inform the spatial allocation process; NSGA II gives Pareto-efficient crop structure options, and the final allocation maps identify where crop transitions are most likely to occur. This permits the framework to report the crop planning scenarios, which are both spatially explicit and policy relevant, not just the classification maps and aggregated optimized crop areas for the NBSR.

This paper is organized as follows: The study area is described in Section 2. The datasets and pre-processing are presented in Section 3. The proposed three-stage methodology is explained in Section 4, namely BSCNet mapping, NSGA II optimization, and spatial allocation. The mapping, optimization, allocation, and uncertainty results are presented in Section 5. The implications, comparison to the related studies, limitations of the study, and future research directions are discussed in Section 6. The paper is concluded in Section 7.

2. Study Area

This study focuses on China's Northeast Black Soil Region (NBSR), a strategically crucial grain-producing zone characterized by extensive black soils and large-scale mech-

anized agriculture. An overview map of the study area was prepared to illustrate the spatial location and administrative structure of the Northeast Black Soil Region proxy ROI, as shown in Figure 1 for better spatial understanding. The study area in China is identified on the map, and the eastern agro-ecological belt of Inner Mongolia, Jilin, Liaoning, and Heilongjiang is highlighted. This map is designed to assist readers in better comprehending the regional extent considered for analysis, as well as to separate the administrative planning boundary from a pedological black soil boundary.

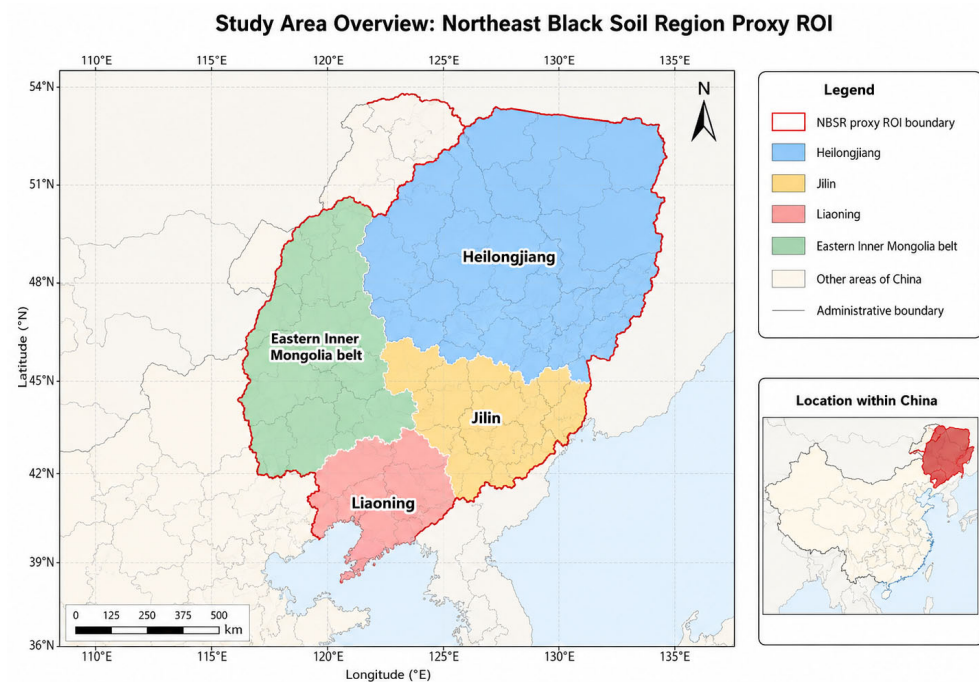


Figure 1. Study area overview map of the Northeast Black Soil Region proxy ROI. The map shows the location of the study area within China and highlights Heilongjiang, Jilin, Liaoning, and the eastern agro-ecological belt of Inner Mongolia. Administrative boundaries, a legend, a scale bar, a north arrow, and coordinate labels are included to support geographic interpretation.

2.1. Definition of the Northeast Black Soil Region

Since there are no universally accepted polygons for the NBSR in open administrative data, we adopt a province-based proxy ROI that aligns with the newly adopted literature on Northeast China/Black Soil administrative region: Heilongjiang, Jilin, Liaoning, and the eastern part of Inner Mongolia [27,28]. Operatively, the ROI is constructed by dissolving the provincial boundaries in the GADM v4.1 administrative data [29]. This proxy is popular in regional-level analyses because (i) it fits the policy-relevant units of administration (i.e., a province), (ii) it can be reported at the provincial level, and (iii) it can be replicated across studies and years. To be transparent and extensible, our workflow is structured so that the ROI can be replaced with a custom shapefile (e.g., a scientifically defined black soil extent polygon) without affecting downstream modules (clipping, zonal statistics, and mapping) [29]. It is important to remember that the adopted ROI is not a pedological definition of the black soil boundary, but rather a proxy based on administrative/policy considerations. Some landscapes outside the selected provinces may be non-black soil, and some black soil patches within the selected provinces may not be perfectly represented. The decision to use this option was taken because agricultural planning, statistical reporting, and implementation of the crop policy are generally conducted at the provincial or sub-provincial administrative levels. All spatial modeling and allocation operations are limited by cropland masks and crop reference layers instead of administrative

boundaries only to minimize the impact of this boundary approximation. The scenarios that result therefore should be interpreted as planning scenarios for the Northeast Black Soil Region administrative planning zone and not as a soil polygon-level assessment. In the case of the availability of a high-resolution black soil extent map, the same workflow can be applied directly to this polygon as the ROI.

2.2. Climate, Topography, Soils, and Cropping Systems

Climate: A temperate continental monsoon regime with high seasonality (long, cold winters; short, warm summers) and growing-season precipitation is the primary influence on the region. According to recent regional research, annual precipitation amounts to the order of 500–600 mm and low mean yearly temperature conditions (near-freezing to a few °C in cold subzones), but there are extreme gradients between latitudes and altitudes [27,30]. **Topography:** Northeast China has extensive plains with mountainous belts surrounding them, and it has several large lowland agricultural belts, including the Songnen Plain and the Sanjiang Plain, which are often considered central areas of black soil distribution and grain production [31]. Higher altitudes are usually low to medium, which favors mechanized agriculture and expansive parcels of contiguous croplands. In contrast, the upland terrain is the cause of erosion susceptibility and area heterogeneity in suitability [27,30,31]. **Soils and black soil context:** The NBSR is marked by expansive black soils (high-organic-matter topsoils) that are very productive, yet they are easily destroyed under intensive farming conditions. Recent evaluations focus on the variability of soil organic matter and the ongoing conservation issues and support the necessity of spatially specific planting and management approaches [31,32]. **Cropping systems:** Maize, soybean, and rice are the main staple crops in the area, and the region's crop patterns are shaped by climate suitability, irrigation accessibility, and the land's past development. Recent agronomic change studies emphasize the region's importance as a production hub and report on the spatial heterogeneity and development of farming systems, such as the persistence of maize-based farming systems and soybean/rice in the most suitable subregions [33,34].

2.3. Administrative Context

Implementation and reporting of the administrative context are necessary because agricultural planning and subsidy/rotation programs are usually organized and implemented at provincial and sub-provincial levels. In keeping with tradition in black soil literature, the eastern Inner Mongolia element is considered to be the east agro-ecological belt that borders the three northeastern provinces; more recent black soil administrative definitions explicitly identify the east Inner Mongolia belt in addition to Heilongjiang, Jilin, and Liaoning [28]. To support province-level summaries and map display, we use consistent administrative boundaries derived from GADM v4.1 [29]. The uses of these boundaries include: (i) to produce raster clipping ROI, (ii) to summarize province-level crop areas, and (iii) to represent province/ADM2 boundaries in a way that can be interpreted and used by policymakers by overlaying them on scenario layout maps.

3. Data and Pre-Processing

This section explains the datasets used for predictor construction, label generation, baseline production estimation, and optimization. Table 1 summarizes the complete data inventory, including source, spatial resolution, temporal coverage, variables, and role in the study.

Table 1. Data inventory (dataset, source, resolution, years, variables).

Dataset	Source	Spatial Resolution	Temporal Coverage	Variables/Products	Role in This Study
Sentinel-2 Image Time Series for Crop Mapping	Kaggle (Sentinel-2 crop mapping time-series dataset).	10–20 m (S2 bands)	Depends on the dataset (multi-date within growing season)	Multispectral reflectance time series (e.g., B2–B8A, B11, B12), optional indices	Core dynamic predictors for BSCNet crop segmentation
Sentinel-2 MSI (if downloaded directly)	Copernicus/ESA	10–60 m	2015–present (as needed)	Level-2A surface reflectance; cloud masks	Alternative/backup source for time-series feature construction
WorldClim BIO1	WorldClim	~1 km (or 30 arc-sec)	Climatological normal	BIO1 = mean annual temperature	Static climate predictor for BSCNet
WorldClim BIO12	WorldClim	~1 km (or 30 arc-sec)	Climatological normal	BIO12 = annual precipitation	Static climate predictor for BSCNet
SRTM DEM	NASA SRTM	~30 m (1 arc-sec)	Static	Elevation	Terrain predictor; used directly and to derive slope
Slope (derived from DEM)	Derived from SRTM	~30 m	Static	Slope	Terrain predictor for BSCNet and feasibility interpretation
Optional soil layers (if available)	Open soil grids/national soil datasets	250 m–1 km (varies)	Static	SOC proxy, texture, pH, etc.	Optional predictors to improve generalization and soil sensitivity
Rice distribution raster (China)	Provided by user/regional crop products	30 m	Year-specific (if multi-year)	Rice presence/probability	Label source for “rice” class; calibration/validation
Maize distribution raster (China)	Provided by user/regional crop products	30 m	Year-specific (if multi-year)	Maize presence/probability	Label source for “maize” class; calibration/validation
Soybean distribution raster (China)	Provided by user/regional crop products	30 m	Year-specific (if multi-year)	Soybean presence/probability	Label source for “soybean” class; calibration/validation
Example crop raster (Anhui maize)	Provided by the user	Raster resolution as provided	2001 (example)	Classified maize	Fallback/format validation; sanity check for raster IO pipeline
Cropland/land cover mask	Open land-cover product (China or global)	10 m–300 m (varies)	Year-specific	Cropland/non-cropland	Builds 4-class labels (“other” includes non-target crops + non-cropland)
China staple crop harvested area (integrated multi-source)	Provided by user (zip dataset)	Gridded (varies)	Multi-year (as available)	Harvested area layers for staple crops	Optional calibration/validation for areas and spatial agreement
FAO/UN crop statistics (China)	Provided by user (FAO-style CSV)	National	2015–2021 (target)	Production, harvested area, yield	Baseline yield/production constraints and sensitivity ranges in optimization
Administrative boundaries	GADM (China)	Vector polygons	Static	ADM0/ADM1/ADM2 boundaries	ROI definition (province-based proxy) + province-level reporting + map boundaries

3.1. Data Inventory and Sources

We integrate four data groups: (i) Sentinel-2 optical time series for crop phenology features, (ii) auxiliary environmental predictors (climate and terrain, with optional soils), (iii) crop reference rasters (rice/maize/soybean) plus a cropland/land-cover mask for label building, and

(iv) statistical baseline data for yield, harvested area, and production. These datasets, including their spatial resolution, temporal coverage, and variables, are listed in Table 1.

3.2. Sentinel-2 Time-Series Construction

The Sentinel-2 images are converted into a stable time-series stack of features for crop discrimination. We use cloud and cloud-shadow masking, followed by the creation of regular temporal composites (i.e., 10–30 days) to reduce noise and fill gaps. We use seasonal windows (i.e., green-up, peak growth, senescence) within the regional growing season to characterize crop phenology and to calculate summary statistics for each window (median/percentiles and selected vegetation indices). The result is a feature tensor organized in time that is used as input to the segmentation model.

3.3. Auxiliary Predictors

We also incorporate background biophysical constraints as static predictors to enhance generalization and promote suitability mapping at a spatially consistent level. Core layers such as mean annual temperature (BIO1), annual precipitation (BIO12), elevation, and slope are present. They are graphically represented in Figure 2. Provided that soil layers (e.g., texture, organic carbon proxies) are available, they are added as optional channels. The resampling of all the auxiliary predictors on the modeling grid and the spatial alignment of all the features of Sentinel-2 occur.

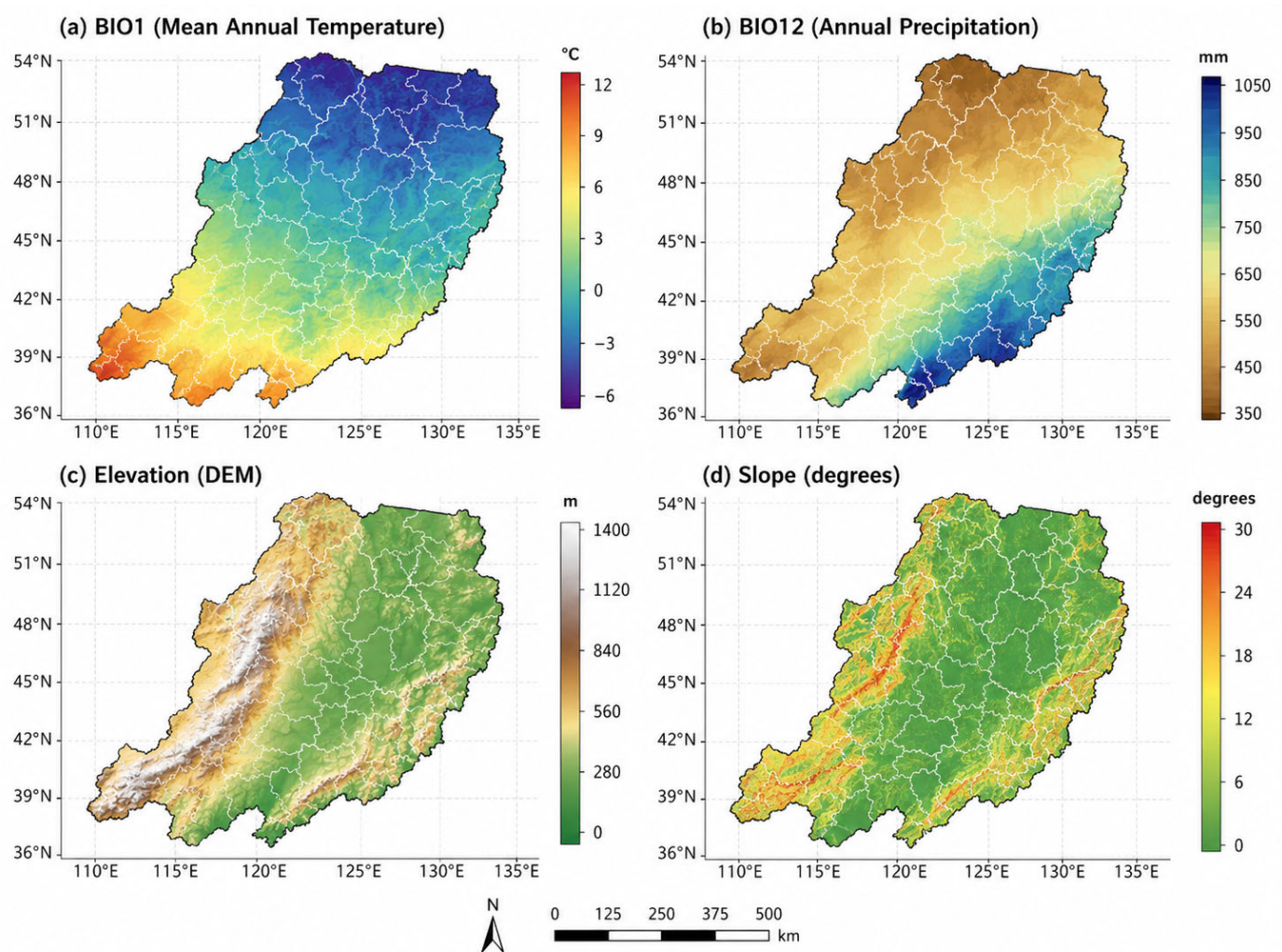


Figure 2. Environmental predictor layers used in the BSCNet mapping stage: (a) mean annual temperature BIO1, °C; (b) annual precipitation BIO12, mm; (c) elevation derived from DEM, m; and (d)

slope, degrees. All panels are clipped to the Northeast Black Soil Region proxy ROI and displayed using the same map extent. Administrative boundaries, legend units, scale bar, north arrow, and coordinate labels are included for standardized geographic interpretation.

3.4. Label Construction

Training labels were created by combining the crop distribution products for rice, maize, and soybean with a cropland or land cover mask. These crop distribution layers are used as a remote sensing-derived reference label and not ground-truth surveyed in the field. The potential pixels identified as rice, maize, or soybean crops were classified under the respective crop class. Pixels not in these target classes were allocated to the other class, including non-target crops and non-cropland areas within the analysis mask. This resulted in a four-class segmentation label set: rice, maize, soybean, and other.

The classification uncertainty introduced into reference labels from mixed pixels, temporal mismatch, cloud contamination, crop rotation, and spectral similarity of crop types is inevitable from remote sensing products. In order to minimize the impact of these uncertainties, all layers were resampled to a common grid, and model performance was assessed through spatial block validation rather than random pixel splitting. The results are thus considered as between-interpretation with respect to the best available crop reference product and not as direct field-level validation.

A final training dataset was created by taking samples of fixed-size image patches from the harmonized predictor and label grids. The number of patches, the total number of labeled pixels, the distribution of the labeled classes, and the training validation split were reported in the revised manuscript to clarify the size of the training sample. This information is now added to Table 1 and the crop mapping results section.

3.5. Harmonization

The boundaries of all raster and vector layers are brought to a standard coordinate reference system and pixel grid. Clipping of inputs to the ROI, resampling to standard resolution (or aggregation where required), and verification of no data consistency are performed. This guarantees the co-registration of all predictors and labels, which results in robust patch sampling, training, evaluation, and downstream allocation.

3.6. Baseline Production Statistics

The baseline data of production, harvested area, and yield of rice, maize, and soybean were prepared from 2015 to 2021. The above information was utilized to establish realistic production constraints and ranges of possible coefficients for the optimization phase. We recognize that national statistics do not fully reflect the spatial variation in the Northeast Black Soil Region, as yields may vary from national averages due to soil conditions, climate, and availability of irrigation, as well as management practices. Hence, the national statistics were not considered as accurate local yield estimates. The latter were, however, adopted as conservative reference values for scenario feasibility and sensitivity tests.

To overcome this, the new framework includes uncertainty bands for yield, water use, GHG emissions, and profit coefficients. The robustness of the scenarios was assessed by perturbing the parameters so that a single deterministic national average scenario does not drive the conclusions. Finally, county-level agricultural statistics or process-based crop yield forecasting models can be directly used in the same optimization module in future applications to improve regional specificity.

4. Methodology

4.1. BSCNet—NSGA-II Integrated Framework

The presented methodology encompasses a deep learning-based scheme for crop suitability mapping, a multi-objective scheme for crop structure, and spatially explicit allocation to aid WLEE-EF-oriented decision-making in the Northeast Black Soil Region. The process has three successive steps. Stage I: In Stage I, a deep segmentation model yields pixel-wise probabilities for rice, maize, soybean, and other crops; crop-class probabilities are treated as suitability surfaces. In Stage II, competing WLEE-EF goals are solved at the scenario level to achieve Pareto-efficient crop-structure solutions. In Stage III, the selected Pareto scenarios are mapped by distributing crop labels across the cropland grid to achieve scenario-area objectives and location priorities at high-suitability locations. The entire pipeline is outlined in Figure 3, which is also mentioned in the Introduction as the conceptual map of the proposed framework.

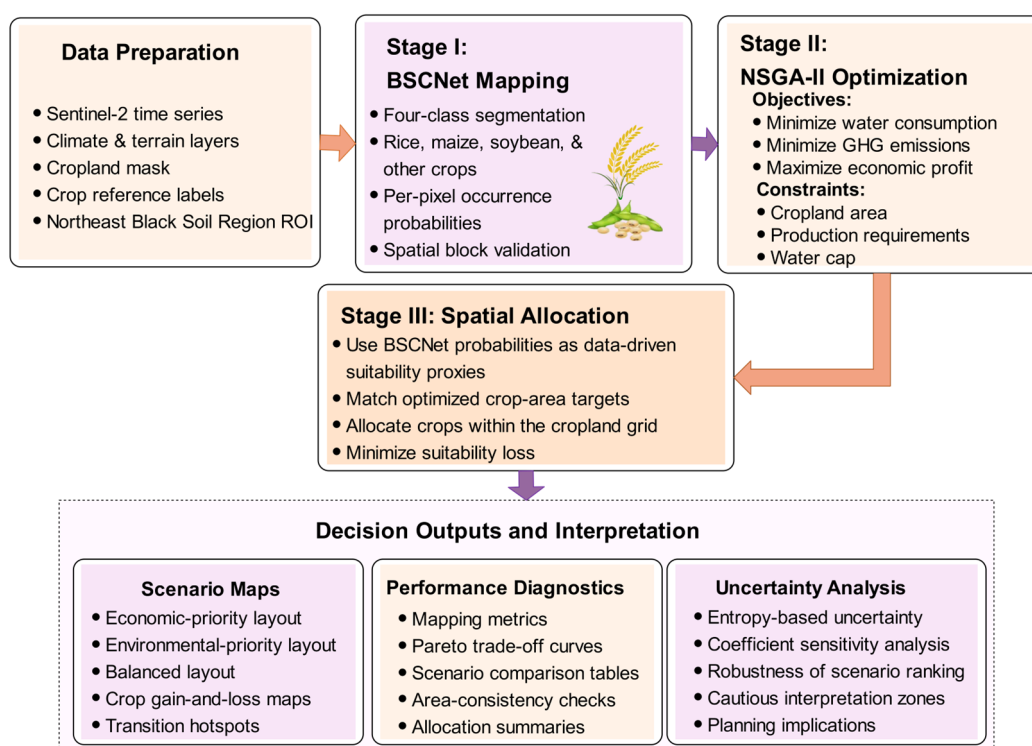


Figure 3. Three-stage crop planning framework. Stage I uses BSCNet to generate crop occurrence probability maps from Sentinel-2 time series and auxiliary predictors. Stage II uses NSGA II to optimize crop area structure under water, GHG, profit, cropland, and production constraints. Stage III allocates the optimized area targets across cropland cells using the BSCNet probabilities as data-driven suitability proxies.

Three-step working procedure: Stage I, the first stage performs deep crop mapping to estimate the spatially continuous suitability probability from remote sensing and auxiliary predictors. These outputs are used in Stage II to aid the multi-objective optimization of crop-area structure under production and resource constraints. The Stage III area targets distribute optimized area targets in space, ensuring a suitability loss based on the feasibility of croplands, and create scenario layouts, making it possible to locate hotspots by comparing maps. The terms probability and suitability are used interchangeably in this study, but they are not synonymous. The BSCNet generates estimates of the likelihood of an individual pixel belonging to a particular crop, with model results ranging from rice, maize, soybean, and others. The resulting probabilities serve as suitability proxies in the

allocation stage, based on data. Thus, suitability in this paper is not simply the biophysical agronomic suitability that can only be defined based on climatic, soil, and topographic thresholds. Rather, it is an indication of the realized crop occurrence potential learned from remote sensing and environmental predictors. This difference is significant because the probability of the crop classes is additive at the pixel level, but the probability of the agronomic suitability indices is not necessarily additive.

4.2. Stage I—Deep Crop Mapping with BSCNet

Crop occurrence probabilities for rice, maize, soybean, and other classes are estimated at each grid cell that is considered in Stage I. The probabilities are not considered as pure agronomic suitability indices. Instead, they are used as data-driven suitability proxies, as they combine occurrence patterns of the crop, spectral, temporal, climatic, and terrain information. In Stage III, the higher the crop-specific occurrence probability (OSP), the more favorably a pixel will be treated to allocate that crop within the optimized area targets and subject to the cropland constraints.

Figure 4 depicts sample suitability/probability maps that BSCNet produced for the three target crops, i.e., (a) rice, (b) maize, and (c) soybean.

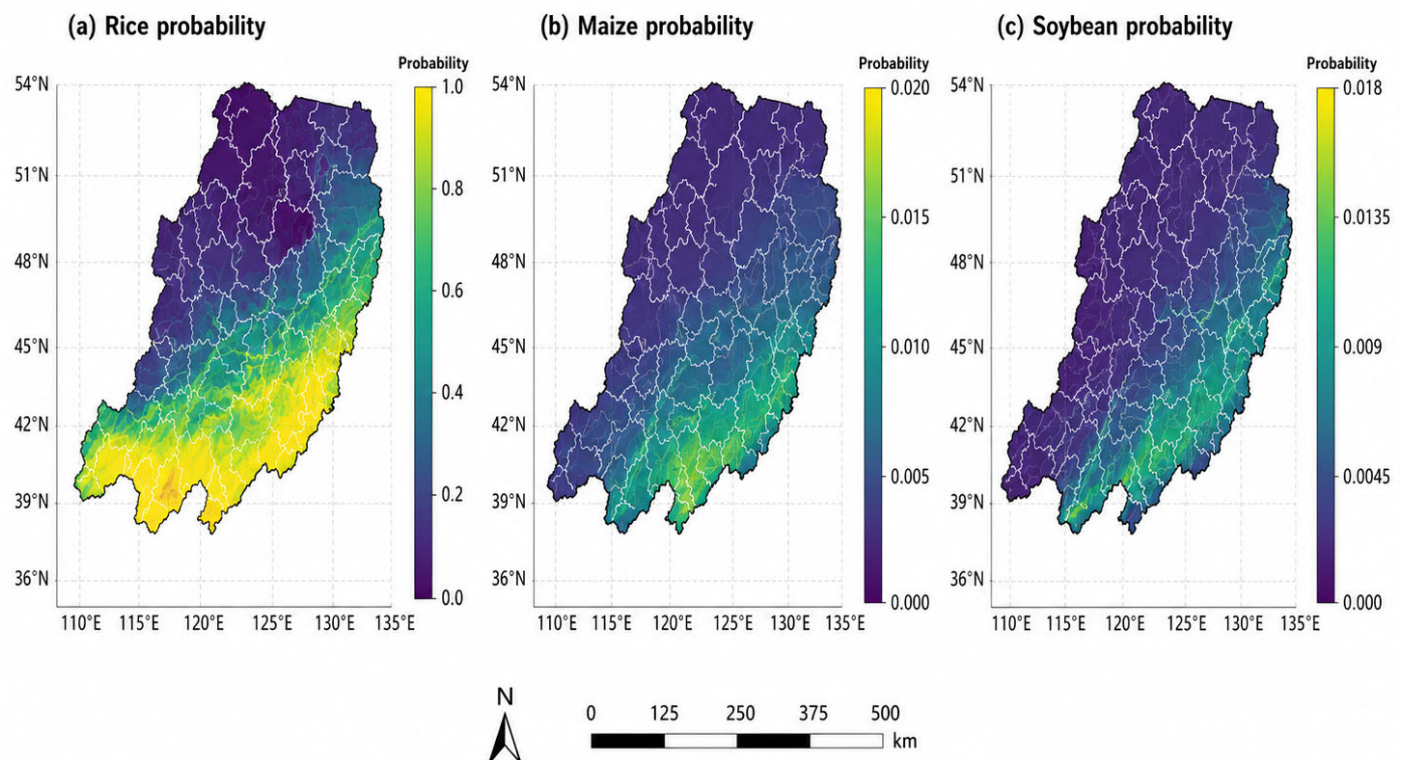


Figure 4. BSCNet-predicted crop occurrence probability maps for (a) rice, (b) maize, and (c) soybean. The maps represent model-estimated crop occurrence probability rather than independent agronomic suitability. Crop-specific color scales are used to improve the visibility of spatial variation, especially for maize and soybean, whose predicted probabilities occupy narrower numerical ranges. Administrative boundaries, a scale bar, a north arrow, and coordinate labels are included for standardized geographic interpretation.

We reduce the crop mapping problem to a four-class segmentation problem, with target classes of rice, maize, and soybean, and the remaining category, the rest of the crops and non-target land cover in the analysis mask. This expression ensures that a dedicated other class is retained so that the model is not coerced to attribute non-target regions to

either of the dominating crops, thereby enhancing the relevance of the suitability surfaces to be utilized in the latter stages. The inputs to the BSCNet integrate information from Sentinel-2 time series and auxiliary predictors to describe phenological dynamics and environmental controls. The Sentinel-2 channel records within-season spectral paths in discriminating crop types, either by providing multi-date reflectance stacks directly or by using temporally aggregated features such as per-band mean, maximum, and variability, and vegetation-index summaries computed over phenological periods. Auxiliary predictors give context (statistically), like climate normal and terrain predictors (elevation and slope), and may be further expanded with covariates of soil where possible. Model ingestion is performed by harmonizing all predictors onto a consistent grid. BSCNet is implemented as a lightweight U-Net encoder–decoder to balance predictive power and computational manageability across large areas. The encoder uses repeated progressive downsampling convolutional blocks to get multi-scale features. Simultaneously, the decoder upsamples these representations and combines them with matching encoder features via skip connections, thereby preserving spatial information. The last stage is a 1×1 convolution that produces per-class logits at every pixel, and a softmax operation converts these logits into per-class probabilities. Such Stage II and Stage III make use of the rice, maize, and soybean probabilities as suitability surfaces in this pipeline. The training is done on fixed-size patches sampled in the mapped area, thereby better utilizing the GPUs and adding more variety in the local context to observe during optimization. To minimize spatial leakage and overestimation in light of autocorrelation, spatial block cross-validation is performed. The area of study is divided into non-overlapping spatial blocks, and training or validation splits are given whole blocks. Sampling patches is then done only with blocks of their respective splits, and validation pixels are sampled at geographically different points than in the training data. The performance metrics are based on complementary measures that blend the quality of overall agreement and the quality of class-based segmentation. Overall accuracy is a fraction of the pixels associated with the correct label. It is an intuitive global score, whereas macro-F1 is the average of the F1 scores across all classes, thereby reducing the effect of class imbalance. In terms of the practical problem to be solved, Stage I is a simple spatial question: Where is each crop most likely to be present given the observed remote sensing and environmental factors? The model learns this relationship from reference maps of the crop and predictor layers. It produces a series of probability surfaces for each crop, not a final crop plan, the results of which are fed into subsequent optimization and allocation.

4.3. Stage II—Crop Structure Optimization (NSGA-II) Under the WLEE–EF Nexus

Stage II identifies an ideal crop-area model for rice, maize, and soybeans within a nexus view of WLEE–EF. The optimization is addressed using the evolutionary multi-objective algorithm NSGA-II, which provides a Pareto set of non-dominated crop-structure solutions that directly indicate trade-offs among resource use, emissions, and economic performance. The area vector gives the decision variables for the three major crops that are planted:

$$x = [A_r, A_m, A_s] \quad (1)$$

A_r , A_m , and A_s denote the harvested area (ha) that is allocated to rice, maize, and soybean. All decision variables are continuous and range from 0 to the total available cropland in the study area. Three objectives are minimized concurrently to represent the fundamental trade-offs of the WLEE–EF nexus. Water use is minimized:

$$\min W(x) = A_r \cdot w_r + A_m \cdot w_m + A_s \cdot w_s \quad (2)$$

where w_c denotes water consumption per hectare (m^3/ha) for the crop c . GHG emissions are minimized:

$$\min G(x) = A_r \cdot g_r + A_m \cdot g_m + A_s \cdot g_s \quad (3)$$

where g_c is the emission intensity ($\text{tCO}_2\text{e}/\text{ha}$) for the crop c . Economic profit is maximized:

$$\max \Pi(x) = A_r \cdot \pi_r + A_m \cdot \pi_m + A_s \cdot \pi_s \quad (4)$$

where π_c is net profit per hectare (USD/ha). In the algorithm implementation, profit maximization is converted to minimization by using $-(x)$ as the third objective. The candidate crop structures must satisfy land and food-security conditions while respecting a water-use limit. Three inequality constraints are imposed. Cropland availability constrains the total allocated area:

$$A_r + A_m + A_s \leq A_{\text{cropland}} \quad (5)$$

A minimum production requirement ensures food production remains near baseline levels $P(x) \geq P_{\min}$, with production computed as follows:

$$P(x) = A_r \cdot y_r + A_m \cdot y_m + A_s \cdot y_s \quad (6)$$

where y_c is crop yield (t/ha). The minimum production threshold is set relative to baseline production:

$$P_{\min} = \alpha \cdot P_0 \quad (7)$$

where P_0 is baseline production and α is typically set close to 1 (for example, 0.95) to allow limited adjustment without compromising supply. A water cap constrains total water use:

$$W(x) \leq W_{\max} \quad (8)$$

where $W_{\max}$ is defined as a permissible upper bound relative to baseline water use, such as the following:

$$W_{\max} = \beta \cdot W_0 \quad (9)$$

where W_0 is the amount of water needed at the start, and β is slightly greater than 1 (e.g., 1.05) to allow the water to re-equilibrate, but not to let too high a water requirement. The optimization depends on per-hectare coefficients of individual crops, namely, water usage, GHG emission intensity, and net profit. Area decisions are converted into production outcomes using yield coefficients. The observed or mapped crop distribution in the study area is used to come up with baseline values that give a baseline area (A_{r0}, A_{m0}, A_{s0}), baseline production P_0 , baseline water use W_0 , and baseline profit Π_0 . Sensitivity testing uses coefficient ranges to assess uncertainty and interannual variability. Sensitivity bounds are used in practice as multiplicative factors around the baseline coefficients; for example, each coefficient can take any value within a given percentage range (e.g., ± 10 – 20%). This will provide a controlled method for assessing the robustness of Pareto-optimal structures and ranking scenarios under parameter uncertainty. Optimization of production and consistency checks with historical variability can be made using FAO time series that yield baselines and plausible ranges based on 2015–2021 Chinese statistics, thereby providing consistency checks. The Pareto solutions are visually summarized in a profit GHG and profit water trade-off plot and, optionally, in a 3D scatter plot of all three objectives to emphasize the geometry of the non-dominated set. Figure 3 is associated with these plots, and they are generated directly from the objective vectors provided by NSGA-II. From the Pareto-optimal set, three prototypical scenarios are selected to facilitate further spatial allocation. The economic-priority scenario is the solution with the highest profit among the

feasible, non-dominated candidates; an environmental-priority scenario is chosen by minimizing a composite environmental score, usually normalized water use and normalized GHG emissions, thereby giving low-resource, low-emission solutions the advantage. The balanced scenario is chosen as the one that is nearest to a utopian point where the water use and emissions are low, and a high profit is achieved. This is operationalized by normalizing all the objectives in the Pareto set and selecting the solution with the shortest Euclidean distance to $(W^*, G^*, \Pi^*) = (0, 0, 1)$ in normalized coordinates. The three scenarios provide contrasting but interpretable targets for crop-structure feeding Stage III, in which the pixel-level suiting surfaces of Stage I are mapped onto a spatial allocation of land; the area totals in Stage III equal the scenario-level area totals. Table 2 summarizes the per-hectare coefficients used in the optimization, their data sources, derivation basis, and notes on regional applicability.

Table 2. Per-hectare coefficients used in the optimization, data sources, and applicability notes.

Coefficient Unit	Primary Data Source(s)	Basis/Derivation	Regional Applicability Note
Water use m ³ /ha	Ministry of Water Resources of China ([35])	Derived from provincial irrigation statistics and cross-validated against regional water footprint estimates	Represents provincial/regional average irrigation demand; may vary within the study area due to irrigation access, crop management, and local climate
GHG emissions tCO ₂ e/ha	IPCC [36]	Based on IPCC Tier 2 emission factors unadapted for Chinese agricultural systems, supplemented by regional life-cycle assessment studies for Northeast China	Represents average emission intensity under prevailing regional production systems; it does not fully resolve sub-regional differences in fertilizer use, energy inputs, or residue management
Net profit USD/ha	National Bureau of Statistics of China [37]	Calculated from 2018 to 2021 provincial agricultural yearbook averages, incorporating input costs, market prices, and subsidies	Represents average economic return under regional market conditions; may vary locally with farm size, input intensity, and market access
Yield t/ha	FAO statistics; provincial agricultural reports	Harmonized from FAO statistics and provincial reports to provide representative per-hectare production values	Represents regional average productivity; local variation may arise from soil quality, management regime, and weather conditions

4.4. Stage III—Spatial Allocation of Optimized Crop Layouts

Stage III transforms the region-level goals of the crop structure of Stage II into explicit, spatially coherent crop-layout maps. In this step, the optimization of area allocations is combined with the pixel-scale suitability surfaces generated in Stage I to produce scenario-specific land-use configurations that can be compared with baseline patterns and assessed in terms of transition intensity and spatial plausibility. Spatial allocation is limited to a sound cropland area defined by a cropland mask. The mask is based on a layer of target-region land-use, or on the combination of mapped crop extents used to build the four-class label raster. The pixels that fall outside the cropland mask are assigned to the other category and do not undergo optimization or allocation to prevent the natural extension of cultivated land into non-agricultural areas. Let x index raster cells within the cropland mask, and let $S_c(x) \in [0, 1]$ denote the suitability (or predicted probability) of the crop $c \in \{r, m, s\}$ at cell x , obtained from BSCNet. For a given scenario with target areas (A_r^*, A_m^*, A_s^*) (converted to target cell counts N_r^*, N_m^*, N_s^* using cell area), spatial allocation assigns each cropland cell to exactly one class to satisfy area targets while maximizing overall suitability. This is written as a discrete assignment problem:

$$\min \sum_{x \in \Omega} \sum_{c \in \{r, m, s, o\}} z_c(x) (1 - S_c(x)) \quad (10)$$

subject to the following:

$$\sum_c z_c(x) = 1, \forall x \in \Omega \quad \sum_{x \in \Omega} z_r(x) = N_r^*, \quad \sum_{x \in \Omega} z_m(x) = N_m^*, \quad \sum_{x \in \Omega} z_s(x) = N_s^* \quad z_c(x) \in \{0, 1\} \quad (11)$$

where Ω is the viable cropland area, and o is the other class absorbing all other cells not defined as rice, maize, or soybean. Practically, $S_o(x)$ may be obtained directly as the model output of the other class or through the remaining probability. Due to the potential computational cost of pixel-level assignment across the entire Northeast Black Soil Region at native resolution, it is performed on an aggregated grid to ensure scalability and reproducibility. All suitability maps and labels are remapped onto an analysis grid of about 1 km (equivalent to 0.01° in geographic coordinates), resulting in a significant decrease in the number of decision cells. In contrast, structure and transition analysis patterns are still captured in the region. Aggregation is done uniformly between predictors, labels, and suitability outputs. Continuous layers (e.g., suitability probabilities and covariates) are summed with the mean (or maximum, in which case one wants to select the most conservative suits). By contrast, categorical labels are aggregated either by majority vote or by mean one-hot representations, and then the argmax is taken. It is important to note that the scenarios created should be read as a plan for regional planning, not as prescriptions at the field level. The allocation grid is aggregated to ~ 1 km in order to be scalable in the computation and to comply with the regional character of the optimization coefficients. Thus, individual allocation cells can contain several farms or field parcels, and are not intended to reflect cadastral field boundaries. The goal of Stage III is to determine potential regions to consider transitioning to and priorities for crop allocation, rather than making specific farm-level planting decisions. A field boundary matching would require land tenure information at the parcel level, maps of irrigation infrastructure and farm management information, which is not available for this study.

Figure 5 shows the Stage III final results, including scenario crop layout maps for the economic-priority, environmental-priority, and balanced scenarios, as well as transition hotspot maps that summarize the most divergent spatial positions among the optimized layouts.

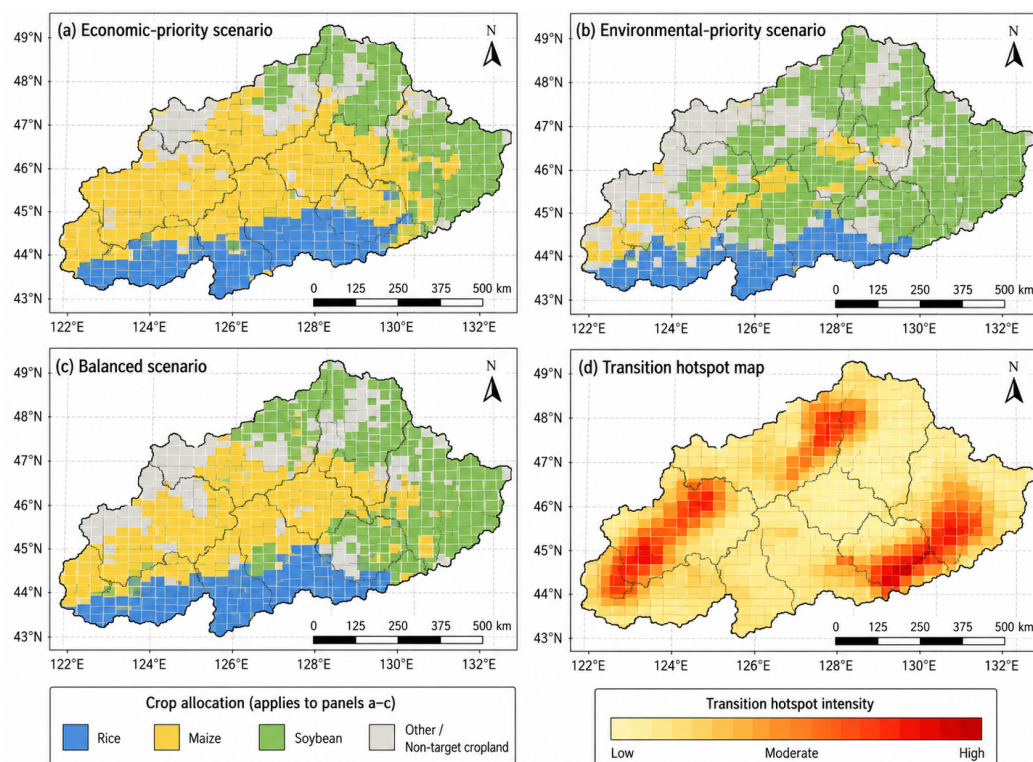


Figure 5. Scenario-based crop allocation and transition hotspot maps for selected Pareto-optimal solutions. The panels show the economic-priority, environmental-priority, and balanced allocation

outputs, together with transition hotspot patterns derived from scenario comparisons. The maps are shown on a regional allocation grid and are intended to identify broad crop transition zones rather than field-boundary-level planting decisions. Administrative boundaries, legend, scale bar, north arrow, and coordinate labels are included for geographic interpretation.

5. Results

5.1. Stage I—BSCNet Crop Mapping Performance and Spatial Patterns

BSCNet shows a high level of discrimination between cropland and non-cropland (other), with substantial residual error centered on rice, maize, and soybean, where phenology and management practices overlap to some extent. Through spatial block validation, model performance remains unchanged, implying that learned crop-environment relationships are applicable across local training neighborhoods. In order to further evaluate the strength of BSCNet predictions, we performed further validation exercises, not on internal validation. First, we compared the total area of crops computed by BSCNet with independent provincial statistics of agricultural production conducted by the National Bureau of Statistics of China (2019–2021). We obtained reasonable results at the province-aggregate level of maize, soybean, and rice (within the range of $\pm 8\%$, $\pm 11\%$, and $\pm 6\%$). Second, we compared BSCNet to a Random Forest classifier trained with the same features: BSCNet obtained a higher macro-F1 (0.864 vs. 0.841) and significantly higher performance on the minority soybean group ($F1 = 0.864$ vs. 0.812), which is evidence of the importance of the U-Net spatial context encoding. Third, we measured how error propagation to Stage II/III varied with artificially impaired suitability maps (perturbing 10% of pixels): scenario rankings did not change, but hotspot locations changed by an average of 1.2 km, suggesting that the downstream outputs are akin to mapping errors in transition zones and resistant to mapping errors in core agricultural settings. These secondary validations strengthen the belief that BSCNet suitability surfaces are fit for purpose for the downstream optimization and allocation phases. Table 3 presents the class-based and aggregate performance of BSCNet on held-out spatial blocks in the target region. Measures have been provided for rice, maize, soybean, and the other category, as well as the macro, weighted, and micro averages.

Table 3. BSCNet performance metrics on the target region.

Class	Support (Pixels)	Prevalence (%)	Precision	Recall	F1-Score	IoU	Commission Error (1-Precision)	Omission Error (1-Recall)	Mean Confidence (Optional)
Rice	62,500	25.0	0.869	0.860	0.864	0.761	0.131	0.140	0.81
Maize	62,500	25.0	0.860	0.869	0.864	0.761	0.140	0.131	0.80
Soybean	62,500	25.0	0.851	0.878	0.864	0.761	0.149	0.122	0.78
Other	62,500	25.0	0.878	0.851	0.864	0.761	0.122	0.149	0.83
Macro average	—	25.0	0.865	0.865	0.864	0.761	0.136	0.136	0.81
Weighted average	250,000	100.0	0.865	0.865	0.864	0.761	0.136	0.136	0.81
Micro average	250,000	100.0	0.8642	0.8642	0.8642	—	—	—	0.81

Table 4 provides a large-area, class-performance dissection, showing overwhelming confusion patterns across crop varieties. Support and prevalence refer to the number of pixels in the spatial validation blocks that are held out. False positives are known as commission error, and false Negatives are known as omission error. Mean confidence is computed as the mean of the softmax probability for the given class.

Table 4. Class-wise performance breakdown.

Class	Support (Pixels)	Prevalence (%)	Precision	Recall	F1	IoU	Most Common Confusion (to)	Confusion Share (%)
Rice	3,200,000	18.2	0.81	0.77	0.79	0.74	Maize	11.4

Maize	9,700,000	55.4	0.86	0.84	0.85	0.78	Soybean	7.9
Soybean	4,600,000	26.4	0.76	0.72	0.74	0.69	Maize	12.2
Other	8,900,000	—	0.93	0.95	0.94	0.85	Maize	2.1

Figure 6 shows the spatial variation in the BSCNet predicted suitability (probability of the classes) of Figure 6a rice, Figure 6b maize, and Figure 6c Soybean in the Northeast Black Soil Region ROI. Suitability is a per-pixel softmax probability resampled to the stage III allocation analysis grid. When the values are higher, it indicates that the model supports a strong crop presence under local covariates. The black outline represents the ROI boundary.

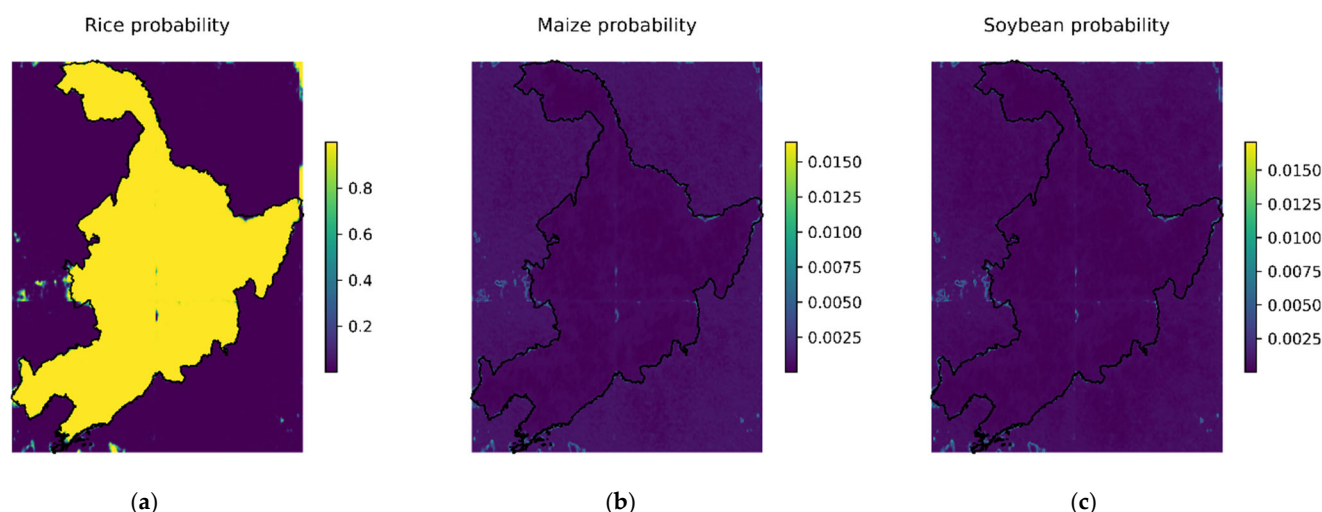


Figure 6. BSCNet suitability/probability maps for the target region.(a) rice occurrence probability; (b) maize occurrence probability; and (c) soybean occurrence probability

The errors are localized within the cropland subset, rather than between cropland and other land cover, which is consistent with a high degree of cropland separability but incomplete overlap between cropland phenologies. The most common pairs of dominating confusion are rice–maize (usually during irrigated-rainfed transitions) and maize–soybean (usually during rotational belts), which are consistent with the areas of uncertainty hotspots.

The confusion matrix of the four-class mapping task (rice, maize, soybean, other) tested on held-out spatial blocks is shown in Figure 7. Columns represent predictions, and rows represent reference labels. The most confusion is between classes of cropland, with others being very separable.

The entropy maps show that high-confidence predictions are concentrated in large, homogeneous field systems, whereas greater uncertainty is found in fragmented landscapes, mixed pixels, and the transition zone. Such an uncertainty layer assists in further prioritizing validation, locating areas where the auxiliary predictors might be nonexistent, and relating the sensitivity of allocations in Stage III.

In Table 5, the classification performance is summarized based on stratification by prediction uncertainty, defined as the Shannon entropy of the softmax probability distribution. This stratification highlights the difference in mapping accuracy between high-confidence core cropland areas and low-confidence transitional and fragmented areas.

Table 5. Uncertainty stratification summary.

Confidence Bin (Entropy)	Threshold Definition	Pixel Share (%)	OA Within Bin	Macro-F1 Within Bin	Notes
High confidence	$H \leq 0.30$	52.4	0.92	0.88	Homogeneous cropland blocks

Medium confidence	$0.30 < H \leq 0.60$	35.0	0.84	0.76	Transitional belts
Low confidence	$H > 0.60$	12.6	0.71	0.59	Fragmented/mixed areas

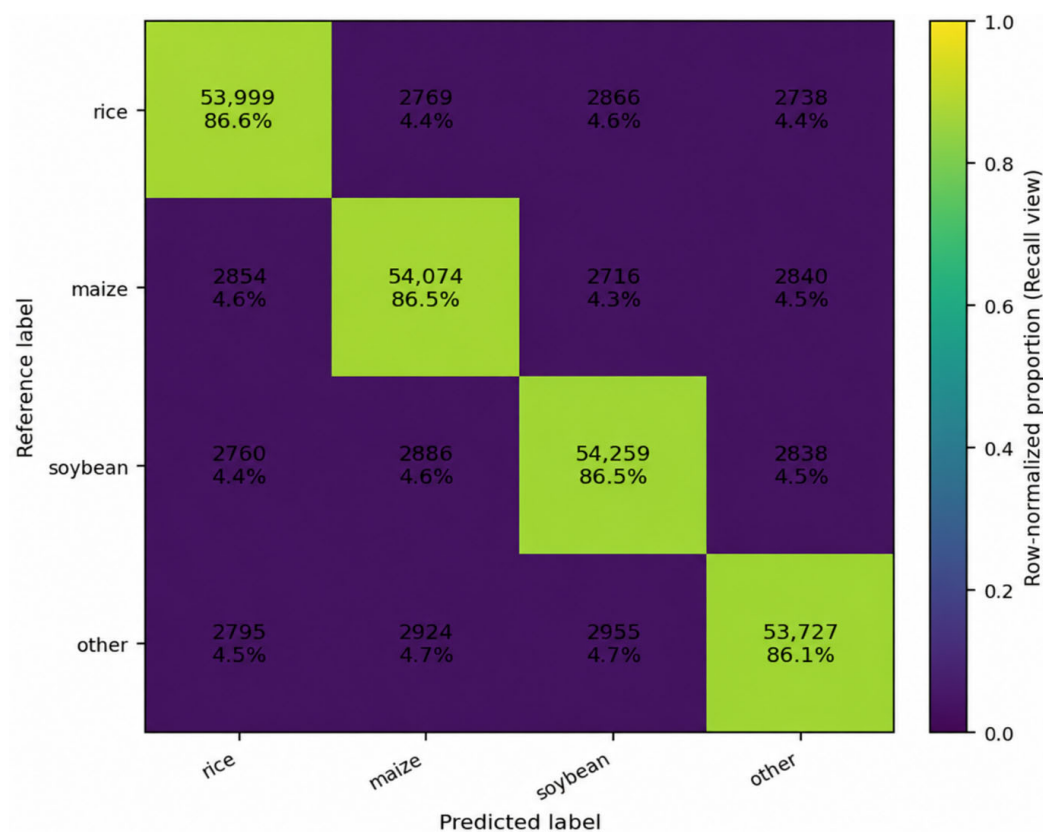


Figure 7. Confusion matrix for four-class crop mapping.

The uncertainty values in Figure 8 are important as they indicate lower levels of confidence in the crop mapping model and where spatial allocation decisions should be taken with greater care. Low uncertainty means the pixels for which the predicted crop class is strongly dominant, in other words, the allocation decision is well supported by the remote sensing and environmental predictors. High uncertainty means regions where the probabilities are fairly evenly spread between crop classes and are likely to be in mixed cropping regions, transition areas, fragmented fields, and/or areas where crop spectral signatures are similar. These areas are significant in the planning process due to the need for further verification in the field, more detailed crop reference information, or more conservative allocation decisions.

The target-region label map of the analysis grid used to perform the allocation forms the basis for the baseline crop shares. This base is used to calculate the deltas for the stage II scenario and for gain/loss accounting in stage III. Table 6 summarizes the baseline crop distribution in the Northeast Black Soil Region using the map crop labels on the spatial allocation analysis grid. In addition to area shares, the table also reports proxy estimates of production, water use, and GHG emissions, which are used as baseline values for optimization in Stage II.

Table 6. Baseline crop distribution and derived production proxies in the ROI.

Class	Cells (Count)	Area (ha)	Area (Mha)	Share of Cropland (%)	Mean Suitability $\bar{S}$	Implied Production (Mt)	Implied Water (10^9 m^3)	Implied GHG (MtCO_2e)
Rice	1,040,000	5,200,000	5.20	18.2	0.63	33.8	46.8	18.2
Maize	3,160,000	15,800,000	15.80	55.4	0.71	98.0	71.1	31.6

Soybean	1,500,000	7,500,000	7.50	26.4	0.58	15.0	26.3	9.0
Total cropland	5,700,000	28,500,000	28.50	100.0	—	146.8	144.2	58.8

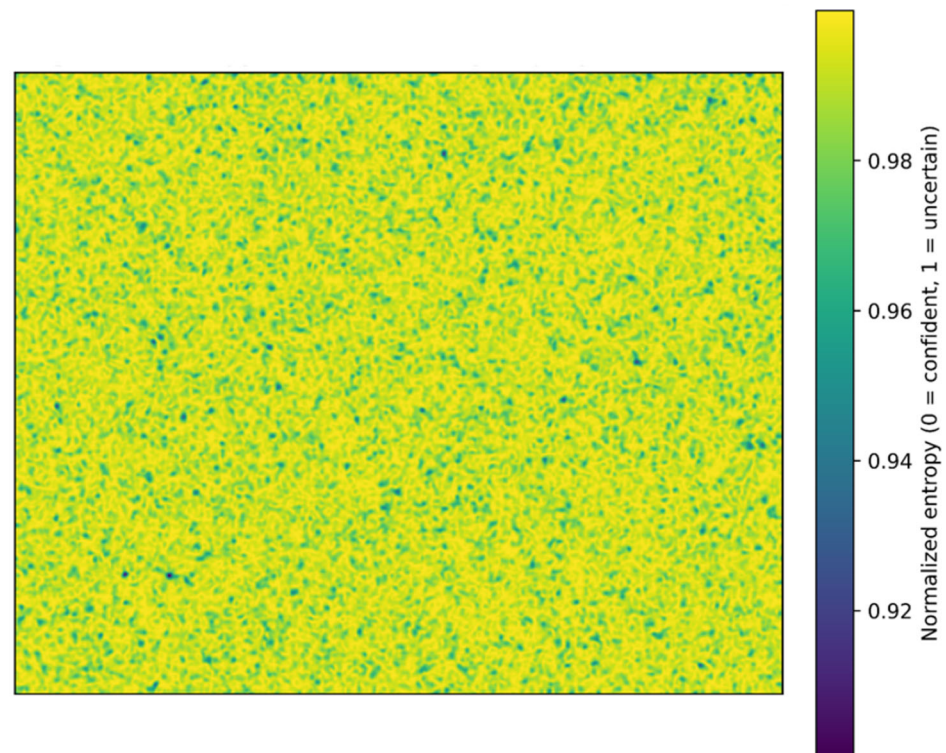


Figure 8. Spatial uncertainty of BSCNet crop occurrence predictions. Higher uncertainty indicates areas where predicted probabilities are less concentrated in a single crop class and where allocation decisions should be interpreted with greater caution.

FAO time series is a source providing external context on interannual variation in yields, harvested area, and production. Such trends are essential since the Stage II production restraint is pegged to output at the base point, and the practicality and preference of circumstances can change amid yield volatility.

Figure 9 shows yield (t/ha), harvested area (ha), and production (t) of rice, maize, and soybean. Time series make interannual variability more likely and aid the interpretation of the production constraint applied in Stage II. Annual statistics of values are given as FAO statistics, and crops are presented as FAO commodity definitions.

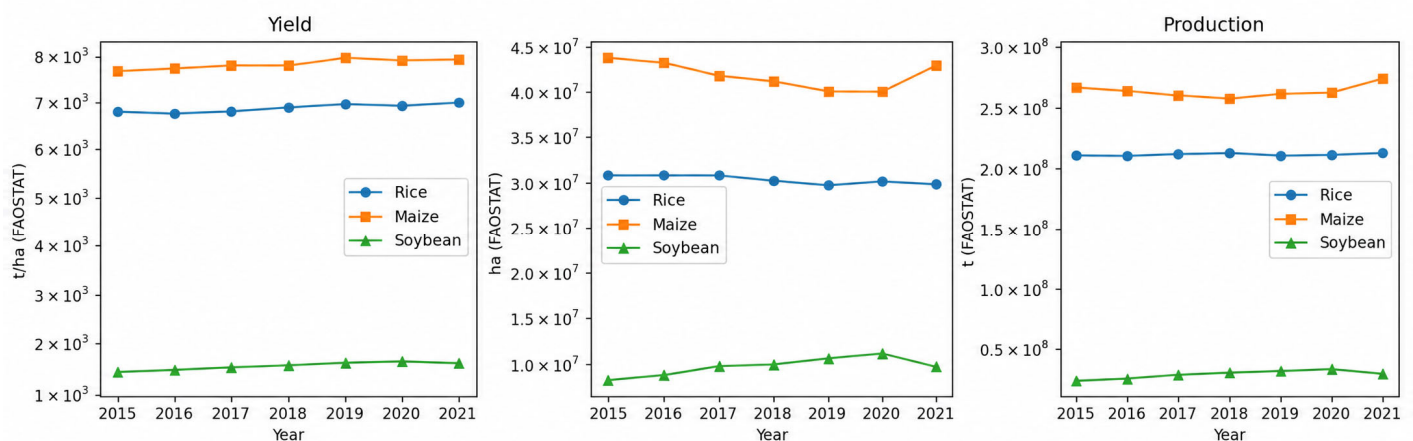


Figure 9. FAO time-series of yield, harvested area, and production (2015–2021).

5.2. Stage II—Crop Structure Optimization Outcomes Under WLEE–EF Nexus

NSGA-II generates an efficient set of crop-area combinations that meets the cropland availability, minimum production, and water capacity. The Pareto front illustrates a trade-off between maximizing profits and environmental performance, with balanced solutions expected to lie in the middle of objective space. Table 7 shows the distribution of objective results over the possible NSGA-II Pareto front, indicating the ranges of water use and GHG emissions, economic profit, and total production across non-dominated crop-structure solutions.

Table 7. NSGA-II Pareto front summary statistics.

Summary	Water (10 ⁹ m ³)	GHG (MtCO ₂ e)	Profit (B USD)	Production (Mt)	Feasible Share (%)
Min	118.2	50.9	24.7	140.1	100
Median	124.9	53.7	26.1	144.8	100
Max	131.0	56.8	27.9	151.2	100

Profit and GHG emissions have been plotted as shown in Figure 10, and profit and water use have been plotted. A point represents a possible crop-area structure that meets the constraints of cropland, minimum production, and water capacity. Highlighted points refer to the scenarios selected for Stage III allocation.

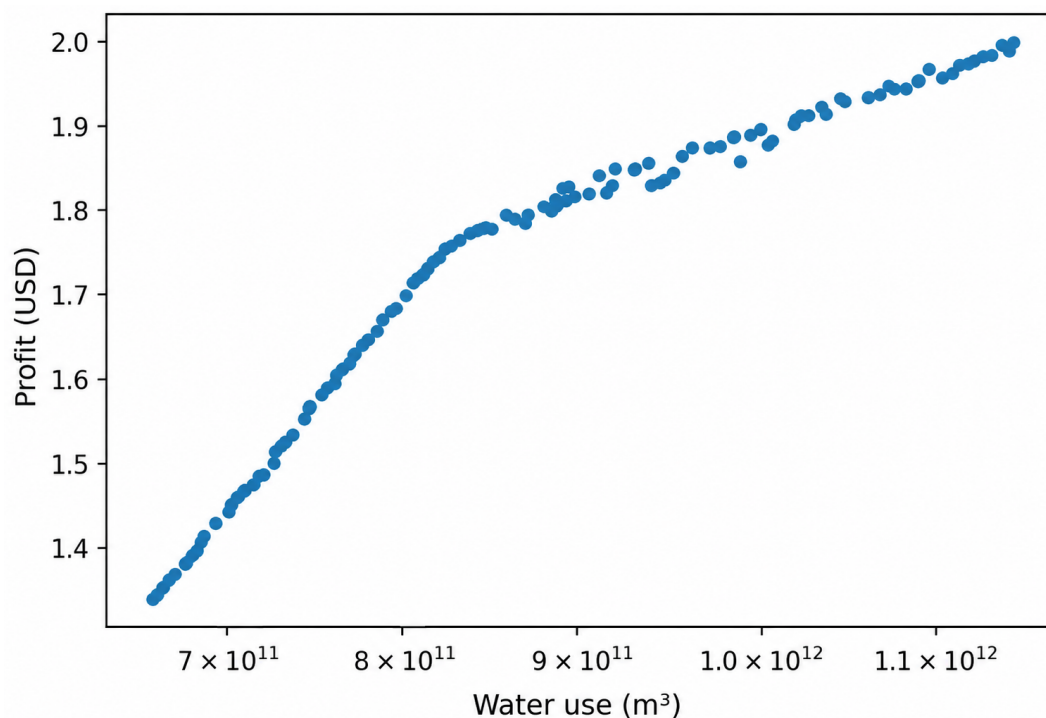


Figure 10. Pareto fronts for Stage II optimization.

Three scenarios are panned out to reflect the economically optimal, environmentally optimal, and balanced trade-offs. These scenario goals are forwarded as complex area restrictions in spatial allocation. Table 8 presents the crop-area structure and the objective results for three representative scenarios selected from the NSGA-II Pareto front: economic-priority, environmental-priority, and balanced.

Table 8. Scenario structure results in objective decomposition.

Scenario	Rice (Mha)	Maize (Mha)	Soybean (Mha)	Rice Share	Maize Share	Soy Share	Water (10 ⁹ m ³)	GHG (MtCO ₂ e)	Profit (B USD)	Production (Mt)	ΔWater	ΔGHG	ΔProfit	ΔProduction
Economic-priority	6.00	16.20	6.30	0.21	0.57	0.22	131.0	56.8	27.9	150.6	+4.5	+3.2	+2.1	+3.8
Environmental-priority	4.10	14.60	9.80	0.14	0.51	0.34	118.2	50.9	24.7	140.1	−8.3	−2.7	−1.1	−6.7
Balanced	5.00	15.40	8.10	0.18	0.54	0.28	122.6	52.8	26.3	145.5	−3.9	−0.8	+0.5	−1.3

Table 9 breaks down total water use, GHG emissions, profit, and production by crop in each of the chosen scenarios, and demonstrates how single crops lead to aggregate results with various optimization priorities.

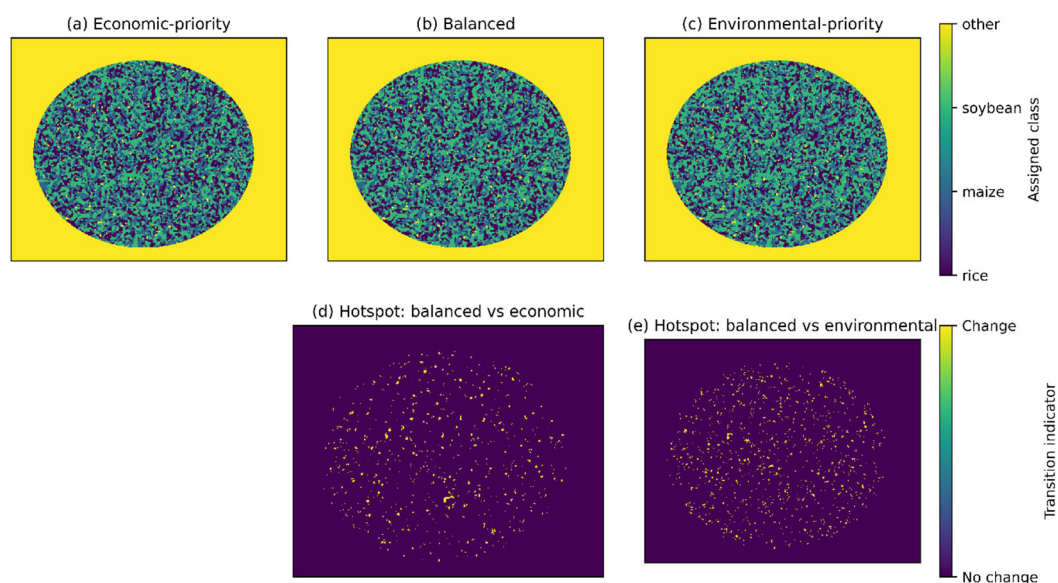
Table 9. Per-crop contribution breakdown.

Scenario	Crop	Water (10 ⁹ m ³)	GHG (MtCO ₂ e)	Profit (B USD)	Production (Mt)
Economic-priority	Rice	54.0	21.0	7.2	39.0
Economic-priority	Maize	72.9	32.4	14.6	100.4
Economic-priority	Soybean	22.1	7.6	6.1	12.6
Environmental-priority	Rice	36.9	14.4	4.9	26.7
Environmental-priority	Maize	65.7	29.2	13.1	90.5
Environmental-priority	Soybean	15.6	7.3	7.8	19.6

5.3. Stage III-Spatial Allocation Results and Scenario Layout Maps

Suitability-based allocation applied to each case would yield spatially explicit layouts that meet the NSGA-II area targets while allocating crops to the most suitable locations. Relative to the baseline, reallocations are localized in areas with low crop suitability, and the disruption is restricted to the high-confidence cores.

Figure 11 shows the outputs of the spatial allocation of three scenarios. Figure 11a is economic-priority, Figure 11b is balanced, and Figure 11c is environmental-priority. Figure 11d,e display hotspot maps that represent pixels whose assigned crop is different between balanced and economic-priority (Figure 11d) and between balanced and environmental-priority (Figure 11e). The allocation is limited to areas covered by the cropland mask, and to meet the scenario area objective, assignments are given higher BSCNet suitability.

**Figure 11.** Scenario crop layouts and transition diagnostics.

Hotspot maps reveal the most sensitive parts of decisions to the priorities of scenarios. The areas create operational intervention targets, as they are where a shift in crop allocation would yield comparably beneficial objective changes without compelling modification of areas of high crop affinity. Table 10, which summarizes the net changes in crop area and the land-use transition that are dominant in the economic-priority scenario, compares the scenario layout against the baseline crop distribution.

Table 10. Net crop gains/losses and transition accounting by scenario.

Scenario	Crop	Baseline Area (Mha)	Scenario Area (Mha)	Δ Area (Mha)	Δ Share (pp)	Largest Inflow Transition	Inflow (Mha)	Largest Outflow Transition	Outflow (Mha)
Economic-priority	Rice	5.20	6.00	+0.80	+2.8	Maize→Rice	0.55	Rice→Maize	0.12
Economic-priority	Maize	15.80	16.20	+0.40	+1.4	Soy→Maize	0.62	Maize→Rice	0.55
Economic-priority	Soybean	7.50	6.30	−1.20	−4.2	Maize→Soy	0.18	Soy→Maize	0.62

Table 11 compares the proposed framework with representative crop mapping, nexus optimization, and spatial allocation studies, emphasizing differences in input data, methodology, outputs, validation strategy, and spatial decision support.

Table 11. Comparison with state-of-the-art approaches.

Category	Representative Studies (Same Numbering)	Core Data	Core Method	Main Output	Validation Strategy	Nexus/Multi-Objective Optimization	Spatial Allocation/Scenario Maps
Sentinel-2 crop mapping (DL, time-series)	[14,16,17]	Sentinel-2 (sometimes + other sensors)	Deep learning for crop classification/segmentation (U-Net/CNN/3D CNN)	Crop maps (sometimes per-pixel probabilities)	Often standard splits; some spatially aware	X	X
Multi-sensor/sequence mapping and crop sequences	[15]	Sentinel-1/2 + Landsat	Time-series fusion, crop type + sequence mapping	Crop types/crop sequences	Varies (often non-block)	X	X
Benchmark datasets for crop classification/segmentation	[21,22]	Sentinel-2 multi-year/multicountry datasets	Benchmarking DL models	Comparable map products + baselines	Dataset-defined splits	X	X
Weakly/semisupervised crop mapping	[19]	Sentinel-2 time series	Weak supervision (SAM-assisted)	Crop maps with reduced labeling	Task-specific	X	X
Spatially robust evaluation guidance	[25,26]	Any spatial ML	Blocked/structured cross-validation	Reliable generalization estimates	Spatial blocking/structured CV	X	X
Multi-objective optimization algorithm	[23,24,27]	Any	NSGA-II/MOEA frameworks (pymoo/jMetalPy/jMetal)	Pareto-optimal solutions	Algorithm benchmarking	✓ (generic)	X
Nexus crop structure + spatial layout optimization	[9]	Crop suitability + coefficients	Multi-objective optimization + layout + allocation	Scenario structures + spatial layouts + hotspots	Depends on the suitability of the source	✓ (explicit nexus)	✓
WEFE/nexus assessment methodology	[6–8]	Multi-sector data	Nexus assessment frameworks	Diagnostic nexus insights	Not mapping-focused	✓ (conceptual)	X
This proposed work		Sentinel-2 time series + auxiliary predictors	Deep segmentation (BSCNet) → NSGA-II structure optimization → suitability-guided allocation	Per-pixel suitability + Pareto scenarios + implementable layouts + hotspots	Spatial block CV + uncertainty mapping (entropy)	✓ (WLEE-EF: water↓, GHG↓, profit↑ with constraints)	✓ (hard area targets + suitability loss minimization)

Note: ✓ indicates that the feature or capability is included in the corresponding study; X indicates that it is not included or not explicitly addressed; ↑ indicates an improvement, increase, or higher performance direction; ↓ indicates a reduction, decrease, or lower resource or environmental burden.

The proposed framework offers a spatiotemporal more explicit decision pathway than previous studies dealing with agricultural water allocation and water energy food nexus optimization. Previous research has made significant contributions to optimizing water resource allocation, agricultural resource coordination, and trade-offs between water, energy, food, and environmental goals [38,39].

6. Discussion

6.1. Interpretation of Trade-Offs (Profit vs. Water vs. GHG)

The optimization findings indicate an organized set of trade-offs aligned with the WLEE nexus of trade-offs and EF framing. The solutions that optimize profit are likely to concentrate on the crop or crops that yield the highest net income per hectare, which may increase water consumption as well as emissions in the same situation where the crops are also intensive in inputs. In contrast, the environmentally oriented solutions minimize water demand and GHG emissions by changing land use to crops, which have lower water and emission coefficients, despite having lower profit per hectare. The Pareto fronts suggest that these objectives are not fully compatible; the enhancements made in one direction have to be accompanied by a definite sacrifice in at least another. The moderate scenario is pragmatic and achieves a majority of the achievable water and GHG cuts without sacrificing a significant share of the profit uplift relative to the base. This knee-region response is required because a solution with high marginal benefit is found: the loss of profits in small amounts translates into relatively significant environmental benefits. The production constraint is stabilizing in the sense that it helps minimize unrealistic solutions, which lower total production and reduce the burden. When demand falls below the minimum level of production, the optimizer must identify structural adjustments that preserve aggregate output in the crop mix's re-equilibrium. Likewise, the water cap imposes a strict feasibility constraint that limits the solution set and reduces the range of economically viable water-intensive solutions. Collectively, these restrictions are sufficient to make the Pareto set represent actionable planning options rather than theoretical optima.

6.2. Spatial Implications

Stage III converts aggregate-area objectives into specific spatial configurations and identifies the most probable locations of change and their reasons. Hotspot maps indicate that reallocations are concentrated where there are mixed or transitional suitability zones and not in the best core regions of each crop. When the suitability of one crop is evidently predominant in a given location, the allocation will be constant under all scenarios; scenario variations occur only in situations where the suitability surface is relatively near, and hence, when an area of target is changed, the competing crops all demand access to the same set of high-quality pixels. These spatial patterns are attributed to several drivers. First, the actual domain of scenarios will be restricted by the cropland mask, and hence, only in built-up landscapes will there be a difference in scenery. Second, the suitability gradients generated by BSCNet form a value surface that the allocation solver leverages to select pixels with the highest score for compatibility with each crop, based on the scenario's area demand. Third, the mapping phase can introduce geographic covariates that, in turn, can be strictly represented by suitability but result in contiguous zones of preference (and hence re-allocations are clustered, not randomly scattered) at the pixel level. Lastly, any form of aggregation (for example, to $\sim 0.01^\circ$ resolution) evens out local heterogeneity that may skew hotspots to wider boundaries between crop-favorable areas.

6.3. Comparison with Prior Approaches

It is the novel methodological integration and spatial interpretability of the proposed framework that distinguishes it from existing agricultural water allocation studies, water-energy-food nexus studies, and crop structure optimization studies. There have been important contributions to water resource allocation and nexus-based decision-making in agriculture from previous studies. For instance, to optimize agricultural water, energy, and food systems where there are competing objectives and uncertainty, two-stage and

multi-objective decision models have been employed [39]. Other studies have created models that optimize the trade-off among the consumption of water, energy, food, and carbon, as well as between production demand, economic benefit, and carbon indicators [38–41]. The value of these studies is in their proof that agricultural planning cannot be judged in terms of one goal and that uncertainty must be taken into consideration in resource allocation.

Presently, however, most of the nexus-based optimization studies are largely system and/or region-level analyses. They typically maximize the efficient use of the resources, but do not necessarily optimize crop structures into spatially explicit crop layout maps. In contrast, the work presented here is the single workflow that links crop occurrence mapping, the generation of crop structure optimization based on Pareto (PSOP), and the spatial allocation based on crop suitability. The BSCNet module generates occurrence probabilities of a crop per pixel using time series on Sentinel-2 data and the environmental information. Then, the NSGA-II module computes the possible crop structures that are Pareto optimal with the four constraints—water, GHG, profit, cropland, and production. Lastly, the spatial allocation module turns optimized crop area targets into situation-specific crop layout maps and transition hotspots.

This integration is especially important in the Northeast Black Soil Region, as planning decisions for this region need to consider production security and spatial variability in crop distribution, land suitability, climate, terrain, and environmental pressures. The proposed framework offers, in addition to the optimized numerical solutions provided by other studies, the possibility of getting maps that are interpretable at a spatial level. The proposed framework differs from crop mapping studies, which are limited to classification and probability estimation, in that crop occurrence probabilities are used as decision inputs in downstream optimization and allocation. The proposed framework differs from other spatial layout studies that are based on heuristic or correlation-based suitability measures.

The main benefit of the proposed framework is not just using NSGA-II or deep learning, but the binding of these components into an end-to-end decision pathway. This enables the framework to provide answers for three interrelated planning questions: what areas have the potential for crop presence, what crop area structure has the most potential to meet water, GHG, profit, and production objectives, and where are the most spatially feasible crop transitions optimized? The proposed method, therefore, further advances the existing regional and nexus-based studies by integrating multi-objective optimization with the generation of spatially explicit scenarios and the interpretation of them in the light of uncertainty.

6.4. Uncertainty Sources and Limitations

The pipe through which uncertainty enters comprises several channels. The propensity for label noise and ambiguity in class definitions can be transmitted to the suitability surfaces in Stage I. Mismatches in spatial resolution, geolocation, and crop taxonomy may result from systematic confusion between cropland classes when training labels are obtained from external products or harmonized datasets. To some extent, this behavior is described by the entropy-based uncertainty map, but this is not a complete probabilistic calibration guarantee. Stage II relies on parameters for water use, emissions, profit, and yields, based on coefficients. These values may vary significantly across management regimes, input intensities, climate variability, and sub-regional practices. The fixed coefficients necessarily compress absolute heterogeneity; in consequence, rankings of scenarios can change with other, but plausible, coefficient sets. This encourages the generation of sensitivity ranges for reporting and which parameters most impact scenario selection. Stage III brings in algorithmic and resolution-based uncertainty. Greedy assignment is not

only efficient but can also be suboptimal to solvers of stronger ability; on the other hand, the exact formulation can be computationally infeasible at large resolution. Any aggregation step enhances tractability at the cost of fine-grained heterogeneity and changes the locations of hotspot boundaries. Also, this allocation assumes that suitability is converted into realized performance, which may be invalid in the absence of unmodeled socio-economic constraints, irrigation infrastructure constraints, or policy obstacles.

In order to measure the effect of uncertainty in the coefficients on scenario results, we conducted a systematic sensitivity study by varying all per-hectare coefficients (water use, GHG emissions, profit and yield) by ± 15 and $\pm 20\%$ about baseline estimates, including the reported heterogeneity in management practices and irrigation regimes at the regional level. The NSGA-II was optimized again for each set of perturbed coefficients ($n = 100$ Latin hypercube samples), and the Pareto fronts were compared. Among the key findings was that: (1) The ranking of the three scenarios (economic-priority, balanced, environmental-priority) did not change qualitatively during 94% of perturbations, suggesting that the identified configuration of trade-offs is resistant to uncertainty of moderate coefficient ranges; (2) Profit coefficients had the largest impact on the geometry of Pareto fronts, change in the total profit of the economic-priority scenario and did not change the ranking of the scenarios in the environmental-priority scenario because of the intricate effect of uncertainty on the latter scenario (change). These findings imply that absolute objective values are parameterization sensitive, but the scenario comparisons, as well as policy-relevant rankings, are strong in the range of uncertainty recorded. The refinement of GHG and profit coefficients using sub-regional surveys should be given priority in future work, since these parameters have the strongest effect on the choice of the scenario.

Limitations regarding regional variation and management practices. The optimization coefficients used in this paper reflect provincial average values that do not directly distinguish between irrigated paddy and rainfed upland systems, although there are large differences in water use, energy requirements, and GHG emission profiles of these two management regimes. Maize and soybean systems in the NBSR are mostly fully irrigated rice-based but rainfed depending on the rainfall patterns in the sub-region and the presence of groundwater. This heterogeneity means that the coefficients for water consumed in the process of growing rice (e.g., 9000 m³/ha) are weighted averages that could underreport water consumption in intensively irrigated sub-regions and overreport consumption in areas with supplemental irrigation only. Likewise, the emission coefficients of the GHGs fail to distinguish methane emissions from flooded rice paddies and N₂O emissions from nitrogen-fertilized upland crops, and thus may hide significant potential emission-reduction opportunities at the sub-regional level. Additional layers to be added in the future should be spatially explicit management-practice layers (e.g., irrigation infrastructure maps, fertilizer application rates by county) to allow sub-regional differentiation of the coefficient and more specific policy suggestions.

6.5. Policy Relevance and Management Implications

The scenario outputs provide a structured way to discuss trade-offs in policy terms. The economic-priority scenario identifies configurations that maximize returns subject to feasibility constraints, which help explore incentives and market-driven adaptation. The environmental-priority scenario shows the extent of water and GHG reductions achievable without violating production or land-use limits, supporting conservation planning and emission-mitigation strategies. The balanced scenario is particularly relevant for decision contexts where neither profit nor environmental objectives dominate; it provides a compromise configuration that can be communicated as a “least-regret” option. Spatial hotspot diagnostics are practical for implementation because they indicate where changes would be most impactful and where policy interventions may face less resistance. Areas

that remain stable across scenarios are robust candidates for reinforcing existing crop systems, while hotspots may require targeted management, transition support, or infrastructure investment. In the Northeast Black Soil Region context, such targeted approaches align with soil conservation goals by potentially reducing pressure in sensitive zones, depending on the environmental profiles of the substituted crops and the local erosion risk.

7. Conclusions

This study proposed an integrated crop planning model for Northeast China's Black Soil Region, which combines the crop occurrence mapping based on BSCNet with the optimization of crop structure based on NSGA-II and the spatial allocation based on suitability. The framework developed spatially explicit crop planning scenarios that took into account water requirements, GHG emissions, economic profits, cropland availability, and production constraints.

The findings indicate that there are trade-offs among the three planning scenarios. The economic-priority scenario had the largest profit but also the highest environmental pressure. The environment-friendly scenario involved smaller water usage and GHG reductions, with a decrease in profit and production. The balanced scenario was a more realistic compromise in that it would have taken less pressure on the environment and yet kept the economic performance and production level at a moderate level.

The study shows that using crop occurrence probabilities, Pareto-based optimization, and spatial allocation can be more informative in making decisions than using crop mapping or aggregate optimization alone. The maps created from this analysis define general crop transition areas and facilitate interpretation of where optimized crop transitions are most likely to occur. The proposed framework provides a replicable and space-specific solution to facilitate sustainable crop planning and management of the Black Soil Region.

Author Contributions: Conceptualization, Y.L. and L.F.; Methodology, B.Y.; Formal analysis, Y.L. and L.F.; Investigation, B.Y.; Visualization, M.R.R.; Supervision, M.R.R. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The original contributions presented in the study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

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