

NortheastChinaSoybeanYield20m: an annual soybean yield dataset at 20 m in Northeast China from 2019 to 2023

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Abstract. Accurate monitoring of crop yield is critical for ensuring food security. While various yield datasets covering Northeast China exist, they were produced at a coarse spatial resolution and remain inadequate for capturing small-scale spatial heterogeneity. Current yield estimation methods, such as machine learning models and the assimilation of remotely sensed
15 biophysical variables into crop growth models, are heavily reliant on ground observations and computationally expensive. To address these limitations, we propose a hybrid framework that couples the World Food Studies Simulation Model (WOFOST) and a Gated Recurrent Unit (GRU) model to generate a high-resolution (20 m) soybean yield dataset in Northeast China from 2019 to 2023 (NortheastChinaSoybeanYield20m). First, to generate a comprehensive training dataset, WOFOST was employed to simulate diverse soybean growth scenarios by accounting for variations in climates, crop varieties, soil types and
20 agro-managements practices. The GRU model was then trained to establish relationships between model simulated leaf area index (LAI) and soybean yield. The trained model was applied to estimate soybean yield in Northeast China using two stage-averaged LAI derived from Sentinel-2 which has been validated as a feasible alternative to time-series LAI. The accuracy of estimates was evaluated using in-situ measurements and government statistical data. The overall accuracy was 287.44 kg ha⁻¹ and 272.36 kg ha⁻¹ in the root mean squared error (RMSE) for field and regional scale, respectively. The model exhibited
25 consistent interannual stability, with mean relative error (MRE) averaging 11.46 % and 7.94% at the municipal scale and the provincial scale, respectively. The dataset effectively captured spatiotemporal yield variability, offering potentials for optimizing soybean production, guiding precise agriculture practices, and informing agricultural policy. The NortheastChinaSoybeanYield20m dataset is publicly available at <https://doi.org/10.5281/zenodo.14263103> (Xu et al., 2024).

1 Introduction

30 Soybean is a crucial crop for both food and oil production, providing more than a quarter of the world's edible protein (Graham and Vance, 2003). Global demand for soybean is projected to increase by 46 % by 2050, driven by rapid population growth (Falcon et al., 2022). As an major traded agricultural commodity, soybean production in key exporting nations has wide-reaching effects on international markets, and can significantly influence agricultural economies worldwide (Qiao et al., 2023). Notably, China is the world's largest consumer of soybeans (FAOSTAT, 2022), and its soybean demand relies heavily on
35 international trade (Zhao et al., 2023). Consequently, accurate monitoring of soybean yield is vital for promoting sustainable agriculture, ensuring food security, and maintaining economic stability from regional to global scale. Moreover, effective yield monitoring and mapping supports farmers by informing field management practices, bolstering agricultural insurance and enhancing poverty alleviation initiatives (Zhuo et al., 2022).

Remote sensing data provides time-series observations for crop yield estimation across multiple scales (e.g., field,
40 regional and national) (Dong et al., 2020; Hunt et al., 2019; Zhao et al., 2023b). Current methodologies for yield estimation can be broadly categorized as data-driven or knowledge-driven approaches.

Data-driven methods leverage satellite-derived variables such as leaf area index (LAI), fraction of absorbed photosynthetically active radiation (FAPAR), and vegetation indices (VIs) to establish linear or nonlinear relationships with measured crop yield (Ang et al., 2022; Xie et al., 2019). Machine learning algorithms such as Random Forest (RF), and
45 Artificial Neural Networks (ANN), due to their ability to process large dataset and model complex nonlinear interactions, have been widely applied in crop yield estimations (Pang et al., 2022; Tian et al., 2021; Yildirim et al., 2022). These methods can extract effective information from multi-source structured or unstructured data without manual intervention. However, they are heavily reliant on extensive ground-truth training data, which is challenging to collect over large areas and high time intervals (Cao et al., 2021). Additionally, these models often overlook the impacts of environmental factors on crop growth,
50 such as the influence of early-season soil moisture on root establishment or the effect of high temperatures during flowering on pod set, and are lack of interpretability, as they cannot explain the causal relationship between input features and outputs, leading to poor spatial-temporal generalization (Gevaert, 2022).

In contrast, knowledge-driven crop growth models simulate crop development from sowing to harvest based on agronomic mechanisms (Kaur and Singh, 2020). Common model types include light-use efficiency models (e.g., SAFY
55 (Duchemin et al., 2008)), soil-driven models (e.g., AquaCrop (Steduto et al., 2009)), and atmospheric-driven models (e.g., WOFOST (Diepen et al., 1989)). These models integrate environmental factors (e.g., climate conditions and soil characteristics) with crop physiological processes (Gaso et al., 2024). Climate variables like temperature, precipitation, and solar radiation are critical in regulating essential physiological processes such as photosynthesis, respiration and transpiration, which influence the rate and duration of crop growth stages (Misaal et al., 2023). Climate anomalies during specific growth stages may disrupt
60 biochemical processes, ultimately affecting yield formation. Similarly, soil properties influence crop productivity by regulating water retention, aeration, and nutrient uptake (Muhuri et al., 2023). Despite their mechanistic rigor, applications of crop models

over large area are typically constrained by (1) insufficient spatial-temporal input data, and (2) parameter uncertainty, which can propagate errors into yield estimations (Dokoohaki et al., 2021). To overcome these challenges, data assimilation techniques to integrate remote sensing observations (e.g., LAI) into crop growth models have been developed to enhance spatial representativity (Huang et al., 2024). However, high resolution remote sensing data drastically increases computational cost, limiting the scalability of these approaches for regional or national mappings efforts (Huang et al., 2019).

Given the limitations above, integrating data-driven and knowledge-driven models has emerged as a critical strategy to enhance spatial-temporal generalization and mitigate sparse training data challenges in crop yield estimations. Hybrid frameworks coupling crop growth model with machine learning algorithm, such as those proposed and evaluated by Ren et al., (2023b) and Xie and Huang, (2021), are gaining tractions. These approaches utilized simulated outputs from crop growth models (e.g., meteorological, soil, crop physiological, and management factors) as inputs for machine learning, reducing reliance on limited ground observations. Many studies have demonstrated hybrid methods are able to enhance yield estimation due to three benefits (Feng et al., 2020; Xie and Huang, 2021; Yang et al., 2021). The simulations from crop growth model can provide biophysical constraints to machine learning, ensuring agronomic plausibility. The crop growth models generate synthetic training datasets to address data scarcity. Finally, the machine learning improves the computational efficiency compared to traditional data assimilation techniques (Xie and Huang, 2021). However, existing studies generally extracted input features (e.g., LAI, and soil moisture) across the entire growth cycle or on coarse temporal scales, increasing computational costs of model calculation and obscuring stage-specific physiological response (Pinke and Lövei, 2017; Wang et al., 2015). Additionally, while deep learning models, such as Long Short-Term Memory (LSTM) and GRU model excel at modelling temporal dependencies, their integration into hybrid frameworks have not been widely explored.

Critically, the primary soybean-producing regions of China lack a publicly available high-resolution yield dataset to analyse spatiotemporal production patterns, hindering precision agriculture and policy optimization. To address this, we developed a hybrid model coupling the World Food Studies (WOFOST) crop growth model with a GRU deep learning method to estimate soybean yield in Northeast China. The objectives include: (1) Design a hybrid framework integrating WOFOST simulations with GRU-based feature extraction; (2) Generate a high-resolution (20 m) soybean yield dataset in Northeast China (NortheastChinaSoybeanYield20m) from 2019 to 2023; (3) Evaluate the accuracy of the dataset across field, municipal, and provincial scales using in situ and statistical benchmarks. The WOFOST model first simulated soybean growth using multi-parameter combinations (varying climate, soil, crop varieties and management conditions) to train the GRU model. The stage-based Sentinel-2 data, capturing soybean growth development, were then input into the GRU model to estimate yield. This approach prioritizes stage-specific physiological dynamics which balancing computational efficiency and spatial granularity, providing a critical advancement for scalable agricultural monitoring.

2 Data preparation and preprocessing

2.1 Study areas

The study was conducted in Northeast China (38°40' N to 53°34' N, 115°05' E to 135°02' E), encompassing Heilongjiang, Jilin, Liaoning province, as well as the eastern parts of the Inner Mongolia Autonomous Region (IMAR) (Fig. 1). The study area includes 40 cities and spans approximately 1.24 million km². The region is characterized by a continental monsoon climate, with an annual accumulated temperature ($\geq 10\text{ }^{\circ}\text{C}$) ranging from 2200 to 3600 $^{\circ}\text{C}$ (Pu et al., 2019), and a frost-free period of 140 to 170 days (Tan et al., 2014). The average annual precipitation exhibits a strong east-west gradient, decreasing from 1000 mm in the east to 350 mm in the west (Zhao et al., 2011). The predominant soil types include brown coniferous forest soil, dark brown forest soil, forest steppe chernozem and meadow grassland chernozem soil (Pu et al., 2019). Soybean is one of the three main crops in the region, primarily cultivated in the northern parts of the Songliao plain in rotation with maize. Notably, this region contributes around 64 % of China's total annual soybean production (National Bureau of Statistics of China (NBSC), 2023). Approximately 97 % of the soybean in the region is rainfed (Guo et al., 2022; Yu et al., 2020), with growing season typically spanning from May to late September (Zhao et al., 2021).

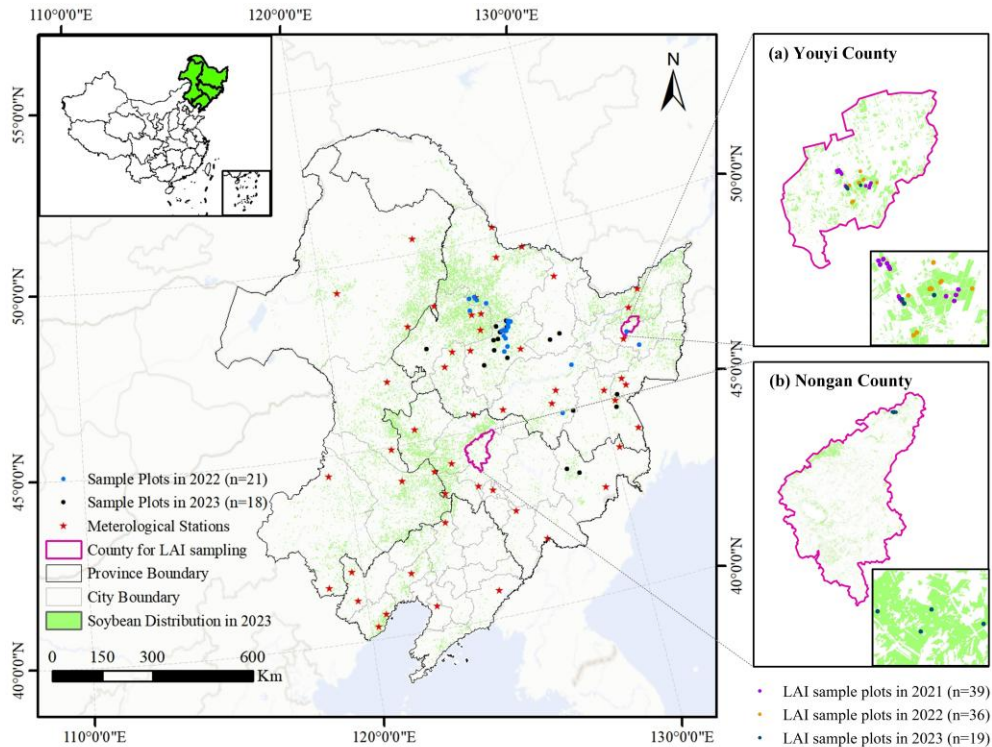


Figure 1: Location of the study area, distribution of sample plots in 2022 and 2023, LAI sampling counties and selected meteorological stations. (a) and (b) display the detailed distribution of LAI sampling plots in Youyi and Nongan counties, respectively. The soybean distribution map was obtained from Zhao et al., (2022), generated using a moment-preserving segmentation method with an overall accuracy exceeding 90% for soybean in 2023 (see Section 2.2.5 for details).

110 2.2 Data collections

2.2.1 In-situ measurement data

Due to limitations of resources and personnel, in-situ measurements were not available during the earlier years (from 2019 to 2021). Field-scale yield data was separately collected through field investigation in September 2022 and 2023. In each year, a total of 21 and 18 sample plots were selected, respectively (Fig. 1). Within each sample plot that was around 100 m × 100 m in area, nine quadrats with area of 1 m × 1 m were selected randomly for destructive sampling of yield in soybean. The central location of each quadrat was recorded using a GPS device with accuracy of 1 m. The harvested beans were then oven-dried about 72 hours in Hailun Agricultural Ecology Experimental Station, Chinese Academy of Sciences to determine the dry weight. Finally, the average yield for the selected nine quadrats represents the soybean yield of the sample plot. In addition, soybean planting dates for different regions were collected through field surveys, providing agro-management data for this study.

Field measured LAI data of soybean was obtained from the Common Application Support Platform for Land Observation Satellites of China's Civil Space Infrastructure (CAPLOS, <https://124.16.188.131:9699/web/server3/build/#/Guide>), an open data portal providing in-situ biophysical variables (e.g., LAI and vegetation cover) for validating remote sensing products and refining retrieval algorithms. Samples were performed on 100 m × 100 m plots. LAI were collected with a LICOR LAI-2200 plant canopy analyzer following a standardized protocol: a reference reading of incoming solar radiation was taken above the canopy, followed by six beneath-canopy readings of transmitting radiation collected approximately 5-cm above ground at each plot. The raw readings were taken rigorous quality control to remove outliers, missing or duplicate values. After processing, 94 LAI observations from Youyi County and Nongan County were retained, spanning 2021 – 2023 three soybean growing seasons. Sampling dates (day-of-year, DOY) were: (a) Youyi County, DOY of 174, 197, and 235 in 2021; DOY of 180, 207, 221, and 246 in 2022; and DOY of 173, 190, and 245 in 2023. (b) Nongan County, DOY of 182, 221, 236, 251, and 264 in 2023.

2.2.2 Meteorological data

In this study, two different climate datasets were used.

The meteorological station data used in this study came from the meteorological stations of the National Meteorological Information Center (<http://data.cma.cn>). There are 238 meteorological stations within the study area. Here 51 of the meteorological stations that located within 1 km buffer zone of the soybean cultivation areas were selected (Fig. 1). The meteorological datasets generally include insolation duration (h), minimum temperature (°C), maximum temperature (°C), daily average temperature (°C), average water vapor pressure (kPa), average wind speed (m sec⁻¹), precipitation (mm) and snow-depth (cm). Observed data from 1980 to 2021 of the 51 selected stations were collected. Missing values and outliers in the data were filtered out. The data were then directly used for setting input climate parameters of the WOFOST model to drive simulations.

The climate reanalysis data was obtained from the ERA5-land Daily Aggregated - ECMWF Climate Reanalysis Product. The data was only used to calculate soybean phenology for preparation of yield estimations. It was a global climate reanalysis product that provides continuous climate data at a resolution of $0.1^\circ \times 0.1^\circ$ (e.g., air temperature and atmospheric pressure) starting from 1950. The daily aggregated air temperature data at 2 m above the surface of land measured in kelvin (K) during the soybean growth periods from 2019 to 2023 was collected in this study from the Google Earth Engine (<http://earthengine.google.com>). The product was resampled to 20 m using bilinear interpolation model to match with the resolution of satellite imagery data.

2.2.3 Soil data

Soil data was obtained from the 1:1000,000 Chinese soil database, established by the Institute of Soil Science, Chinese Academy of Sciences (Shi et al., 2004). The dataset consisted of two parts: soil spatial data (digital soil maps) and soil attribute data. In this study, the 1:1000,000 soil spatial data was obtained. The spatial database was developed by digitizing, mosaicking, and reassembling sheets from the 1:1,000,000 Soil Map of the People's Republic of China (National Soil Survey Office, 1995), with the Genetic Soil Classification of China (GSCC) soil families as the fundamental mapping units. The final dataset includes 909 soil types and over 94,000 polygons. The dataset was utilized to determine the dominant soil types within the study area, serving as the basis for assigning soil parameter settings according to literatures.

2.2.4 Satellite imagery data

Two satellite data including: 1) Sentinel-2 Multi-Spectral Instrument (MSI) Level - 2A Surface reflectance product (10 – 60 m spatial resolution, 5-day revisit), and 2) the Moderate Resolution Imaging Spectroradiometer (MODIS) Leaf Area Index (LAI)/ Fraction of Photosynthetically Active Radiation (FPAR) Level 4 product (MCD15A3H, v061, 500 m spatial resolution, 4-day period) were used to generate yield maps. All data spanning soybean growth periods (2019 – 2023) were accessed and pre-processed via the Google Earth Engine (GEE, <http://earthengine.google.com>).

The MSI aboard Sentinel-2A/B satellites provides 10 m (visible and near-infrared bands), 20 m (red-edge and shortwave infrared bands) and 60 m (atmospheric bands) bands at 5-day revisit. The Level-2A data, which are geometrically and atmospherically corrected via the Sen2Cor, were masked for clouds and shadows using the Quality Assurance (QA) band. The 60 m band was excluded due to their low spatial resolution and limited relevance for yield estimation and the 10 m (B2: Blue, B3: Green, B4: Red, B8: Near-Infrared) and 20 m (B5–B7: Red-edge, B8A: Near-Infrared, B11–B12: Shortwave Infrared) bands were retained. To harmonize spatial resolution, the 10 m bands were resampled to 20 m using bilinear interpolation model. The number of available Sentinel-2 images per pixel during different soybean growth stages from 2019 to 2023 is presented in Fig. A1.

The MODIS MCD15A3H (Collection 6.1, Level 4) provides 4-day composite LAI and FAPAR at 500 m derived from Terra and Aqua satellite sensors LAI/FAPAR are primarily inverted via a 3D radiative transfer model-based look-up-table (LUT) algorithm (Knyazikhin et al., 2018). When the primary algorithm fails, they are estimated using an empirical NDVI-

LAI model. The LAI data was similarly reprojected to WGS -84 to ensure spatial alignment with Sentinel-2 imagery. These
175 coarse-resolution LAI data were used to generate 500 m yield maps. The coarse-resolution yield maps were then used to bias-
correct the 20 m Sentinel-2 yield maps, improving their regional consistency. Details about the bias correction are present in
following 3.3.2 Section.

2.2.5 Crop distribution data

The soybean distribution maps for the study area (2019 – 2023) were obtained from Zhao et al., (2022), which employed a
180 novel methodology for crop type identification. The study proposed an optimal identification feature (OIF) knowledge graph
coupled with a moment-preserving segmentation method to classify crop types without ground-truth data. The method
achieved overall accuracy above 90% and producer’s accuracy exceeding 93% for maize, soybean and rice, with a Kappa
coefficient greater than 0.90.

2.2.6 Statistical data

185 Crop yield records (1980-2022) were obtained from the Statistical Yearbooks published by the Statistic Bureau of Heilongjiang
(<http://tjj.hlj.gov.cn>), Jilin (<http://tjj.jl.gov.cn>), Liaoning (<https://tjj.ln.gov.cn>) and Inner Mongolia Autonomous Region
(<https://tj.nmg.gov.cn>) to validate the crop yield estimates. Because the 2022 Statistical Yearbook was not fully released, yield
records for that year cover only a subset of cities. The statistical data served two main purposes, model simulation validation
and regional-scale accuracy evaluation in this study. To ensure that the soybean growth dataset captures the full range of
190 production conditions—including multi-year meteorological variations, various soil types, multiple soybean varieties, and
diverse management practices—yield records from 1980 to 2022, along with published data and field observations, were used
to evaluate the plausibility of the simulated yields. For the spatial validation, regionally aggregated statistical yield data (2019
– 2022) were applied to evaluate the accuracy of the hybrid framework at municipal and provincial scales.

3 Methodology

195 Our proposed hybrid model utilizes both the advantages of machine learning in data mining and the mechanism advantages of
crop growth model. Figure 2 presents the flowchart of the hybrid methodology for soybean yield estimation. It mainly includes
1) Generating a training dataset based on the WOFOST model that simulate soybean growth and yields under various climates,
soil, cultivars and agro-management practices, 2) Training a GRU model to identify the relationships between simulated LAI
and yield, 3) Producing soybean yield maps under multi-scale using LAI derived from MODIS and Sentinel-2 remote sensing
200 data.

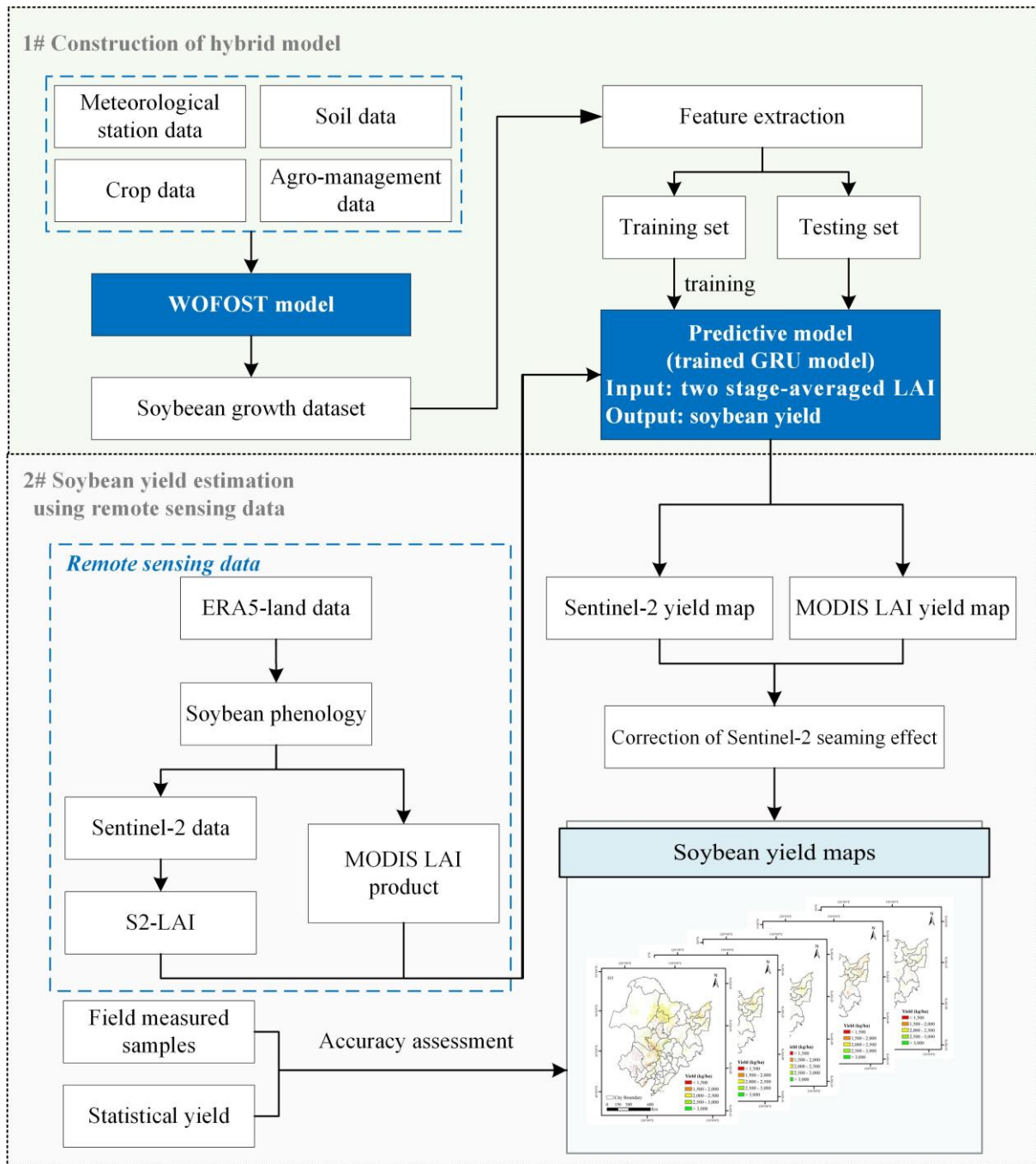


Figure 2: The flowchart of the overall yield estimation methodology in this study.

3.1 Construction of soybean growth dataset

205 The soybean growth dataset used in this study was a knowledge-based dataset derived from crop growth model based on multi-parameter combinations. The dataset provided a quantitative description of yield formation by simulating soybean development under diverse agricultural production scenarios including variations in meteorology (temperature, precipitation, solar radiation), soil types (texture, organic matter), crop varieties (phenology, thermal requirements) and agro-managements (sowing date).

210 To generate the dataset, we employed the World Food Studies Simulation Model (WOFOST) (Diepen et al., 1989), implemented via the Python Crop Simulation Environment framework (PCSE, v5.5). The WOFOST model is well-suited for large-scale simulations and has been extensively validated (Huang et al., 2015). Given that soybean cultivation in the study region is predominantly rainfed, we adopted the water-limited mode (Wofost72_WLP_CWB) for simulations. Driven by daily weather data, soil profiles, and cultivar parameters, the water-limited model simulated CO₂-driven photosynthesis, water
215 deficits, and biomass partitioning, outputting daily LAI, daily biomass accumulation, and final grain yield. Crop development is modelled through development stages (DVS) : 0 for emergence, 1 for anthesis and 2 for maturity (Diepen et al., 1989). This dataset mechanistically captures yield-limiting processes (e.g., drought during critical growth phases) while enabling scalable scenario analysis across Northeast China's rainfed soybean systems.

3.1.1 Preparation of model input parameters

220 Site-specific calibration and validation are essential to ensure the biological realism and representativeness of WOFOST-based crop growth simulations. To ensure the biological realism and representativeness of the synthetic dataset generated for model training, we adopted a careful, literature- and observation-informed parameterization and performed multiple checks in this study. We compiled soybean-specific model parameters from established sources relevant Northeast China, including peer-reviewed studies, publicly available field reports, agronomic databases, and WOFOST defaults adapted to the regional context.

225 Parameters were delineated into four groups:

(1) Meteorological parameters

The meteorological parameters required in WOFOST is shown in Table 1. To capture the climatic diversity of soybean-growing areas across the study region, we compiled daily meteorological data (e.g., temperature, precipitation, and solar radiation) from 51 representative weather stations spanning 42 years (1980–2021). The collected data were pre-processed into
230 the model's required input format (e.g., daily time steps, unit conversions) to ensure model compatibility and to generate a synthetic climate input dataset capturing climatic variability across the soybean growing areas.

235

Table 1 Meteorological parameters required in WOFOST.

Parameter	Description	Units
IRRAD	Incoming global shortwave radiation	KJ m ⁻² d ⁻¹
TMIN	Daily minimum temperature	°C
TMAX	Daily maximum temperature	°C
VAP	Daily mean vapour pressure	kPa
WIND	Daily mean windspeed at 2 m above the surface	m s ⁻¹
RAIN	Daily rainfall	mm
SNOWDEPTH	Snow depth	cm

(2) Soil parameters

The soil parameters in the WOFOST mainly include soil moisture content at wilting point (SMW), field capacity (SMFCF) and saturation (SM0) as well as hydraulic conductivity of saturated soil (K0). Based on the 1:1,000,000 Chinese soil database, the study area predominantly comprises loam soil that is further classified into sandy, light, medium and heavy loam. The parameters for sandy, loam and medium loam were sourced from Du et al., (2025), while the parameters for heavy loam came from Sun et al., (2022). All soil parameter values, summarized in Table 2, were integrated into the model to evaluate the influence of soil variability on soybean yield (Du et al., 2025; Sun et al., 2022).

Table 2 Values of main soil parameters in WOFOST.

Soil type	SMW (cm ³ cm ⁻³)	SMFCF (cm ³ cm ⁻³)	SM0 (cm ³ cm ⁻³)	K0 (cm d ⁻¹)
Sandy loam	0.060	0.280	0.350	22.6
Light loam	0.090	0.280	0.340	19.3
Medium loam	0.110	0.280	0.340	18.1
Heavy loam	0.194	0.355	0.356	34.6

(3) Crop-specific parameters

In this study, phenological and physiological parameters were sourced from studies conducted in the same agro-climatic zone and on soybean varieties with comparable growth characteristics to those in this study, ensuring the regional applicability and biological relevance of the adopted values. The soybeans were classified into five types including early, medium-early, intermediate, medium-late and late maturity following the classification by Qu et al., (2023). In the WOFOST model, soybean phenology is governed by temperature-driven parameters: the minimum (TBASEM) and maximum (TEFFMX) threshold temperature for emergence, and accumulated thermal time (TSUMEM: sowing to emergence; TSUM1: emergence to anthesis; TSUM2: anthesis to maturity). These thermal parameters are cultivar-sensitive and were set based on historical meteorological data and regional phenological observations reported in Qu et al., (2023). Remaining crop parameters (e.g., SLATB: specific

leaf area) were assigned default values or optimal values from Sun et al., (2022). Full parameter specifications are provided in
255 Table A1.

(4) Agro-management parameters

Planting date is the major agro-management factors for soybean in the study area. The difference of planting date can
significantly impact on soybean growth development, pod count, and biomass accumulation (Urda et al., 2024). Four planting
dates 20 April, 30 April, 10 May, and 20 May reflecting the typical planting window (late April to late May) of the study area
260 were set for model simulation according to Mei et al., (2024) which also focused on soybean cultivation in the similar study
area.

3.1.2 Crop simulations using multi-parameter combinations

Following parameter preparation, the four parameter categories, including meteorological (51 stations \times 42 years), soil (4
types), crop-specific (5 varieties) and agro-management (4 planting dates), were systematically combined to create 171,360
265 unique parameter combinations (Table 3). These parameter combinations were executed in the WOFOST simulations, yielding
a dataset of 171,360 various simulations that quantify yield responses to diverse agricultural production conditions.

Table 3 Parameter combinations for WOFOST simulations.

Parameters	Number of categories	Details
Meteorological parameters	51 \times 42	Meteorological data from 51 stations over 42 years (1980 – 2021)
Soil parameters	4	Sandy loam, light loam, medium loam and heavy loam
Crop-specific parameters	5	Early maturity, medium-early maturity, intermediate maturity, medium-late maturity and late maturity
Agro-management parameters	4	Four planting dates 20 April, 30 April, 10 May, and 20 May

3.2 Development of the Grated Recurrent Unit model (GRU)

A GRU (Grated Recurrent Unit) model, a streamlined variant of recurrent neural networks (RNNs), was employed to be trained
270 using the simulated soybean growth dataset for large-scale soybean yield estimation. Unlike LSTM (Long short-term memory),
GRU simplifies gating mechanisms to two adaptive gates, update and reset gates (Cho et al., 2014). The update gate retains
the past information for future calculations. The reset gate aims to remove irrelevant historical context for simplifying the new
candidate hidden states. Using the two gates together is benefit to balance long-term dependency capture and computational

275 efficiency (Peng and Yili, 2022; Zhang et al., 2022). This design mitigates vanishing gradient issues while accelerating model training, making GRU particularly effective for time-series yield estimation (Gopi and Karthikeyan, 2023; Ren et al., 2023b).

280 Trained on the simulated dataset, the GRU constructed based on TensorFlow 2.6 linked simulated environmental inputs to yield outputs. For field scale yield estimation, we first identified all available Sentinel-2 observation dates for each sample plot based on its corresponding Sentinel-2 tiles in 2022 and 2023 (Table 4), and computed the development stage value (DVS) for each date (Section 3.3.1). As LAI is a key biophysical indicator of soybean photosynthetic capacity and productivity (Malone et al., 2002; Shi et al., 2025), we extracted LAI values at the corresponding DVS from the soybean growth dataset to construct DVS-aligned LAI time-series. These DVS-aligned LAI were served as inputs to the GRU model, with simulated yield used as the target variable.

Table 4 DOY of available Sentinel-2 images for LAI extraction.

Sentinel-2 tiles	DOY
Available Sentinel-2 data in 2022	
51UYP	118, 128, 138, 143, 158, 213, 218, 228, 253, 263, 268
52TCT	105, 128, 138, 143, 158, 170, 193, 213, 218, 228, 235, 238, 245, 253, 263, 270
52TDQ	105, 117, 130, 140, 160, 222, 245, 250, 265, 270
52TES	102, 110, 117, 130, 140, 162, 172, 187, 202, 207, 220, 240, 245, 252, 257, 262, 270
52TFR	104, 117, 129, 139, 159, 167, 187, 222, 229, 252, 257, 262, 269
52TGS	107, 114, 119, 129, 161, 187, 222, 229, 232, 252, 257, 262, 269
Available Sentinel-2 data in 2023	
51TWN	98, 103, 108, 113, 118, 121, 126, 138, 143, 148, 153, 163, 193, 211, 218, 226, 231, 248, 253, 263, 268
51TYM	98, 103, 113, 123, 128, 138, 143, 148, 193, 218, 248, 253, 258, 263, 273
52TCT	98, 103, 125, 130, 138, 143, 173, 183, 193, 218, 235, 245, 250, 255, 263
52TDP	102, 122, 127, 142, 165, 170, 187, 230, 245, 250, 255, 272
52TDQ	112, 117, 130, 142, 165, 245, 250, 257, 272
52TDT	105, 130, 137, 142, 147, 167, 177, 232, 245, 250, 255, 265, 272

285 However, the spatiotemporal variability of Sentinel-2 image availability across regions posed challenges for regional-scale yield modelling, as constructing separate GRU models for each date combination demands considerable computational and storage resources. Accounting for the computational efficiency of the model in large areas, two stage-averaged LAI include LAI_{mean1} (mean value of LAI during vegetative growth: emergence to flowering) and LAI_{mean2} (mean value of LAI during reproductive growth: flowering to maturity), were calculated as inputs, while simulated yields acted as outputs. Boken and Shaykewich, (2002) has demonstrated the feasibility of estimating crop yield using average features derived from a specific phenological stage or from the entire growing season. To evaluate the effectiveness of the two stage-averaged LAI in soybean 290

yield estimation, we applied the GRU model trained by the two stage-averaged LAI to yield estimation at the field scale for comparison with model based on DVS-aligned LAI time-series, and further extended its application to the regional scale.

295 The simulated soybean growth dataset was partitioned using 10-fold cross-validation, with hyperparameters (e.g. learning rate and batch size) optimized using a grid search to achieve minimal root mean squared error (RMSE, Eq. (5)) (Açikkar, 2024). Once trained, the GRU model taken Sentinel-2-derived LAI as inputs to generate 20 m yield maps.

3.3 Generation of NortheastChinaSoybeanYield20m

3.3.1 Determination of soybean phenology

300 Soybean phenology of the study area exhibits significant spatial variability due to climatic and varietal differences (Gaso et al., 2024). To address this, soybean phenology maps were generated from daily thermal time by integrating thermal zone divisions and regional adapted cultivars (Fig. A2). Soybean phenology (including emergence, anthesis and maturity) were calculated using daily aggregated air temperature data from ERA5-land dataset and a thermal time model (T_e) (Eq. (1)). The DVS of soybean could be further calculated as Eq. (2).

$$T_e = \begin{cases} 0, & (T_{mean} \leq T_{base}) \\ T_{mean} - T_{base}, & (T_{base} < T_{mean} < T_{max}) \\ T_{max} - T_{base}, & (T_{mean} \geq T_{max}) \end{cases} \quad (1)$$

$$DVS = \frac{T_e}{T_{SUM}_i} \quad (2)$$

305 where T_{mean} is daily mean temperature, T_{base} (8 °C) and T_{max} (37 °C) represent the minimum and the maximum temperature for soybean development, respectively (Allen et al., 1997; Choi et al., 2016). T_{SUM}_i represents thermal time requirement for completing a specific developmental stage. Soybean growth proceeds from a growth stage to the next stage when accumulated T_e reached the threshold of accumulated temperature required for growth according to the setting of crop parameters of WOFOST model (Table A1).

310 Based on field surveys and literatures, the planting dates of soybean were fixed as 5 May for Heilongjiang Province and Inner Mongolia Autonomous Region, and 1 May for Jilin and Liaoning Province (Huang and Liu, 2024), with emergence constrained to before 1 June (Mei et al., 2024), and maturity to before 1 October (Huang and Liu, 2024). Under the constraints of T_e (Table A1) and the agro-management, phenological dates (emergence, anthesis and maturity) were computed for each Sentinel-2 pixel (2019 – 2023). Finally, the phenological maps were clustered into 10 phenology classes using K-means
315 clustering method (Jain and Dubes, 1988), aligning with Sentinel-2's revisit cycle to optimize imagery selection for yield estimation.

3.3.2 Model estimations of soybean yield

The red-edge normalized difference vegetation index ($NDVI_{RE}$) (Gitelson and Merzlyak, 1994) was employed for LAI mapping(Eq. (3)).

$$320 \quad NDVI_{RE} = \frac{B8A-B5}{B8A+B5} \quad (3)$$

where B8A (near-infrared) and B5 (red-edge) are Sentinel-2 bands.

The soybean LAI was estimated from $NDVI_{RE}$ using a linear regression (Eq. (4)) which has been shown to provide robust transferability across crop types and regions ($R^2 = 0.732$, $RMSE = 0.69$) (Pasqualotto et al., 2019). To verify the applicability of the method for soybean, we paired cloud-free Sentinel-2 images (± 2 days of sampling) with ground-measured LAI and re-estimated LAI via the $NDVI_{RE}$ regression, achieving a similar accuracy ($R^2 = 0.81$, $RMSE = 0.89$, Fig. A3). While performance was strong overall, a modest overestimation was observed for $LAI < 3$, likely due to local soil-background effects not present in the original European calibration.

$$325 \quad LAI = 5.405 \cdot NDVI_{RE} - 0.114 \quad (4)$$

DVS-aligned LAI values derived from available Sentinel-2 data (Table 4) were firstly used as input of the GRU model for yield estimation at field scale. Meanwhile, averaged LAI values during the vegetative (LAI_{mean1}) and reproductive (LAI_{mean2}) growth stages were calculated and used as model input for estimations at both field and regional scales. For pixels with missing values during these stages, LAI values were replaced by the average of eight neighbouring pixels. Final 20 m yield maps were marked using soybean distribution maps to exclude non-soybean areas. To ensure consistency across all data sources, both the WOFOST outputs and our field measurements, which were originally reported as dry matter, as well as the yield records used for comparison, were converted to the 13% moisture content according to Mulvaney and Devkota, (2020):

$$335 \quad Yield = Dry_weight / (1 - 0.13) \quad (5)$$

For large area estimations, a total of 194 Sentinel-2 tiles were required to fully cover the study area. Affected by cloud cover, the frequency of available data varied across each tile. Therefore, the yield maps often exhibited discontinuities along the edges of different tiles (“seaming effects”). This seaming effect could obscure real yield variations. To address this issue, a bias correction method proposed by Azzari et al., (2017) was applied. The overall framework is to use yield estimation based on MODIS LAI to correct the yield estimation from Sentinel-2. MCD15A3H generally provided more continuous estimation results of LAI due to its higher temporal resolution (4-day composites) and broader coverage. Yield maps were generated from the trained GRU taking MCD15A3LAI products as inputs. Sentinel-2 yield maps were adjusted by adding the difference between MODIS-derived mean yield and initial Sentinel-2 mean yield for each tile. This process minimized seams while preserving fine-scale yield variability within tiles.

3.4 Accuracy evaluation

The accuracy of soybean yield estimation was evaluated on multiple scales. For field scale, in-situ yield data in 2022 and 2023 was used for assessment. For regional scale, the averaged soybean yield for each city and province were separately calculated for each year, and compared with the statistical data. Accuracy evaluation was based on the coefficient of determination (R^2 , Eq. (6)), the root mean squared error (RMSE, Eq. (7)) and mean relative error (MRE, Eq. (8)).

$$350 \quad R^2 = 1 - \frac{\sum_i (y_{o,i} - y_{m,i})^2}{\sum_i (y_{o,i} - \bar{y}_o)^2} \quad (6)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_{o,i} - y_{m,i})^2}{n}} \quad (7)$$

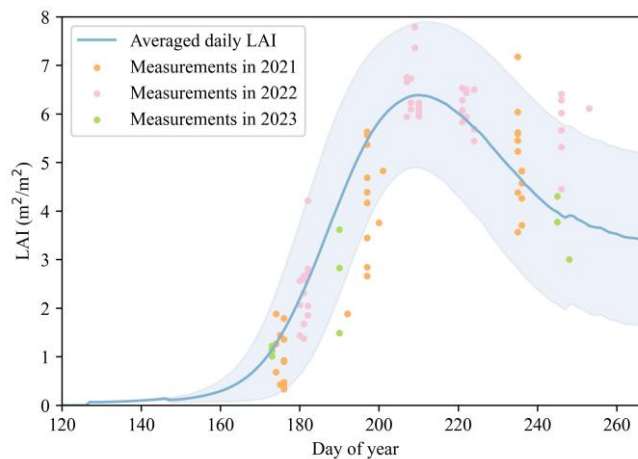
$$MRE = \frac{\sum_{i=1}^n |y_{o,i} - y_{m,i}|}{n \cdot \bar{y}_o} \quad (8)$$

where $y_{o,i}$ and $y_{m,i}$ represent the actual yield (observed or statistical yield) and model estimated yield, respectively, \bar{y}_o is the
 355 mean value of the actual yield.

4 Results and analysis

4.1 Simulations of the WOFOST model

Since LAI was used as the input feature, the accuracy of WOFOST-simulated LAI directly influenced the reliability of the
 GRU model for soybean yield prediction. To validate simulated LAI, field-measured LAI from 2021 to 2023 were compared
 360 against mean LAI curve calculated from value of 5,000 simulated LAI curves randomly selected from the simulated soybean
 growth dataset (Fig. 3). The results showed that simulated LAI trends aligned closely with observed field variations, capturing
 88 % of the field-measured sample sites ($n = 83$) within the simulated range. This demonstrated robust agreement between
 model outputs and ground truth, confirming the WOFOST simulations' ability to represent realistic LAI dynamics for GRU
 training.



365

Figure 3: Comparison of averaged daily LAI randomly selected from model simulations ($n = 5000$) with field-measured LAI in 2021 ($n = 38$), 2022 ($n = 46$) and 2023 ($n = 10$). The gray shading represents one standard deviation, indicating the uncertainty in LAI simulation.

Figure 4 (a) displays the histogram distribution of simulated soybean yields, revealing an approximately normal
 370 distribution (mean = 2675.66 kg ha⁻¹). The soybean growth dataset effectively captured wide range of production conditions,
 spanning low to high yield extremes. Fig. 4 (b) shows a box plot for comparing the simulated yield with historical statistics
 from 1980 to 2022, published yield data from literatures, and field measurements from 2022 and 2023. The simulated dataset

exhibited the widest value range, demonstrating the comprehensiveness of the multi-scenario knowledge base and the robustness of the simulation outcomes.

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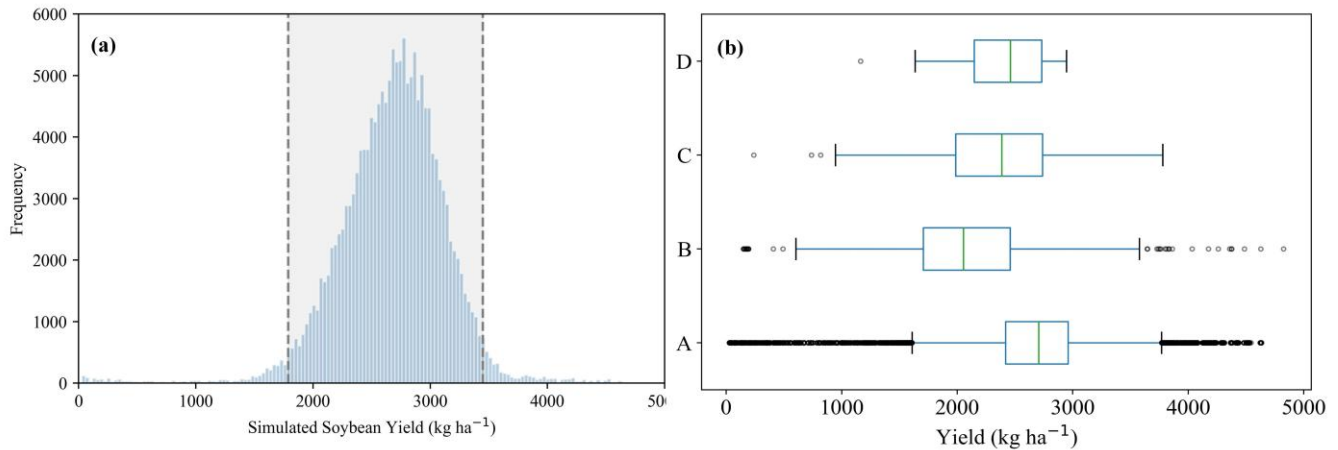


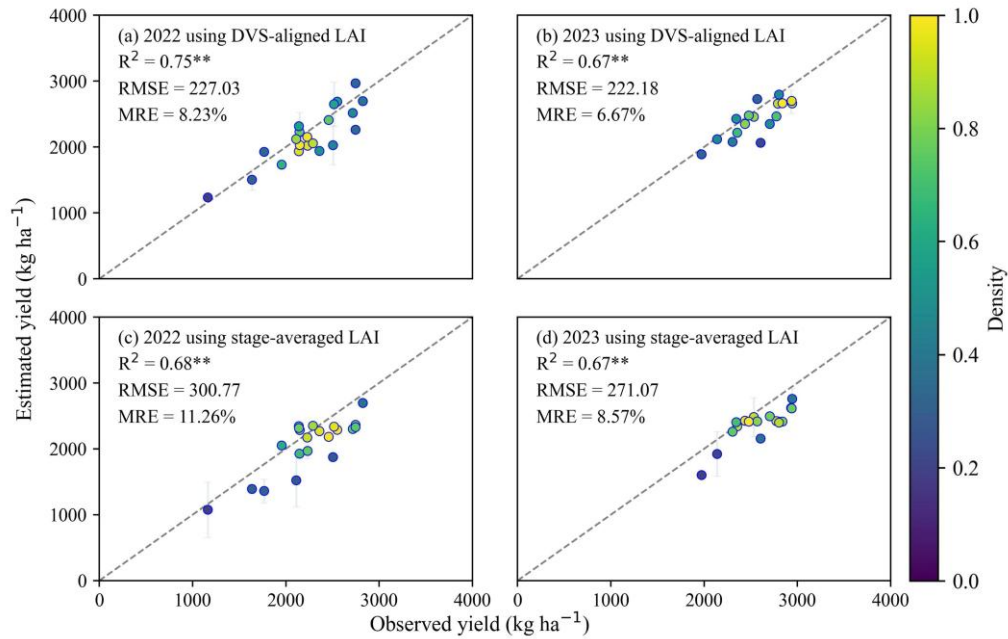
Figure 4: (a) Histogram statistics of simulated soybean yield where the gray area in the histogram represents 95 % confidence intervals; (b) distribution of simulated soybean yield compared with other datasets where A represents simulated yield in this study (n = 171,360), B represents statistical yield from 1980 to 2022 (n = 961), C represents specific measurements from the literature (Chen et al., 2011; Fan et al., 2012; Liu et al., 2005, 2008; Liu and Herbert, 2002; Wang et al., 2020, 2024; Zheng and Zhang, 2021) (n = 138) and D represents measurements in 2022 and 2023 carried by this study (n = 39).

380

4.2 Yield estimation at field scale

The field scale performance of GRU models using full DVS-aligned LAI and two stage-averaged LAI was validated against in-situ measurement from 2022 and 2023 (Fig. 5). The estimated yields exhibited strong agreement with observed yield, with $R^2 > 0.65$ ($p < 0.01$) in all scenarios. Validation results (Fig. 5 and Fig. A4) showed that the DVS-aligned GRU model achieved slightly better accuracy (RMSE = 224.81 kg ha⁻¹, MRE = 7.50%), while the stage-averaged model remained competitive (RMSE = 287.44 kg ha⁻¹, MRE = 10.02%). The difference in MRE was around 3% across both years, suggesting that the simplified approach using two stage-averaged LAI was a feasible alternative for yield estimation.

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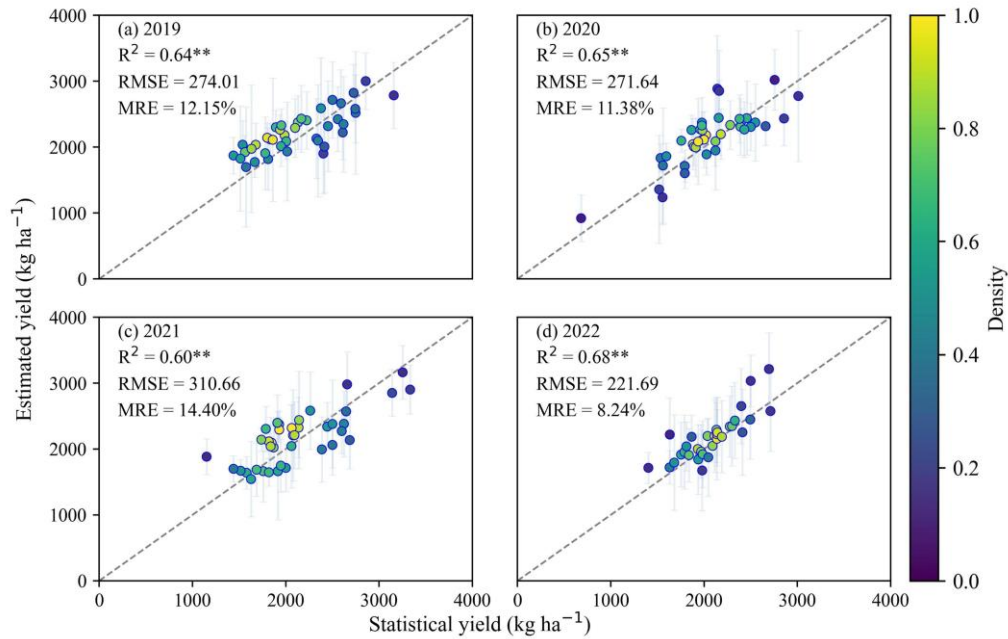


395 **Figure 5: Scatterplots between estimated and observed soybean yield for 2022 and 2023. (a) and (b) show results for 2022 and 2023, respectively, using the full DVS-aligned LAI; (c) and (d) show results for 2022 and 2023, respectively, using two stage-averaged LAI. Error-bars represent one standard deviation indicating the uncertainty of yield estimations. The dashed line represents 1:1 line. ** denotes statistical significance at $p < 0.01$.**

4.3 Yield estimation at regional scale

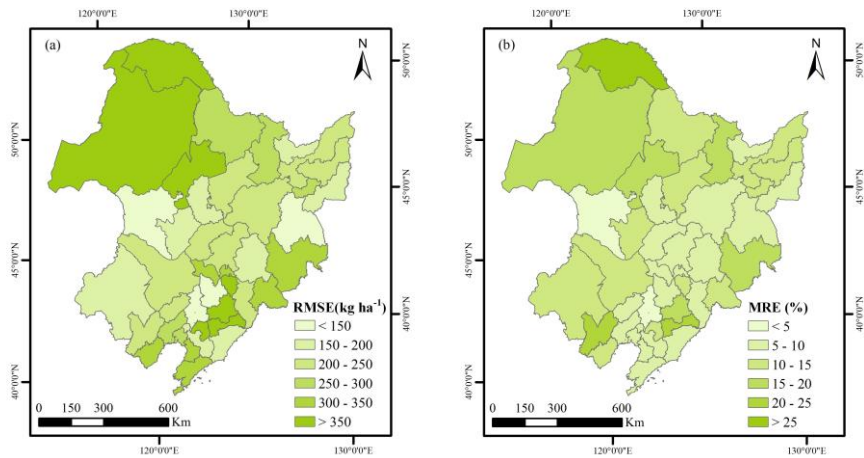
4.3.1 Variability of accuracy through years

The performance of GRU model at regional scale using the two stage-averaged LAI was validated at the municipal scale (2019 to 2022) by aggregating yield maps to match statistical data (Fig. 6). Compared to the field-scale validation, the municipal-scale estimates exhibited greater uncertainty, likely reflecting increased heterogeneity of soybean yields over larger areas. The estimates maintained stable interannual performance, with correlation between estimated and statistical yields consistently exceeding 0.60 ($p < 0.01$). The overall accuracy, pooled across 2019- 2022, for municipal-scale achieved $R^2 = 0.62$ ($p < 0.01$), $RMSE = 272.36 \text{ kg ha}^{-1}$, and $MRE = 12.08 \%$ (Fig. 12a). Annual accuracy metrics ranged from $221.69 \text{ kg ha}^{-1}$ to $310.66 \text{ kg ha}^{-1}$ for RMSE and from 8.24% to 14.40% for MRE, with the 2022 year achieving the highest accuracy ($MRE < 10\%$, Fig. 405 6d).



410 **Figure 6: Scatterplots between estimated soybean yield from Sentinel-2 and municipal statistical yields for 2019 – 2022 (excluding 2023 for which no statistical data was not available from the government). Error-bars represent one standard deviation indicating the uncertainty of yield estimations. The dashed line represents 1:1 line. ** denotes statistical significance at $p < 0.01$.**

415 For temporal performance at the municipal scale, the RMSE between estimated and statistical yields from 2019 to 2022 remained below 500 kg ha^{-1} , with 80 % of cities exhibiting RMSE under 350 kg ha^{-1} (Fig. 7a). Spatially, large errors were concentrated in the northern part of Northeast China especially for the Greater Khingan Mountains area, while the flatter region, central regions of Northeast China, showed smaller deviations. The spatial distribution pattern of MRE closely mirrored that of RMSE (Fig. 7b), averaging value of 11.46 % across all cities over the four-year period. These findings underscore the model's robust capacity to capture interannual variability of soybean yield.

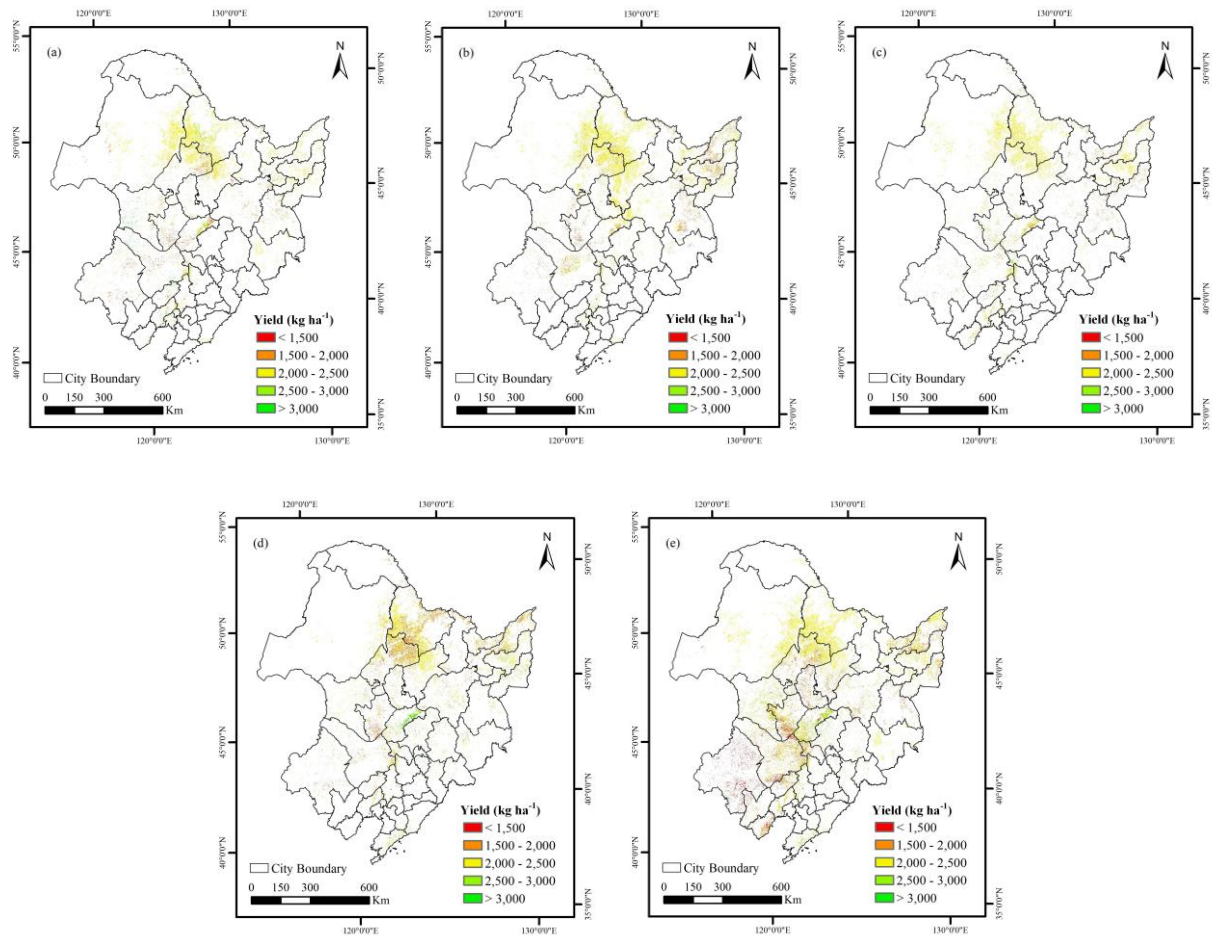


420 **Figure 7: Spatial patterns of the mean value of the root mean squared error and mean relative error between model estimated yields from Sentinel-2 and statistical yields from 2019 to 2022 (excluding 2023 for which no statistical data was not available from the government), (a) and (b), respectively. For years from 2019 to 2021, a total of 40 cities were calculated. For 2022, 32 cities were calculated due to missing statistics.**

4.3.2 Spatial-temporal dynamics of soybean yield

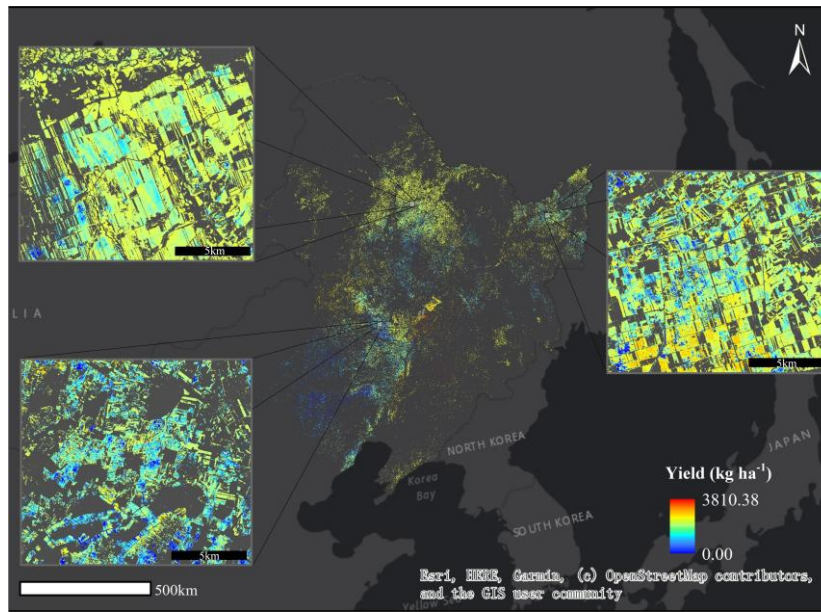
425 To examine spatial patterns of soybean yield across Northeast China, yield distribution maps for 2019 - 2023 were generated (Fig. 8a-e). After bias correction with estimated yield derived from MODIS LAI products, the Sentinel-2 striping artifacts were markedly reduced (Fig. 8 vs. uncorrected estimates in Fig. A5), resulting in seamless 20 m yield surfaces with strong spatial continuity. Detailed yield estimations can be found in Fig. 9. Across five-year estimates, soybean yield in Northeast China predominantly ranged between 1500 and 2500 kg ha⁻¹, with higher yield concentrated in the central part plains where a region

430 characterized by flat terrain and factorable agroclimatic conditions. The predicted yield is consistent with the municipal-scale statistical data (Table 5). Spatial variability, quantified by the coefficient of variation (CV), ranged from 17.51 % to 29.65 % over the study period, reflecting both inter and intra-annual heterogeneity in soybean productivity (Table 5).



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Figure 8: Spatial distribution of annual soybean yield derived from Sentinel-2 after calibration in Northeast China from 2019 to 2023.

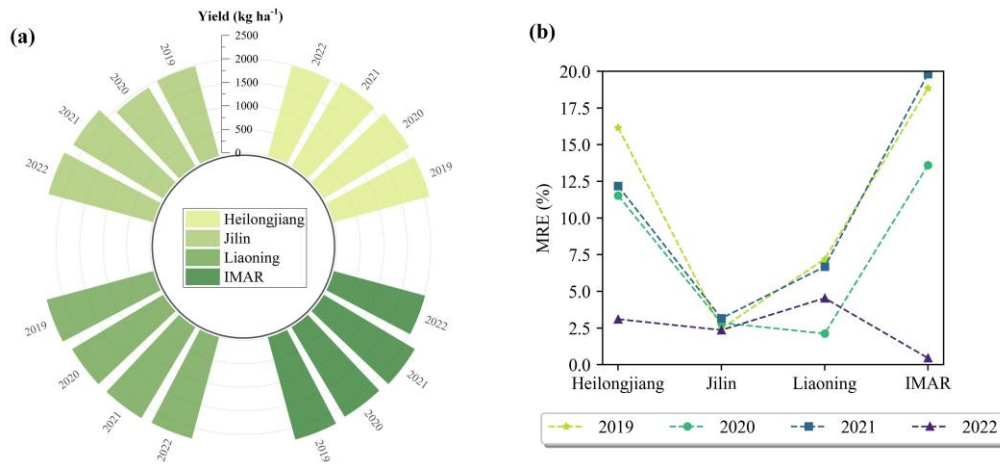


440 **Figure 9: An example of yield estimation result (for the year 2023) used to showcase detailed local estimates.**

Table 5 Mean values of statistical soybean yield at municipal scale in Northeast China compared with mean values, standard deviation (STD) and coefficient of variation (CV) for estimated soybean yield in Northeast China.

Year	Statistics (kg ha ⁻¹)	Mean (kg ha ⁻¹)	STD (kg ha ⁻¹)	CV (%)
2019	2137.24	2150.02	504.61	23.47
2020	2069.08	2125.49	372.21	17.51
2021	2115.57	2136.65	374.58	17.53
2022	2073.68	2036.89	465.26	22.84
2023	—	2035.34	603.43	29.65

We further analysed the spatial-temporal variation of soybean yield at the provincial scale (Fig. 10). On average, provincial-scale estimates achieved a mean relative error (MRE) of 7.94 % (Fig. 10b), with the highest accuracy observed in 2022 (Fig. 10b), mirroring municipal-level results (Fig. 6d). Over 2019 – 2022, Liaoning Province consistently exhibited the highest yields, whereas Heilongjiang Province, despite having the largest soybean planting area, recorded the lowest yields (Fig. 10a). This disparity likely due to Heilongjiang’s cooler climate, where later planting date result in shorter soybean development length. Across the four provinces, yields remained relatively stable, except in Jilin Province showed greatest interannual fluctuation exhibiting distinct decline followed by recovery. These results underscore the capacity of the proposed hybrid framework to capture spatial-temporal variations in soybean production.



455 **Figure 10: Accuracy of the soybean yield estimation at provincial scale in Northeast China from 2019 to 2022. (a) represents the change in estimated yield for each province through the years; (b) represents MRE of results compared with statistical yield for each province**

5 Discussion

5.1 Selection of model input features

In this study, two stage-averaged LAI (LAI_{mean1} and LAI_{mean2}) were selected as alternative input features to DVS-aligned LAI for soybean yield estimation. Although full LAI sequences yielded higher accuracy at local scale (Fig. 5 and Fig. A4), their regional application was limited by (a) strong spatiotemporal heterogeneity of Sentinel-2 image availability (Fig. A1), which required constructing a specific time-series input for every site impartial, and (b) resource-intensive in computational and data-management costs associated with model training and maintaining models for many different sequence-patterns. The two stage-averaged LAI features are a computationally efficient solution for regional yield mapping, while full time-series inputs offer modest accuracy gains that are best exploited at local scales or where dense, regular observations are available.

460
465

For further analysis, we systematically evaluated a broad set of candidate features derived from LAI, transpiration (TRA), and surface soil moisture (SM) extracted from the simulated soybean growth dataset. To develop a unified model suitable for long-term and large-scale soybean yield estimation, we employed statistical summaries of these features rather than time-series features tied to specific image acquisition dates (as done by Du et al., (2025)). For each variable, four statistical descriptors—including mean, maximum, median, and cumulative sum—were calculated separately for the vegetative growth stage, the reproductive growth stage, and the whole growing season, following the approach of Ren et al., (2023b).

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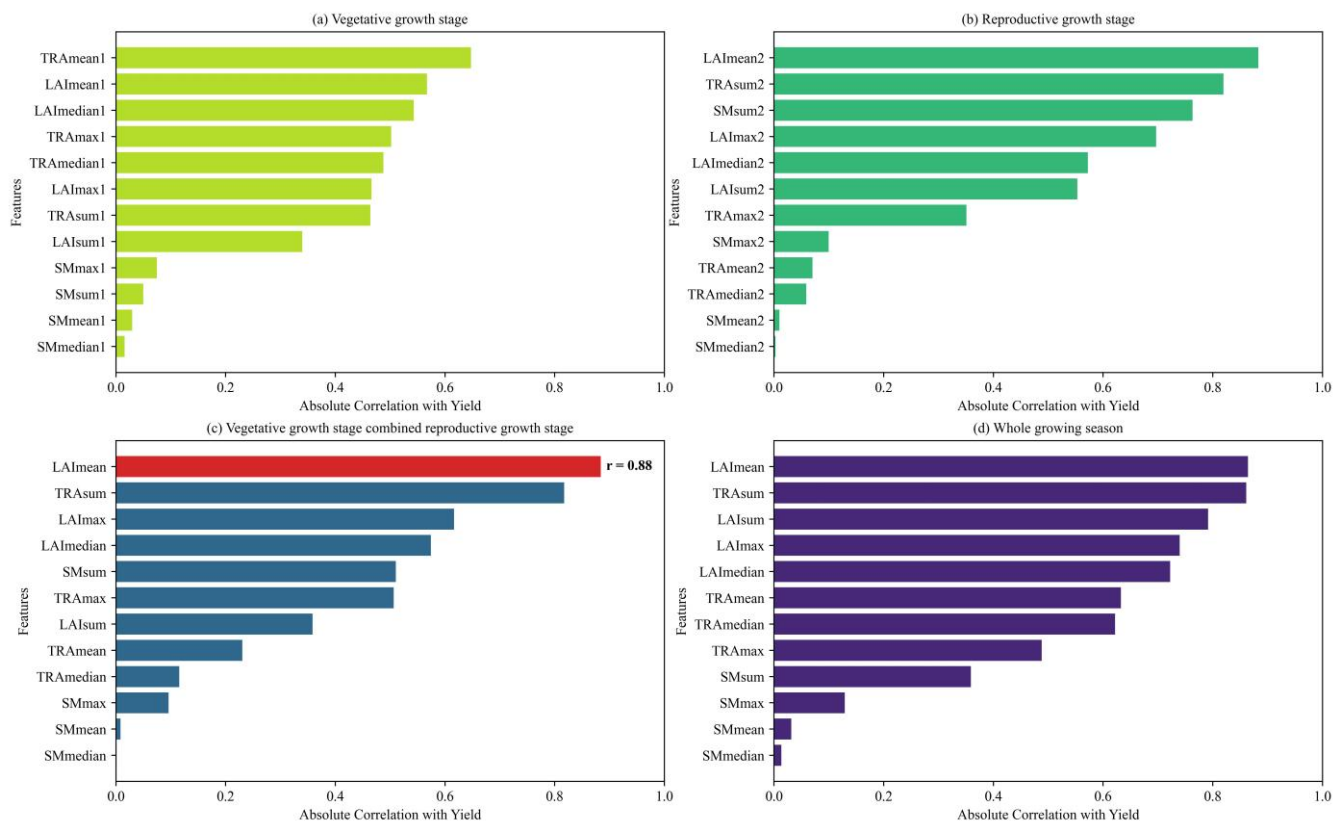
As shown in Fig. 11, LAI-derived features exhibited consistently strong correlations with simulated yield ($r = 0.54$ to 0.88), reflecting the role of LAI as a critical proxy for canopy development, light interception, and biomass accumulation (Cao et al., 2025; Shi et al., 2025). The multi-spectral retrieval of LAI therefore effectively characterizes both structure and physiological status of the crop canopy, supporting its dominant predictive power in our feature set.

475

Notably, the two stage-averaged LAI (LAI_{mean1} and LAI_{mean2}) exhibited stronger correlations with yield than features derived from either single phenological stage or the entire growing season, which is consistent with Ren et al., (2023b). Conceptually, LAI_{mean1} captures vegetative vigor (establishment and biomass accumulation, Kodadinne Narayana et al., (2024)), while LAI_{mean2} reflects reproductive canopy status. These two features jointly summarize the two most yield-
480 informative phases and mitigate the redundancy present in full sequences. Among the candidate features, mean-based features outperformed maximum, median, and cumulative counterparts. This likely due to their lower sensitivity to extreme values and day-to-day fluctuations, making them a more stable and representative indicator of canopy conditions across the two growth periods.

While some TRA-based features (e.g., TRA_{sum}) showed relatively high correlation with yield, they were excluded owing
485 to practical constraints. Current TRA retrieval methods primarily rely on thermal-infrared remote sensing, which typically has coarse spatial and temporal resolution (Hou et al., 2018; Zhang, 2003) limiting its utility for high-resolution, regional mapping. Similarly, SM-related features showed weak or inconsistent correlations with yield across growth stages in our simulations, indicating a limited direct influence on soybean yield production under modeled conditions.

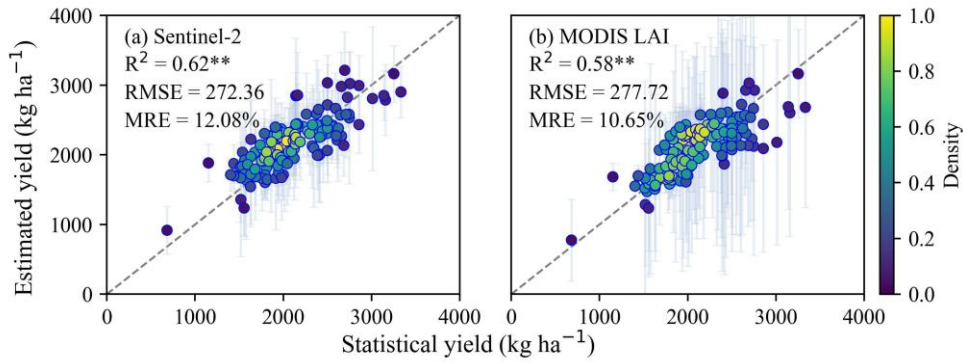
In summary, to optimize model inputs for efficient, large-scale applications, and to facilitate the generation of soybean
490 yield dataset, the two stage-averaged LAI features (LAI_{mean1} and LAI_{mean2}) were selected. This selection balances physiological relevance and temporal specificity with strong predictive performance and practical feasibility, enabling competitive yield estimation using only two interpretable, remotely sensed retrievable predictors.



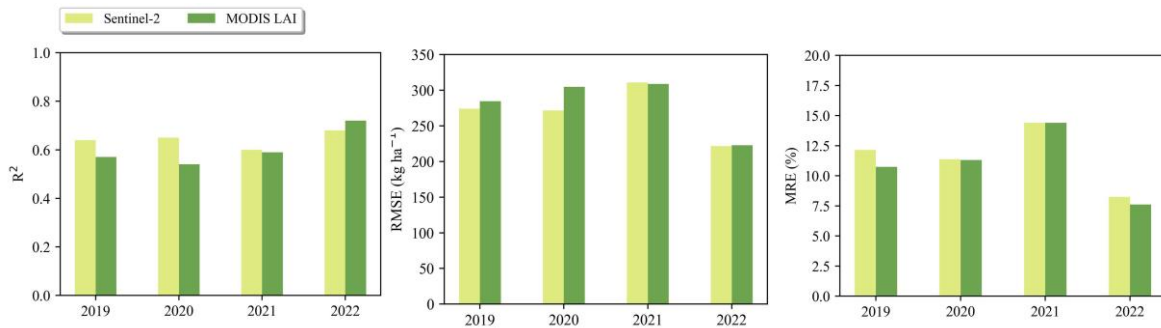
495 **Figure 11: The absolute Pearson correlation coefficients between each candidate feature and simulated soybean yield, grouped by growth stages: (a) vegetative growth stage; (b) reproductive growth stage; (c) vegetative growth stage combined reproductive growth stage and (d) whole growing season, respectively.**

5.2 The complementarity between MODIS and Sentinel-2

This study generated soybean yield estimates using both MODIS LAI (500 m) products and S2 derived LAI (20 m) data. Over 2019 – 2022, the MODIS-based estimates achieved an overall R^2 of 0.58 ($p < 0.01$), an RMSE of 272.36 kg ha⁻¹ and an MRE
500 of 12.08 % (Fig. 12b), slightly lower than the Sentinel-2 based results (Fig. 12a). The uncertainty of MODIS based estimates was higher than that the Sentinel-2 based estimates, likely reflecting MODIS’s coarser resolution. However, the Sentinel-2 based estimates exhibit inherent seaming effects caused by cloud-affected tile edges. We additionally used MODIS LAI to bias-correct Sentinel-2 yield maps, effectively minimizing the striping (“seaming”) effects in the 20 m products (Fig. 9), while preserving pixel-level detail through tile-based calibration. Despite difference in spatial resolution, both MODIS and Sentinel-
505 2 satellite data demonstrated comparable ability to capture spatiotemporal variation in soybean yield (Fig. 13), achieving correlations with statistical data > 0.55 and overall errors < 13 % across all years.



510 **Figure 12: Comparison between estimated and statistical yield for 2019 – 2022 using Sentinel-2 (a) and MODIS LAI (b), respectively (excluding 2023 for which no statistical data was reported). Error-bars represent one standard deviation indicating the uncertainty of yield estimations. The dashed line represents 1:1 line. ** denotes statistical significance at $p < 0.01$.**



515 **Figure 13: Comparison of accuracy evaluation results for soybean yield estimation in 2019 – 2022 (excluding 2023, for which no statistical data was reported) using Sentinel-2 and MODIS LAI data, respectively.**

In practical applications, balancing both temporal and spatial resolution is critical for achieving robust yield prediction results (Azzari et al., 2017). Figure 14 compares the Sentinel-2 yield maps and the MODIS LAI yield maps within a 10 km grid under different soybean coverage. Thanks to 4-day revisit, MODIS LAI provides more cloud-free observations during the critical growth stages, improving the reliability of two stage-averaged LAI (LAI_{mean1} and LAI_{mean2}). Its coarser spatial resolution also accelerates spatial processing over large areas. However, Sentinel-2's finer more effectively resolves intra-field yield heterogeneity (Fig. 14). MODIS-derived maps occasionally underestimated yields due to mixed pixels containing non-crop features (e.g., infrastructure), whereas Sentinel-2 minimized such errors.

520 While this study prioritized high-resolution mapping (using MODIS solely for Sentinel-2 seam correction), combing high spatial data (e.g., Sentinel-2 or UAV imagery) with high temporal frequency satellites (e.g., geostationary sensors or radar)
 525 could provide an optimal data source for crop-yield modelling (Gao and Anderson, 2019; He et al., 2018).

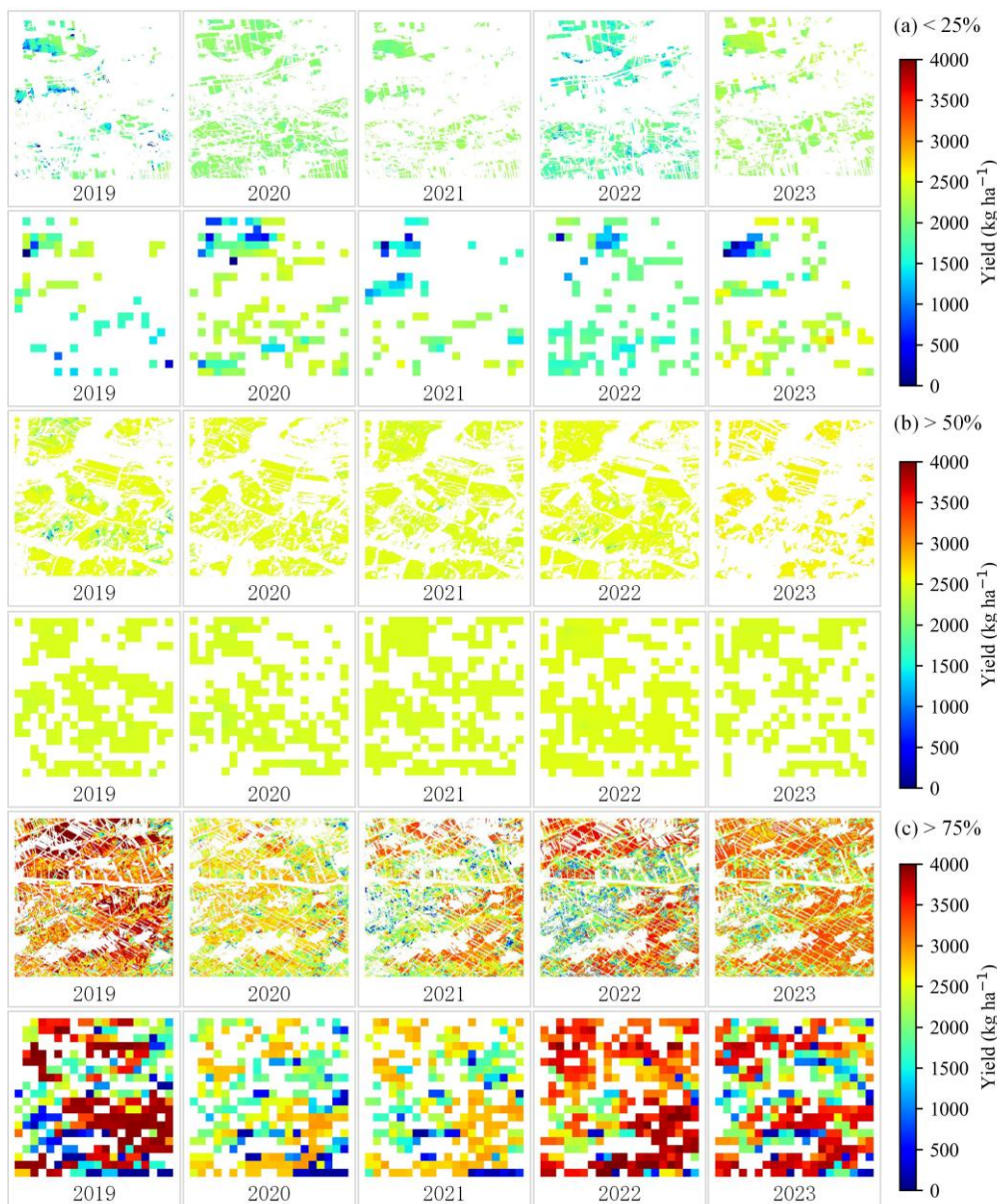


Figure 14: Comparisons of soybean yield estimation within a 10 km grid under different soybean coverage using Sentinel-2 (20 m) and MODIS LAI (500 m) data, where (a), (b), (c) represent soybean coverage less than 25%, more than 50% and more than 75%, respectively.

530

5.3 Advancements in this study

Accurate monitoring of soybean yield is crucial for food policy decision-making and security assessment. While previous studies have primarily explored the impact of environmental factors such as climate on soybean productivity (Guo et al., 2022; Zhao et al., 2023a), few efforts have focused on producing high-resolution soybean yield dataset for China's major soybean-

535 producing regions. To address this gap, our study produced the NortheastChinaSoybeanYield20m dataset, a 20-meter resolution dataset generated through a hybrid framework integrating the mechanistic WOFOST crop growth model and a GRU deep learning algorithm. Unlike purely data-driven approaches that rely on extensive ground data, our approach leveraged both data mining capabilities and mechanistic modelling, which improve the model's interpretability and enhances its potential for transferability across regions. The integration of the WOFOST model ensured the simulation of diverse production conditions
540 under varying climate, soil, crop variety and management conditions, providing a robust synthetic training data for the GRU network. This combination allowed the model to generate well, even in areas with limited observational data, therefore overcoming common limitations related to data scarcity and high computational costs. Accuracy assessments using both in-situ and statistical yield data confirmed that the generated NortheastChinaSoybeanYield20m dataset delivered reliable yield estimates across field and regional scales (Fig. 5 and 6). The results also verified the model's stability across time and space,
545 reinforcing its potential for large-scale agricultural monitoring and strategic planning.

When compared to previous studies using integrated remote sensing data and process-based model to estimate soybean yield, for instance, Baup et al., (2015) reported estimation error ranging from 2% to 18%, our method achieved comparable levels of accuracy. It also outperformed existing field-scale studies (e.g., RMSE = 400.946 kg ha⁻¹ in Ren et al., (2023) and MRE of 29.73% in Du et al., (2014)) and municipal-scale models (e.g., RMSE = 16 % in Von Bloh et al., (2023)). Furthermore,
550 the NortheastChinaSoybeanYield20m dataset showed improved performance relative to similar high-resolution soybean yield products from other countries (e.g., annual 30 m soybean yield mapping in Brazil, with R² values between 0.31 and 0.71 and RMSEs ranging from 275 to 740 kg ha⁻¹ (Song et al., 2022).

Although studies based on UAV and RGB data have demonstrated even higher soybean yield estimation accuracy (Li et al., 2021, 2024), such methods are often constrained by high costs and limited spatial coverage, making them impractical for
555 large-scale applications. In contrast, the method developed in this study offers a well-balanced solution that combines computational efficiency, high spatial resolution, and strong predictive accuracy. Our approach offers scalable and practical solution for producing high-resolution, large-scale crop yield datasets.

5.4 Limitations and future developments

In this study, a soybean growth dataset was developed by simulating various combinations of input parameters within the
560 WOFOST model. These diverse parameter combinations were designed to reflect different environmental and management conditions, ultimately serving as training data for the yield estimation model. One advantage of the model is its scalability, it can be readily applied to other regions and countries that lack sufficient ground observation data, such as parts of Africa and India, thus offering a promising tool for global agricultural monitoring.

However, the validation results revealed some notable limitations. Specifically, the model exhibited a tendency to produce
565 large uncertainty in low- or high- yielding areas, introducing error into the overall yield estimation (Fig. 5 and 6). This pattern suggests a systematic bias in the model's predictions, particularly in regions with extreme yield values. Additionally, spatial analysis showed that estimation errors were more pronounced in the northern region, where is characterized by complex terrain,

compared to the relatively flat central region (Fig. 7). These discrepancies highlight the need to refine parameterization for extreme yield conditions and integrate higher-resolution environmental drivers (e.g., terrain, localized weather).

570 First, the estimation errors may be attributed to the inherent limitations of the WOFOST model. As a process-based model, WOFOST simplifies its calculations for simulating physiological processes, which can hinder its ability to fully replicate the complex realities of soybean in the field. Factors, such as pest infestations, diseases, and abiotic stresses are either oversimplified or excluded (Gaso et al., 2024). These omissions can lead to systematic simulation errors, particularly under stress conditions that significantly affect crop yield. Moreover, the parameterization of the WOFOST model in this study
575 purely relied on values from literature and existing dataset rather than site-specific optimization against independent observations. As a result, local variability because of farming practices, soil properties, and environmental conditions may not have been adequately captured. This lacks local optimization likely result in higher estimation error, especially in complex landscapes with sparse ground observations. For future studies, the use of targeted field-measured and remotely sensed products (e.g., surface soil moisture, solar-induced chlorophyll fluorescence (SIF), LiDAR-based biomass, and leaf chlorophyll content),
580 integration of advanced data assimilation approaches (e.g., assimilating SIF or leaf chlorophyll content) and model sensitivity analyses will further increase biological realism. Moreover, given the spatial variability in soybean growth within the study area, constructing ecological zones based on factors like climate, elevation, and management practices might provide a more targeted model approach. For instance, Huang et al., (2023) defined the ecological zones through using Theissen polygons derived from meteorological station locations. This zoning strategy could enhance the representativeness of the training data
585 and reduce yield estimation uncertainties.

Second, the estimation errors may stem from the overfitting of the GRU model. The GRU was trained on the simulated soybean growth dataset, a large number of simulations that included all available combinations (e.g., all meteorological data), which introduced a significant amount of redundant information. The redundancy not only potentially reduce the dataset's representativeness, but also increase the computational burden during model training. As a result, the trained GRU model may
590 have become overly turned to specific temporal patterns in certain years, limiting its ability to generalize to other time period or regions with different growth conditions. This overfitting effect might result in large yield estimation errors across different years and regions, particularly in areas where soybean yields deviated significantly from the norm. To address these issues, refining the structure and composition of the training dataset, and removing redundant information would enhance the diversity and quality of the training inputs. One potential approach to reduce redundancy is through spatiotemporal clustering of various
595 environmental (e.g., meteorological station data), which could filter out stations with highly similar information. Moreover, monitoring the validation error throughout the training process, and implementing regularization techniques (e.g., L2 weight regularization) could help to prevent overfitting and improve the GRU model's generalization capability, leading to improve soybean estimation across varying conditions.

Third, using the two stage-averaged LAI introduces additional sources of uncertainty in yield estimation. Excessive
600 temporal aggregation inevitably obscures growth dynamics. Different growth trajectories can produce similar stage-based LAI yet correspond to different yields, increasing the risk of non-unique LAI for spatially yield mappings. This simplification also

limits the modelling capacity of GRU architectures, which are specifically designed to exploit sequential dependencies in time series inputs. Future work can explore hybrid approaches that combine stage-based summaries with higher-frequency or full-season time series of vegetation indicators to improve both interpretability and yield prediction robustness. On the other hand, errors in LAI retrieval from remote sensing data also contributed uncertainty in yield predictions. The published LAI–NDVI_{RE} relationship is broadly transferable because red-edge based VIs are less sensitive than traditional VIs (e.g., NDVI, CI_{green} and EVI) to variations in canopy structure, phenology, and site locations (Dong et al., 2019; Nguy-Robertson et al., 2014; Viña et al., 2011). Red-edge based VIs (e.g., NDVI_{RE}) also mitigate soil-background influences. Nevertheless, the modest overestimation we observe at low LAI indicates that residual soil-background differences between our Northeast China sites and the original Spanish and Italian calibration plots can still bias the regression under sparse canopies. Directly applying the published LAI–NDVI_{RE} regression without regional re-calibration may therefore propagate bias into yield estimates. Integrating agronomic knowledge with remote sensing mechanisms has emerged as a promising way to reduce the uncertainty and improve model reliability (Chen et al., 2022; Hu et al., 2024). In future work, coupling radiative transfer model such as PROSAIL (Jacquemoud et al., 2009)) with crop growth model would allow the direct use of satellite reflectance and is expected to reduce bias from site-specific LAI regressions and further improve model accuracy (Ntakos et al., 2024).

Finally, the combination of IoT, blockchain, and precision agriculture with machine learning and biophysical models can offer a powerful framework for sustainable agricultural monitoring, addressing challenges in data heterogeneity, model scalability, and decision-making processes. These technologies can facilitate real-time data collection, ensure data security and transparency. Precision agriculture techniques, combined with advanced sensing technologies, can effectively improve the accuracy and timeliness of input data, addressing current limitations in model calibration, validation and prediction.

6 Data availability

The soybean yield dataset for Northeast China (NortheastChinaSoybeanYield20m) during the 2019-2023 period is available at <https://doi.org/10.5281/zenodo.14263103> (Xu et al., 2024).

7 Conclusions

This study generated a high-resolution (20 m) soybean yield dataset for Northeast China from 2019 to 2023 (NortheastChinaSoybeanYield20m) using a hybrid framework that couple the WOFOST crop growth model with a Gated Recurrent Unit (GRU) deep learning algorithm. The framework leveraged a comprehensive soybean growth dataset simulated by WOFOST, which accounted for diverse production conditions, including variations in climates, crop varieties, soil types and agro-managements practices. This approach effectively reduces reliance on ground observation data, which demonstrating enhanced spatiotemporal generalization capabilities.

The dataset was conducted using multi-source remote sensing data, with Sentinel-2 derived two staged-averaged LAI as the primary input. Yield estimations showed robust performance at both field and municipal scales, achieving RMSE of 287.44 kg ha⁻¹ and 272.36 kg ha⁻¹, respectively. To address spatial discontinuities in Sentinel-2 data, corrections using MODIS LAI-derived yield maps effectively mitigated seam effects, achieving complementary benefits in temporal and spatial resolution. 635 The final dataset exhibits high temporal stability and spatial continuity, with mean relative errors (MRE) averaging of 11.46 % at the municipal scale and 7.94 % at the provincial scale.

The NortheastChinaSoybeanYield20m dataset successfully captures fine-scale spatiotemporal variations in soybean yield, offering potentials for optimizing production strategies, guiding precision agriculture, and enhancing food security and policy.

Authorship contributions

640 JX (first author) and QL – conceptualization; JX (first author), XD, YZ, HW, JX, YS and YD – data curation; JX (first author), XD, TD – methodology; JX (first author), XD, JX and JZ – investigation; TD and QL – supervision; HW, JX (first author) and JZ – validation; YZ, HW and JZ – visualization; JX (first author) – original draft preparation; XD, TD and YZ – reviewing and editing the manuscript.

Competing interests

645 The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Table A1 Values of crop parameters in WOFOST.

Parameter	Description	Units	Value	Source
Crop initial parameters				
TDWI	Initial total crop dry weight	kg ha ⁻¹	120	Default value in WOFOST

RGRLAI	Maximum relative increase in LAI	ha ha ⁻¹ d ⁻¹	0.01	Default value in WOFOST
Parameters for emergence				
TBASEM	Minimum threshold temperature for emergence	°C	8.0	Qu et al., (2023)
TEFFMX	Maximum threshold temperature for emergence	°C	22.0	Qu et al., (2023)
TSUMEM	Accumulated temperature from sowing to emergence	°C	70.0	Qu et al., (2023)
Phenological parameters				
DLO	Optimal daylength for development	h	-99	Default value in WOFOST
DLC	Critical daylength	h	-99	Default value in WOFOST
TSUM1	Cumulative temperature from emergence to anthesis	°C	450 (early maturity) 480 (medium-early maturity) 520 (intermediate maturity) 540 (medium-late maturity) 580 (late maturity)	Qu et al., (2023)
TSUM2	Cumulative temperature from anthesis to maturity	°C	660 (early maturity) 770 (medium-early maturity) 870 (intermediate maturity) 960 (medium-late maturity) 1000 (late maturity)	Qu et al., (2023)
Green area parameters				
TBASE	Lower threshold temperature for aging of leaves	°C	7.0	Default value in WOFOST
SPAN	Life span of leaves growing at 35 °C	d	23	Default value in WOFOST
SLATB00	Specific leaf area at DVS = 0.00	ha kg ⁻¹	0.00140	Default value in WOFOST
SLATB045	Specific leaf area at DVS = 0.45	ha kg ⁻¹	0.00250	Default value in WOFOST

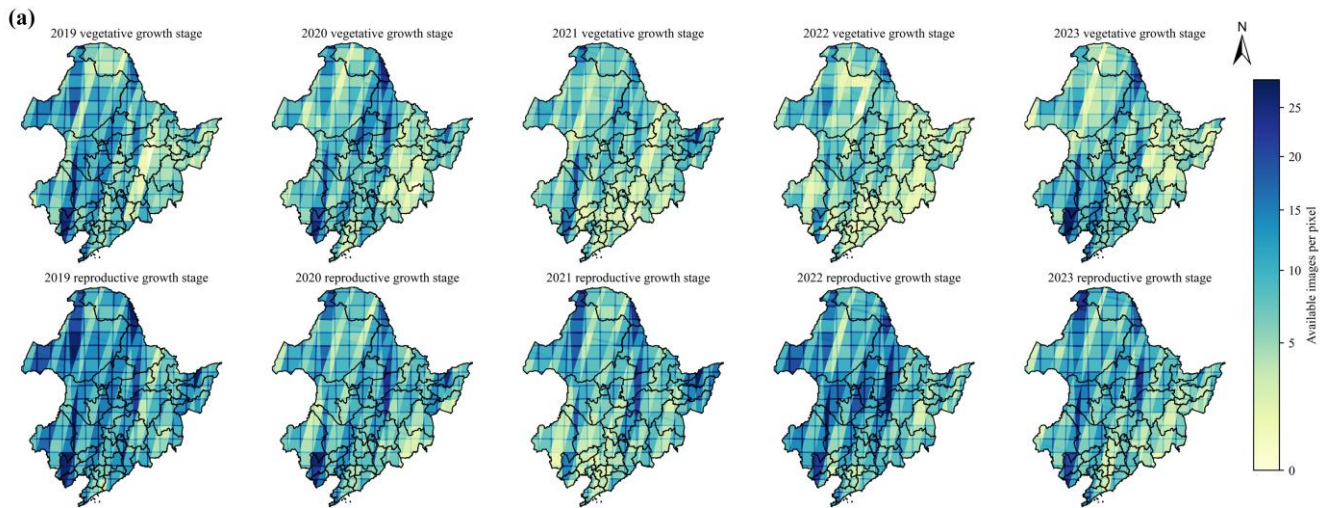
SLATB090	Specific leaf area at DVS = 0.90	ha kg ⁻¹	0.00250	Default value in WOFOST
SLATB200	Specific leaf area at DVS = 2.00	ha kg ⁻¹	0.00070	Default value in WOFOST
Assimilation parameters				
KDIFTB00	Extinction coefficient for diffuse visible light (DVS = 0)	-	0.80	Default value in WOFOST
KDIFTB200	Extinction coefficient for diffuse visible light (DVS = 2)	-	0.80	Default value in WOFOST
EFFTB0	Light use efficiency of a single leaf (T = 0 °C)	kg ha ⁻¹ h ⁻¹ J ⁻¹ m ² s ⁻¹	0.40	Default value in WOFOST
EFTB40	Light use efficiency of a single leaf (T = 40 °C)	kg ha ⁻¹ h ⁻¹ J ⁻¹ m ² s ⁻¹	0.40	Default value in WOFOST
AMAXTB00	Maximum leaf CO ₂ assimilation rate (DVS = 0)	kg ha ⁻¹ h ⁻¹	29.00	Default value in WOFOST
AMAXTB170	Maximum leaf CO ₂ assimilation rate (DVS = 1.7)	kg ha ⁻¹ h ⁻¹	25.31	Sun et al., (2022)
AMAXTB200	Maximum leaf CO ₂ assimilation rate (DVS = 2)	kg ha ⁻¹ h ⁻¹	0.00	Default value in WOFOST
TMPFTB00	Reduction factor of AMAX (T = 0 °C)	-	0.00	Default value in WOFOST
TMPFTB10	Reduction factor of AMAX (T = 10 °C)	-	0.30	Default value in WOFOST
TMPFTB20	Reduction factor of AMAX (T = 20 °C)	-	0.60	Default value in WOFOST
TMPFTB25	Reduction factor of AMAX (T = 25 °C)	-	0.80	Default value in WOFOST
TMPFTB30	Reduction factor of AMAX (T = 30 °C)	-	1.00	Default value in WOFOST
TMPFTB35	Reduction factor of AMAX (T = 35 °C)	-	1.00	Default value in WOFOST
Conversion of assimilates into biomass				
CVL	Conversion efficiency of assimilates into leaf tissue	kg kg ⁻¹	0.72	Default value in WOFOST

CVO	Conversion efficiency of assimilates into storage organs	kg kg ⁻¹	0.48	Default value in WOFOST
CVR	Conversion efficiency of assimilates into root tissue	kg kg ⁻¹	0.72	Default value in WOFOST
CVS	Conversion efficiency of assimilates into stem tissue	kg kg ⁻¹	0.69	Default value in WOFOST
Maintenance respiration parameters				
Q10	Relative change in respiration rate per 10 °C temperature increase	-	2.0	Default value in WOFOST
RML	Ralative maintenance respiration rate of leaves	kg CH ₂ O kg ⁻¹ d ⁻¹	0.03	Default value in WOFOST
RMO	Ralative maintenance respiration rate of storage organs	kg CH ₂ O kg ⁻¹ d ⁻¹	0.017	Default value in WOFOST
RMR	Ralative maintenance respiration rate of toots	kg CH ₂ O kg ⁻¹ d ⁻¹	0.01	Default value in WOFOST
RMS	Ralative maintenance respiration rate of stems	kg CH ₂ O kg ⁻¹ d ⁻¹	0.015	Default value in WOFOST
Partitioning parameters				
FRTB00	Fraction of total dry matter to roots at DVS = 0	kg kg ⁻¹	0.62	Sun et al., (2022)
FRTB075	Fraction of total dry matter to roots at DVS = 0.75	kg kg ⁻¹	0.35	Default value in WOFOST
FRTB100	Fraction of total dry matter to roots at DVS = 1	kg kg ⁻¹	0.15	Default value in WOFOST
FRTB150	Fraction of total dry matter to roots at DVS = 1.5	kg kg ⁻¹	0.00	Default value in WOFOST
FRTB200	Fraction of total dry matter to roots at DVS = 2.0	kg kg ⁻¹	0.00	Default value in WOFOST
FLTB00	Fraction of total dry matter to leaves at DVS = 0	kg kg ⁻¹	0.70	Default value in WOFOST
FLTB100	Fraction of total dry matter to leaves at DVS = 1.0	kg kg ⁻¹	0.70	Default value in WOFOST

FLTB115	Fraction of total dry matter to leaves at DVS = 1.15	kg kg ⁻¹	0.60	Default value in WOFOST
FLTB130	Fraction of total dry matter to leaves at DVS = 1.3	kg kg ⁻¹	0.43	Default value in WOFOST
FLTB150	Fraction of total dry matter to leaves at DVS = 1.5	kg kg ⁻¹	0.15	Default value in WOFOST
FLTB200	Fraction of total dry matter to leaves at DVS = 2.0	kg kg ⁻¹	0.00	Default value in WOFOST
FSTB00	Fraction of total dry matter to stems at DVS = 0	kg kg ⁻¹	0.30	Default value in WOFOST
FSTB100	Fraction of total dry matter to stems at DVS = 1.0	kg kg ⁻¹	0.30	Default value in WOFOST
FSTB115	Fraction of total dry matter to stems at DVS = 1.15	kg kg ⁻¹	0.25	Default value in WOFOST
FSTB130	Fraction of total dry matter to stems at DVS = 1.3	kg kg ⁻¹	0.10	Default value in WOFOST
FSTB150	Fraction of total dry matter to stems at DVS = 1.5	kg kg ⁻¹	0.10	Default value in WOFOST
FSTB200	Fraction of total dry matter to stems at DVS = 2.0	kg kg ⁻¹	0.00	Default value in WOFOST
FOTB00	Fraction of total dry matter to storage organs at DVS = 0	kg kg ⁻¹	0.00	Default value in WOFOST
FOTB100	Fraction of total dry matter to storage organs at DVS = 1.0	kg kg ⁻¹	0.00	Default value in WOFOST
FOTB115	Fraction of total dry matter to storage organs at DVS = 1.15	kg kg ⁻¹	0.15	Default value in WOFOST
FOTB130	Fraction of total dry matter to storage organs at DVS = 1.3	kg kg ⁻¹	0.47	Default value in WOFOST
FOTB150	Fraction of total dry matter to storage organs at DVS = 1.5	kg kg ⁻¹	0.75	Default value in WOFOST
FOTB200	Fraction of total dry matter to storage organs at DVS = 2.0	kg kg ⁻¹	1.00	Default value in WOFOST

Death rate parameters

PERDL	Maximum relative death rate of leaves due to water stress	kg kg ⁻¹ d ⁻¹	0.03	Default value in WOFOST
RDRRTB00	Relative death rate of roots at DVS = 0	kg kg ⁻¹ d ⁻¹	0.00	Default value in WOFOST
RDRRTB150	Relative death rate of roots at DVS = 1.5	kg kg ⁻¹ d ⁻¹	0.00	Default value in WOFOST
RDRRTB151	Relative death rate of roots at DVS = 1.51	kg kg ⁻¹ d ⁻¹	0.02	Default value in WOFOST
RDRRTB200	Relative death rate of roots at DVS = 2.0	kg kg ⁻¹ d ⁻¹	0.02	Default value in WOFOST
RDRSTB00	Relative death rate of stems at DVS = 0	kg kg ⁻¹ d ⁻¹	0.00	Default value in WOFOST
RDRSTB150	Relative death rate of stems at DVS = 1.5	kg kg ⁻¹ d ⁻¹	0.00	Default value in WOFOST
RDRSTB151	Relative death rate of stems at DVS = 1.51	kg kg ⁻¹ d ⁻¹	0.02	Default value in WOFOST
RDRSTB200	Relative death rate of stems at DVS = 2.0	kg kg ⁻¹ d ⁻¹	0.02	Default value in WOFOST
Water use parameters				
CFET	Correction factor transpiration rate	-	1.0	Default value in WOFOST
DEPNR	Crop group number for soil water depletion	-	5.0	Default value in WOFOST
IAIRDU	Air ducts in roots present (=1) or not (=0)	-	0	Default value in WOFOST
IOX	Oxygen stress effect enabled (=1) or not (=0)	-	0	Default value in WOFOST
Rooting parameters				
RDI	Initial rooting depth	cm	10	Default value in WOFOST
RRI	Maximum daily increase in rooting depth	cm d ⁻¹	1.2	Default value in WOFOST
RDMCR	Maximum rooting depth	cm	120	Default value in WOFOST



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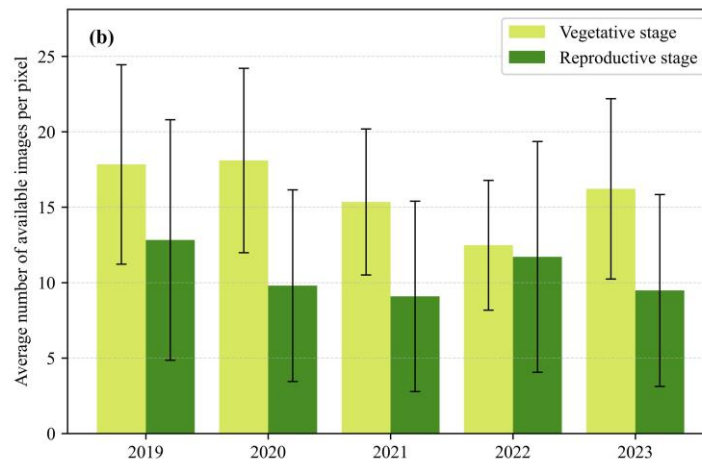


Figure A1: Spatial distribution of the number of available Sentinel-2 images per pixel for each year: vegetative growth stage (top) and reproductive growth stage (bottom) (a) and yearly averages for each growth stage with error-bars representing spatial standard deviation across pixels within the study area (b).

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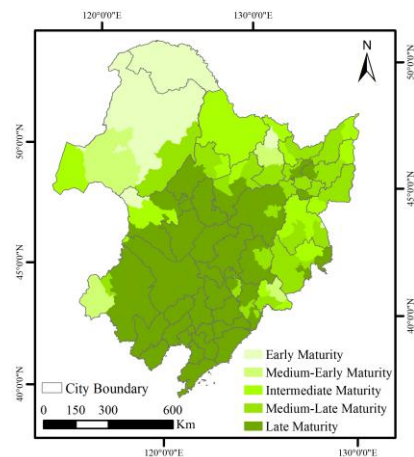


Figure A2: Spatial distribution of soybean types in Northeast China.

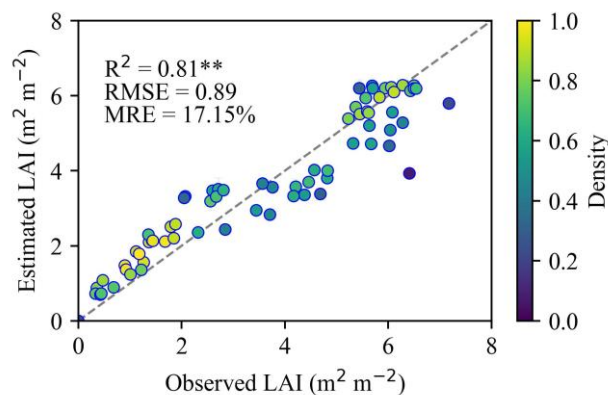
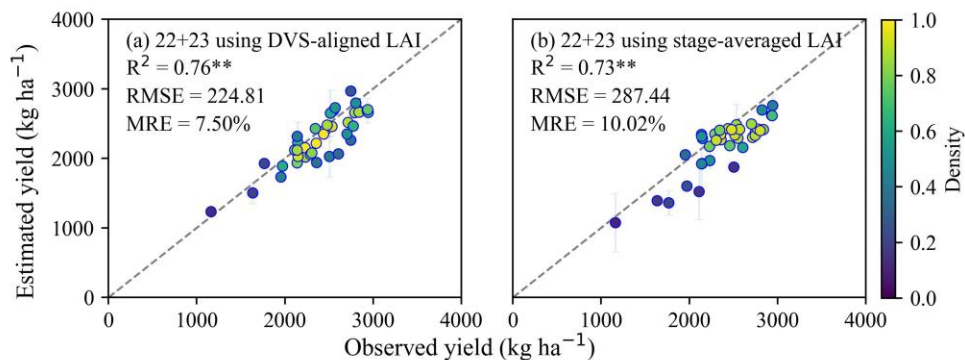


Figure A3: Comparison between estimated and field measured LAI from 2021 to 2023. Error-bars represent one standard deviation indicating the uncertainty of LAI estimations. The dashed lines represent the 1:1 line. ** denotes statistical significance at $p < 0.01$.



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Figure A4: Comparison between estimated and observed yield (2022 + 2023). (a) shows the estimates using the full DVS-aligned LAI and (b) shows the results using two stage-averaged LAI. The error-bars represent one standard deviation indicating the uncertainty of yield estimations. Dashed lines represent 1:1 line. ** denotes statistical significance at $p < 0.01$.

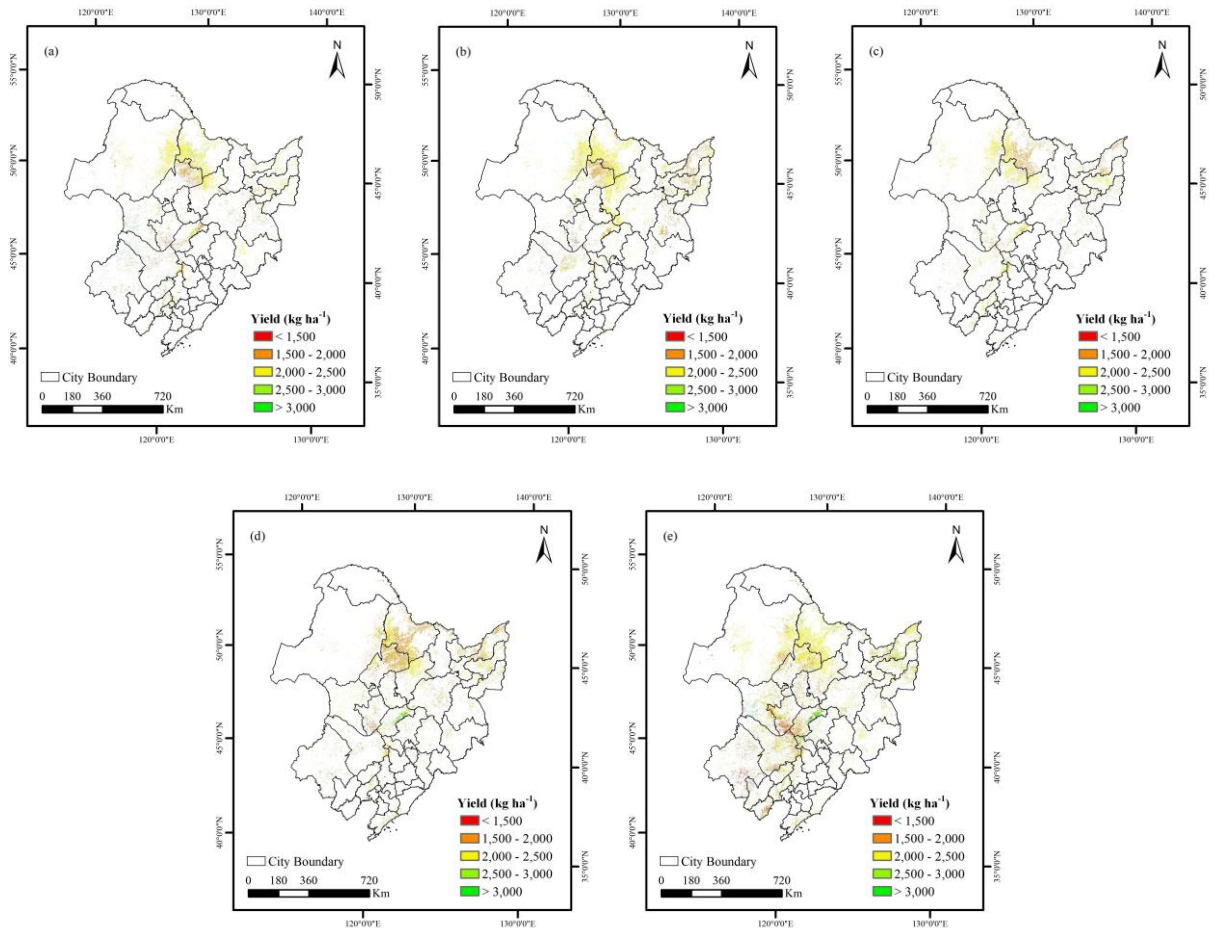


Figure A5: Spatial distribution of annual soybean yield derived from Sentinel-2 before calibration in Northeast China from 2019 to 2023.

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