Supplementary Materials

There are four tables in Supplementary Materials:

(1) Table S1. Spectral indexes
(2) Table S2. Climate factors
(3) Table S3. Combined indexes
(4) Table S4. Comparison between this research and other research methods

There are four figures in Supplementary Materials:

(1) Figure S1. Proportion of total maize yield of each country in the world in 2020.
(2) Figure S2. Statistics of total grain and maize yield in China from 2005 to 2020.
(3) Figure S3. Time series curves of the main indicators of maize in China
(4) Figure S4. Spatial distribution of difference between observed yield and estimated yield

There are two code links in Supplementary Materials:

(1) The code for calculating mean indexes
https://code.earthengine.google.com/da20f0cba348d9353c21b24c878587ba?noload=1
(2) The code for calculating 8-day time series indexes
https://code.earthengine.google.com/20f2b0e027dbe856613f65795dbe26e9

Multiple dimensional indexes

(1) Spectral indexes

Table S1. Spectral index.

Index Type	Indices
Vegetation	Enhanced Vegetation Index (EVI2)[1], Normalized Difference Vegetation Index(NDVI) [2], Global Environment Monitoring Index (GEMI)[3], Atmospherically resistant vegetation index2 (ARVI2)[4], Optimized Soil Adjusted Vegetation index (OSAVI) [5], Photosynthetic Vigour Ratio (PVR) [6], Wide dynamic range vegetation index (WDRVI)[7], Normalized Difference NIR/Blue Blue-normalized difference vegetation index (BNDVI) [8], Normalized Difference Phenology Index (NDPI) [9], near-infrared reflectance of vegetation (NIRv)[10], Visible atmospherically resistant index(VARIgreen) [11], Specific leaf area vegetation index (SLAVI) [12], Adjusted transformed soil-adjusted VI(ATSAVI) [13], Leaf Area Index of brown vegetation (LAIbrown) [14], LZC [15], Visible atmospherically resistant indices Green (VIgreen) [16], Green Chromatic Coordinate (GCC) [17]
water content	Normalized Difference Moisture Index (NDMI) [18], Normalized difference infrared index (NDII) [19], Land Surface Water Index (LSWI) [20], SIWSI6 SIWSI7, Modified Normalized Multi-band Drought Index (MNDWI) [21], Normalized Multi-band Drought Index (NMDI)[22], Global Vegetation Moisture Index (GVMI) [23]
Carotenoid content	Pigment specific simple ratio (PSSRc) [24], Pigment specific normalized difference (PSNDc) [25], Carotenoid reflectance index (CRI_{550})[26], Modified photochemical reflectance index (PRI)[27], Structure Insensitive Pigment Index (SIPI)[28]
Chlorophyll content	Green Normalized Difference Vegetation Index (GNDVI)[29], Pigment specific simple ratio (PSSRb) [24], Green chlorophyll vegetation Index (GCVI) [30], ($NDFI_{685}$) [31], Chlorophyll vegetation Index (CVI) [32], Chlorophyll Index (CIgreen) [33] modified anthocyanin content index (mACI) [34]
Nutrient	Normalized Difference Nitrogen Index(NDNI) [35], Nitrogen Index (NRI_{1510})[36],

content	Narrow-band Normalized Difference Spectral Index (NDSI)[37]
Biomass	Gross Primary Production (GPP) [38], Shortwave Angle Normalized Index(SANI) [39], Dry Matter Content Index (DMCI) [40]

(2) Climatic factors

Table S2. Climatic factors.

Data	Climate factors	Resenting meaning	Spatial resolution	Time resolution	Units
ERA5	Temperature_ max	Maximum air temperature at 2m height	27830m	Daily	K
	Temperature_ mean	Average air temperature at 2m height	27830m	Daily	K
	Temperature_ min	Minimum air temperature at 2m height	27830m	Daily	K
	Total_ precipitation	Total precipitation	27830m	Daily	m
TerraClimate	Evapotranspiration	Actual evapotranspiration	4638.3m	Monthly	mm
	Radiation	Downward surface shortwave radiation	4638.3m	Monthly	W/m^2
	Soil moisture	Soil moisture	4638.3m	Monthly	mm
	VPD	Vapor pressure deficit	4638.3m	Monthly	kPa
MOD09A1	Temperature_ day	Day land surface temperature	1km	Daily	Kelvin
	Temperature_ night	Night land surface temperature	1km	Daily	Kelvin

(3) Combined indexes

Table S3. Combined indexes.

Indexes	Combination method	Index A	Combined index
NMDI	(NMDI−A)/(NMDI+A)	SIPI, CVI, LZC, PSSRc, CRI_{550}, NDNI, SANI, GCC, PPR	NMDIA
NMDI	(NMDI−A)/ NMDI	SIPI, CVI, LZC	NMDIA
SIPI	(SIPI−A)/ (SIPI +A)	NMDI, CVI	SIPIA
LZC	(LZC−A)/ (LZC +A)	NMDI, SIPI, CVI	LZCA
SANI	(SANI−A)/ (SANI +A)	NMDI, SIPI, PSSRc, CRI_{550}, NRI_{1510}	SANIA

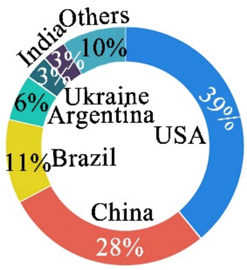

Figure S1. Proportion of total maize yield of each country in the world in 2020.

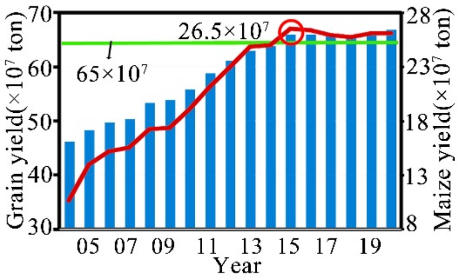

Figure S2. Statistics of total grain and maize yield in China from 2005 to 2020.

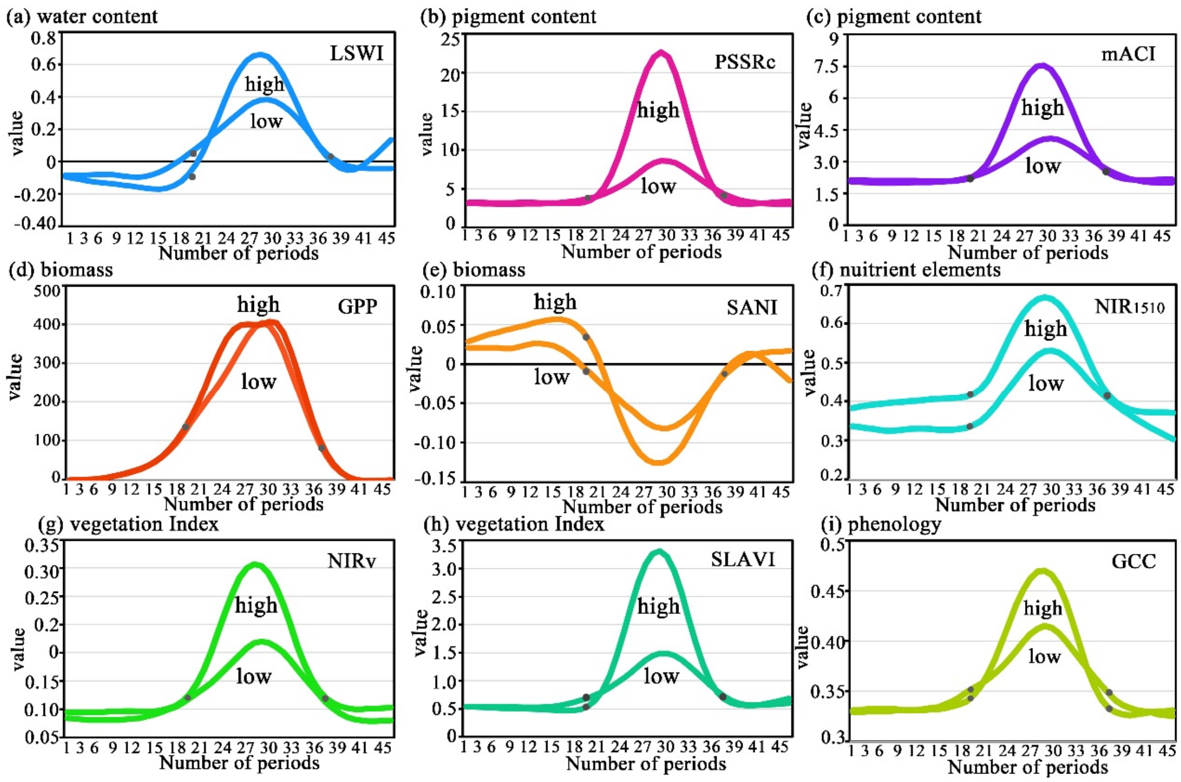

Figure S3. Time series curves of the main indicators of maize in China.

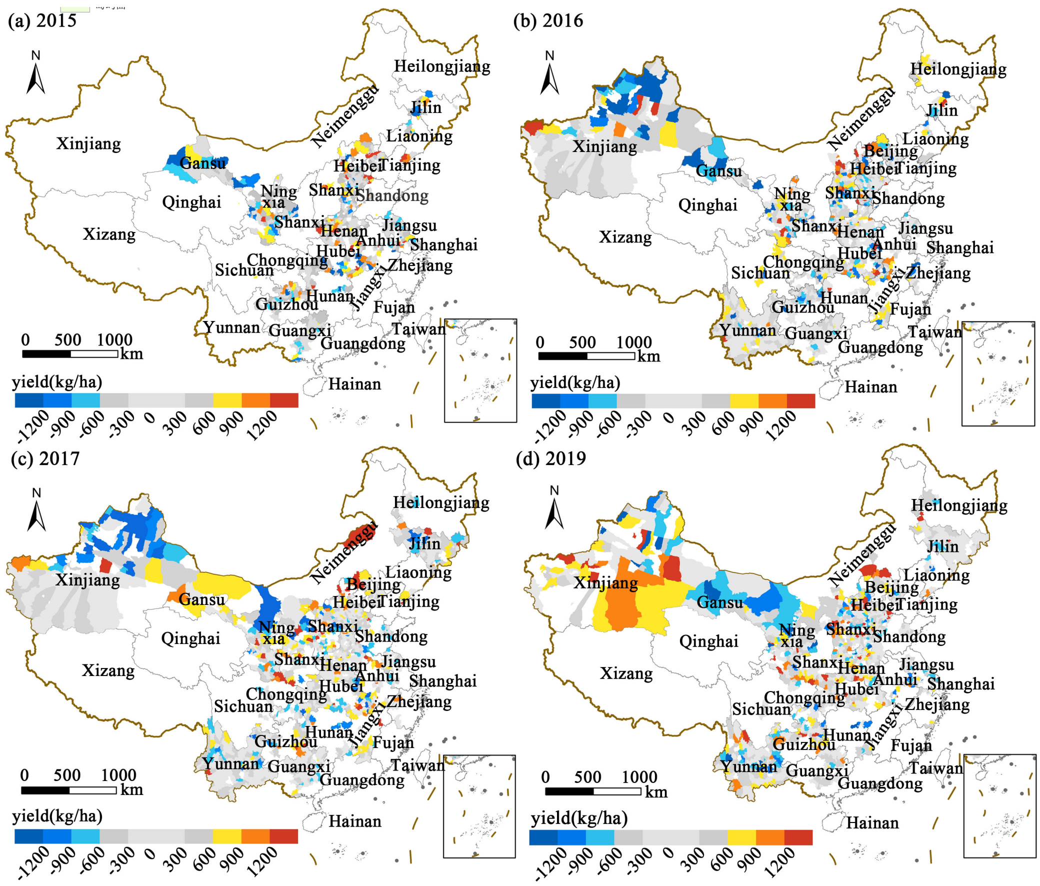

Figure S4. Spatial distribution of difference between observed yield and estimated yield.

Comparison of methods of maize yield estimation:

At present, research on yield estimation mainly focuses on the United States and China, which account for more than 50% of the global corn production. Sun et al. (2020) proposed a novel multilevel deep learning model combining satellite reflectivity, surface temperature, climate and soil data, which combined RNN and CNN to extract spatial and temporal features, and the R^2 reached 0.75 [41]. Based on the Bayesian neural network method, and the satellite, climate, soil and historical yield of maize are used, and the R^2 reached 0.77 [42]. In China, Zhang (2019) combined optical, fluorescence, thermal satellite and environmental data to estimate the yield by using random forest, and the R^2 reached 0.75 [43]. Zhang et al. (2021) combined satellite, climate (temperature and precipitation), field survey yield and heterogeneous geospatial data, and the R^2 reached 0.78 in China at county [44]. The R^2 of yield estimation in China at county level and the United States is mainly between 0.75 and 0.78. In this study, this method mainly combines satellite and climate data, and the maize yield at county level is estimated by integrating different growth periods and indexes reflecting soil, genes and management from side, the R^2 reaches 0.78. Besides, with the increase of indexes, the highest R^2 reaches 0.8. Our method obtains similar results to the existing methods without using soil and geographic space, which proves the effectiveness of our method. Without using soil and geographic space data, our method has achieved similar results to the existing methods, which prove the effectiveness of our method.

Table S4. Comparison between this research and other research methods.

Region, Study period	Penological period	Method	Data	R^2; RMSE (kg/ha)	Method comparison
America, county level 2010-2019	end of season, Growth period	Deep Bayesian network	Time series satellite data, continuous climate observation, soil attribute data	R^2: 0.7–0.8 (Every year) RMSE:860-1410 kg/ha	Obtain the best yield estimation effect by Deep Bayesian network[42]
America. county level 2013-2016	Growth period	Combining RNN with CNN	MODIS surface reflectance data, LST and weather data, soil property data	R^2: 0.74-0.78 (Every year) RMSE:1010.6-11056.5 kg/ha	Combining RNN with CNN, the spatial and temporal features are extracted [41]
China, county level 2010–2012	Growth period	LSTM, LightGBM	VIs, heterogeneous geospatial data, daily surface temperature (LST) and precipitation, temperature.	R^2=0.78	With the passage of time, the R^2 obtained by LSTM model continuously improved, while the LightGBM is saturated or even decreased in the late growth period[44]
China, county level 2001-2015	Growth period	RF, XGBoost, LSTM	Optical, fluorescence, thermal satellite, EVI, SIF and environmental factor LST(GDD/KDD/FDD)	RF: R^2=0.75, RMSE=744.70 kg/ha; XGBoost: R^2=0.77, RMSE=730.72 kg/ha; LSTM: R^2=0.68, RMSE=820.85kg/ha	Multi-source data are used to realize crop yield estimation, and RF and XGBoost obtain better yield estimation effect than LSTM[43]
China, county level, 2015-2019	Vegetative and reproductive growth period	RF	integrate of biophysical variables and temporal convergence	R^2=0.78; RMSE=741.15kg/ha	In this study, Compared with LSTM, the RF show higher yield estimation effect. Random forest could deal with imbalance and lost data. The maize yield at county level is estimated by integrating different growth periods and indexes reflecting soil, genes and management from side, and the results are close to other studies.
China, county level, 2015-2019 (excluding 2016)	8-day time series data	RF	integrate of biophysical variables and temporal convergence	R^2=0.69; RMSE=715.91kg/ha	
China, county level, 2015-2019 (excluding 2016)	8-day time series data	CNN-LSTM	integrate of biophysical variables and temporal convergence	R^2=0.62; RMSE=897.88kg/ha	

The link to code

(1) **The Code for calculating mean indicators**

https://code.earthengine.google.com/da20f0cba348d9353c21b24c878587ba?noload=1

(2) **The Code for calculating time series indicators**

https://code.earthengine.google.com/20f2b0e027dbe856613f65795dbe26e9

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