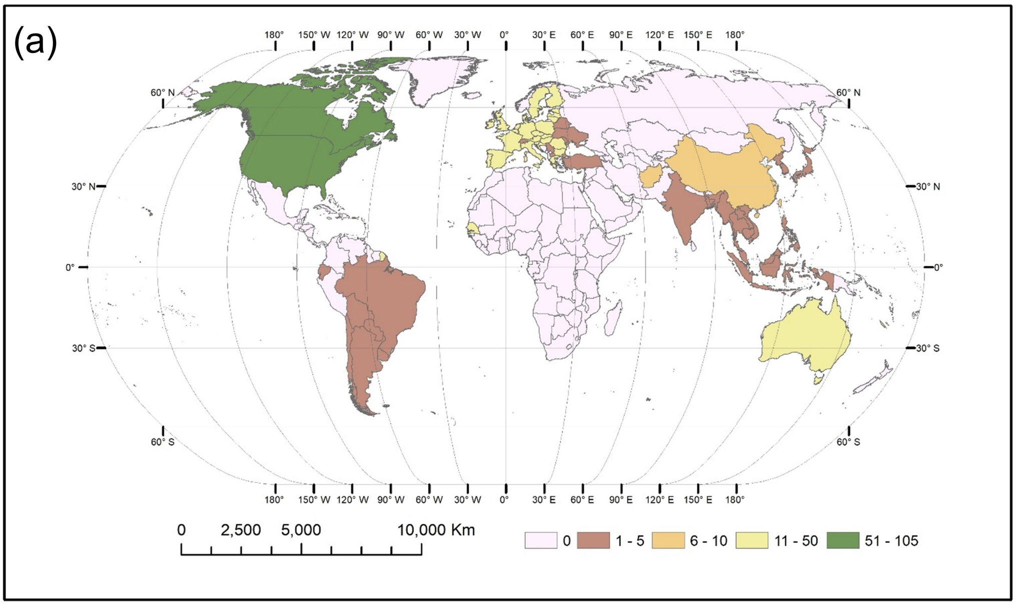
Supplement Information

S1. Overview of crop type mapping products

Here, we listed the crop type maps produced by previous studies in Table S1, as a supplement to Introduction. We collected information of each dataset about several aspects including year period, spatial coverage, resolution, crop type, etc. Among them, there are some datasets that are produced by statistics allocation and are given relatively detailed description in the Introduction for they are closely related to this study's mapping framework. While there are other datasets that are produced by remote sensing, which provide key information of timely spatial distribution of crop-specific areas. Due to the crop statistics are relatively even in space, we further analyzed information coverage of crop distribution in global countries (Figure S1) based on datasets produced by remote sensing (medium and high resolution crop mapping products). As for crop type, we calculated the sum of crop types in each country covered by medium and high resolution crop mapping products. While as for year coverage, we calculated the median value of year coverage of these datasets in each country (With one crop as the minimum unit, if a dataset contains N crops, it is calculated as N datasets), which means if only one crop has a dataset covering a long time series, and the rest have only a single year of mapping or no dataset has yet been published, it will be calculated as 1 or 0 years.

According to the information coverage of crop distribution calculated above, three regions were selected as study areas, respectively Africa, China, and USA. They correspond to three conditions of the information coverage of crop distribution (low, median, and high). In Africa, there are only crop statistics provided in mostly areas. While in China, except for statistics, there have been many studies producing single-type crop maps in recent years but not integrated multi-type maps. But in USA, Crop Data Layer product (CDL) provides annual-update ground truth layer covering the whole crop categories.



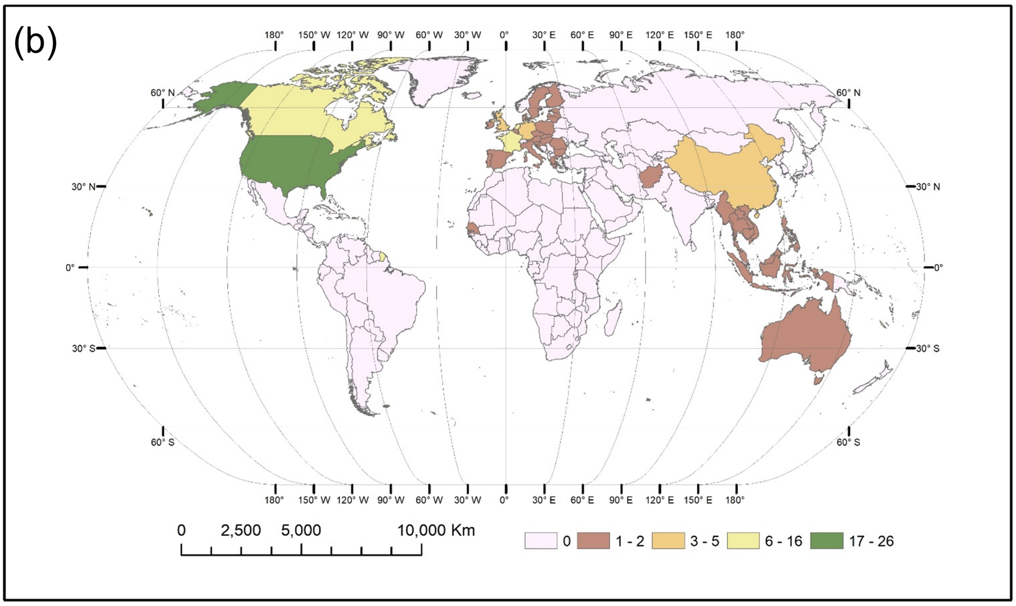


Fig S1 Global information coverage of crop distribution. Crop types (Fig S1a) and year (Fig S1b) coverage of medium and high resolution crop mapping products.

Table S1. Overview of crop type mapping products

Datasets	Year period	Spatial coverage	Spatial scale	Resolution	Crop type	num of crop types	Reference
Leff	1990	Global	Global	5 Arcmin	Multi types(18)	18	Leff et al. (2004) [1]
M3	2000	Global	Global	5 Arcmin	Multi types(175)	175	Monfreda et al. (2008) [2]
MIRCA	2000 monthly	Global	Global	5 Arcmin	Multi types(26)	26	Portmann et al. (2010) [3]
SPAM-2000	2000	Global	Global	5 Arcmin	Multi types(20)	20	You et al. (2014) [4]
SPAM-2005	2005	Global	Global	5 Arcmin	Multi types(42)	42	IFPRI. (2016) [5]
SPAM-2010	2010	Global	Global	5 Arcmin	Multi types(42)	42	Yu et al. (2020) [6]
SPAM-AF17	2017	Africa	Africa	5 Arcmin	Multi types(42)	42	IFPRI. (2020) [7]
GAEZ	2000, 2010	Global	Global	5 Arcmin	Multi types(23)	23	Fischer et al. (2021) [8]
GAEZ+2015	2015 monthly	Global	Global	5 Arcmin	Multi types(26)	26	Gorgon et al. (2022) [9]
GEOGLAM-BACS	2020	Global	Global	0.05 degree	rice, maize, soybean, wheat	4	Becker-Reshef et al.(2023) [10]
Ray-Stat	1961-2008	Global	Global	adm level	rice, maize, soybean, wheat	4	Ray et al. (2012) [11]
PCAM	1961-2014	Global	Global	0.5 degree	Multi types(17)	17	Jackson et al. (2019) [12]
IAGSA-HLJ	2011	Heilongjiang, China	Provincial	500m	rice, maize, soybean	3	Hu et al. (2021) [13]
CropPheStat-CHN	2000, 2010, 2015	China	National	1km	Multi types(14)	14	Wang et al. (2022) [14]
WheatDL-USA	2001-2017	Kansas and northern Texas, USA	Provincial	250m	winter wheat	1	Zhong et al. (2019) [15]
CROPGRIDS	2020	Global	Global	0.05 degree	Multi types(173)	173	Tang et al. (2024) [16]
USA-CDL	1997-2022	USA	National	30m	Multi types(105)	105	Boryan et al. (2011) [17]
CA-ACI	2009-2021	Canada	National	30m	Multi types(52)	52	Fisette et al. (2013) [18]

Datasets	Year period	Spatial coverage	Spatial scale	Resolution	Crop type	num of crop types	Reference
ENG-CROME	2016-2020	England	National	90m	Multi types(50)	50	Agrimetrics (2023) [19]
FR-RPG	2006-2021	France	National	vecter	Multi types(22)	22	Géoservices (2023) [20]
NLD-BRP	2009-2023	Netherlands	National	vecter	Multi types(20)	20	PDOK (2023) [21]
Germany	2017-2019	Germany	National	10m	Multi types(24)	24	Blickensdörfer et al. (2022) [22]
EU18	2018	European Union countries (28)	Regional	10m	Multi types(18)	18	d'Andrimont et al. (2021) [23]
AFG	2020	Afghanistan	National	10m	Multi types(6)	6	FAO (2021) [24]
Senegal	2018	Senegal	National	10m	Multi types(22)	22	FAO (2021) [25]
Ecuador	2021	Ecuador	National	10m	rice, maize	2	FAO (2021) [26]
Australia	2010, 2015	Australia	National	250m	Multi types(25)	25	ABARS (2022) [27]
Japan_Rice	2018-2020	Japan	National	10m	rice	1	JAXA EORA (2021) [28]
OPG	2019	Global	Global	10m	oilpalm	1	Descals et al. (2021) [29]
OPGA	1982-2019	Global	Global	30m	Multi types(tree crops like oilpalm)	190	Du et al. (2022) [30]
RAPG10	2017-2019	Global	Global	10m	rapeseed	1	Han, et al. (2021) [31]
SASOY	2000-2021	South America	Continental	30m	soybean	1	Song et al. (2021) [32]
OP3C	1984-2017	Indonesia, Malaysia, Thailand	Regional	30m	oilpalm	1	Danylo et al. (2021) [33]
ASIARICE	2000-2020	Asia	Continental	500m	rice	1	Han, et al. (2022) [34]
COCOA	2019	Cote d 'Ivoire, Ghana	Regional	10m	cocoa	1	Abu et al. (2021) [35]
CHN_MZ_500m_15-17	2005-2017	China	National	500m	maize	1	Qiu et al. (2018) [36]
CHN_Pattern	2015-2021	China	National	500m	Multi types(rice, maize, soybean)	3	Qiu et al. (2022) [37]

Datasets	Year period	Spatial coverage	Spatial scale	Resolution	Crop type	num of crop types	Reference
SouthAsia_Rice_17	2017	Bangladesh, northeast India	Regional	10m	rice	1	Singha et al. (2019) [38]
CHN_Wheat_17	2017-2018	North China	Regional	20m	winter wheat	1	Dong et al. (2020) [39]
CHN_Rapeseed_17-21	2017-2021	China	National	20m	rapeseed	1	Zang et al. (2023) [40]
CHN_NE_10m_17-19	2017-2019	Northeast China	Regional	10m	maize, soybean, rice	3	You et al. (2021) [41]
CHN_NE_30m_13-21	2013-2021	Northeast China	Regional	30m	maize, soybean, rice	3	Xuan et al. (2023) [42]
CHNCropArea1 km	2000-2015	China	National	1000m	maize, rice, wheat	3	Luo et al. (2020) [43]
CHN_winter_wheat_16-20	2016-2020	China	National	30m	whint wheat	1	Dong et al. (2020) [44]
CHN_double_rice_16-20	2016-2020	China	National	10m	double season rice	1	Pan et al. (2021) [45]
CHN_maize_30m_16-20	2016-2020	China	National	30m	maize	1	Shen et al. (2022) [46]
Brazil_sugarcane_16-19	2016–2019	Brazil	National	30m	sugarcane	1	Zheng et al. (2022) [47]
CHN_sugarcane_16-20	2016-2020	China	National	30m	sugarcane	1	Zheng et al. (2022) [48]
Europe_winterwheat_16-20	2016-2020	Europe	Continental	30m	winter wheat	1	Huang et al. (2022) [49]
USA-CSDL	1999-2018	USA middle west	Regional	30m	soybean, maize	2	Wang et al. (2020) [50]
CHN_RapeSeed_Yangtze_10m	2017-2021	Yangtze River Economic Belt, China	Regional	10m	rapeseed	1	Liu et al. (2023) [51]
Southeast Asia_Rice	2019	Southeast Asia	Regional	20m	rice	1	Sun et al. (2023) [52]
CHN_soybean_10m_19	2019	China	National	10m	soybean, maize	2	Li et al. (2023) [53]
NESEA_Rice10	2017-2019	Northeast Asia, Southeast Asia	Continental	10m	rice	1	Han et al. (2021) [54]
EU18_4	2018	Europe (10 countries)	Regional	10m	maize, rapeseed, triticeae crops	4	Luo et al. (2022) [55]
CHN_Cotton	2018-2021	Xinjiang, China	Provincial	10m	cotton	1	Kang et al. (2023) [56]

Datasets	Year period	Spatial coverage	Spatial scale	Resolution	Crop type	num of crop types	Reference
CHN_maize_30m_13-21	2013-2021	Northern China	Regional	30m	maize	1	Xin et al. (2023) [57]
CHN_maize_10m_17-21	2017-2021	China	National	10m	maize	1	Li et al. (2023) [58]
CHN_single_rice_17-22	2017-2022	China	National	10m	single season rice	1	Shen et al. (2023) [59]
CHN_rapeseed_00-22	2000-2022	China	National	30m	rapeseed	1	Liu et al. (2024) [60]
CHN_maize_30m_01-20	2001-2020	China	National	30m	maize	1	Peng et al. (2023) [61]
CHN_soy_10m_19-22	2019-2022	China	National	10m	soybean	1	Zhang et al. (2024) [62]

S2. Crop categories

There are very different definitions of crop categories among multiple sources of data products. Here, we relate other data sources based on SPAM product crop categories. Table S2-1 lists the SPAM crop names and their respective FAO code (corresponding to FAOSTAT). Table S2-2 lists the SPAM crop names and their respective USDA crop name and CDL values (corresponding to USA Statistics and maps). Table S2-3 lists the SPAM crop names and their respective China statistic crop name (corresponding to China Statistics). Table S2-4 lists the SPAM crop names and their respective GAEZ crop name (corresponding to GAEZ crop categories).

Table S2-1. SPAM product crop categories (corresponding to FAOSTAT)

ID	Long Name	Short Name	Group	FAO Crop code
1	wheat	whea	Cereals	15
2	rice	rice	Cereals	27
3	maize	maiz	Cereals	56
4	barley	barl	Cereals	44
5	pearl millet	pmil	Cereals	79
6	small millet	smil	Cereals	79
7	sorghum	sorg	Cereals	83
8	other cereals	ocer	Cereals	68,71,75,89,92,94,97,101,103,108
9	potato	pota	Roots & Tubers	116
10	sweet potato	swpo	Roots & Tubers	122
11	yams	yams	Roots & Tubers	137
12	cassava	cass	Roots & Tubers	125
13	other roots	orts	Roots & Tubers	135,136,149
14	bean	bean	Pulses	176
15	chickpea	chic	Pulses	191
16	cowpea	cowp	Pulses	195
17	pigeonpea	pige	Pulses	197
18	lentil	lent	Pulses	201
19	other pulses	opul	Pulses	181,187,203,205,210,211
20	soybean	soyb	Oilcrops	236
21	groundnut	grou	Oilcrops	242
22	coconut	cnut	Oilcrops	249
23	oilpalm	oilp	Oilcrops	254

ID	Long Name	Short Name	Group	FAO Crop code
24	sunflower	sunf	Oilcrops	267
25	rapeseed	rape	Oilcrops	270,292
26	sesameseed	sesa	Oilcrops	289
27	other oil crops	ooil	Oilcrops	260,263,265,275,280,296,299,333,336,339
28	sugarcane	sugc	Sugar Crops	156
29	sugarbeet	sugb	Sugar Crops	157
30	cotton	cott	Fibres	328
31	other fibre crops ofib	ofib	Fibres	773,777,780,782,788,789,800,809,821
32	arabica coffee	acof	Stimulates	656
33	robusta coffee	rcof	Stimulates	656
34	cocoa	coco	Stimulates	661
35	tea	teas	Stimulates	667
36	tobacco	toba	Stimulates	826
37	banana	bana	Fruits	486
38	plantain	plnt	Fruits	489
39	tropical fruit	trof	Fruits	490,491,492,493,494,495,497,507,512,567,568,569,571,572,574,577,587,591,600,693
40	temperate fruit	temf	Fruits	515,521,523,526,530,531,534,536,541,542,544,547,549,550,552,554,558,560,592,619
41	vegetables	vege	Vegetables	358,366,367,372,373,388,393,394,397,399,401,402,406,407,414,417,420,423,426,430, 446,449,459,461,463
42	rest of crops	rest	Rest	161,216,217,220,221,222,223,224,225,226,234,671,677,687,689,692,693,698,702,711, 720,723,748,754,836,839

Table S2-2. SPAM product crop categories (corresponding to USA Statistics and maps)

ID	Long Name	Short Name	Group	USDA Crop Name	CDL Value
1	wheat	whea	Cereals	WHEAT	22,23,24,26,225,230,234,236,238
2	rice	rice	Cereals	RICE	3
3	maize	maiz	Cereals	CORN	1,225,226,228,237,241
4	barley	barl	Cereals	BARLEY	21,233,235,237,254
5	pearl millet	pmil	Cereals	MILLET	29
6	small millet	smil	Cereals	MILLET	29
7	sorghum	sorg	Cereals	SORGHUM	4,234,235,236
8	other cereals	ocer	Cereals		12,13,25,27,28,39,205,226,228,231,240
9	potato	pota	Roots & Tubers		43
10	sweet potato	swpo	Roots & Tubers		46
11	yams	yams	Roots & Tubers		
12	cassava	cass	Roots & Tubers		
13	other roots	orts	Roots & Tubers		
14	bean	bean	Pulses	BEANS	42
15	chickpea	chic	Pulses	CHICKPEAS	51
16	cowpea	cowp	Pulses		
17	pigeonpea	pige	Pulses		
18	lentil	lent	Pulses	LENTILS	52
19	other pulses	opul	Pulses		53,
20	soybean	soyb	Oilcrops	SOYBEANS	5,26,239,240,241,254
21	groundnut	grou	Oilcrops	PEANUTS	10
22	coconut	cnut	Oilcrops		
23	oilpalm	oilp	Oilcrops		

ID	Long Name	Short Name	Group	USDA Crop Name	CDL Value
24	sunflower	sunf	Oilcrops	SUNFLOWER	6
25	rapeseed	rape	Oilcrops		31,34,35
26	sesameseed	sesa	Oilcrops		
27	other oil crops	ooil	Oilcrops		33,38,211
28	sugarcane	sugc	Sugar Crops	SUGARCANE	45
29	sugarbeet	sugb	Sugar Crops	SUGARBEETS	41
30	cotton	cott	Fibres	COTTON	2,232,238,239
31	other fibre crops ofib	ofib	Fibres		
32	arabica coffee	acof	Stimulates		
33	robusta coffee	rcof	Stimulates		
34	cocoa	coco	Stimulates		
35	tea	teas	Stimulates		
36	tobacco	toba	Stimulates	TOBACCO	11
37	banana	bana	Fruits		
38	plantain	plnt	Fruits		
39	tropical fruit	trof	Fruits		48,72,209,212,213,215
40	temperate fruit	temf	Fruits		55,66,67,68,69,75,77,210,217,218,219,220,221,223,242,250
41	vegetables	vege	Vegetables		49,50,54,206,207,208,214,216,222,227,229,230,231,232,233,243,244,245,246,247,248,249
42	rest of crops	rest	Rest		14,44,56,74,76,204,224

Table S2-3. SPAM product crop categories (corresponding to China Statistic)

ID	SPAM_longName	SPAM_shortName	Group	CHN Stat Name	CHN Name	CHN shortName
1	wheat	whea	Cereals	wheat	小麦	whea
2	rice	rice	Cereals	rice	稻谷	rice
3	maize	maiz	Cereals	maize	玉米	maiz
4	barley	barl	Cereals			
5	pearl millet	pmil	Cereals			
6	small millet	smil	Cereals			
7	sorghum	sorg	Cereals			
8	other cereals	ocer	Cereals			
9	potato	pota	Roots & Tubers	Roots & Tubers	薯类	cass
10	sweet potato	swpo	Roots & Tubers	Roots & Tubers	薯类	cass
11	yams	yams	Roots & Tubers	Roots & Tubers	薯类	cass
12	cassava	cass	Roots & Tubers	Roots & Tubers	薯类	cass
13	other roots	orts	Roots & Tubers	Roots & Tubers	薯类	cass
14	bean	bean	Pulses	Pulses	豆类	bean
15	chickpea	chic	Pulses	Pulses	豆类	bean
16	cowpea	cowp	Pulses	Pulses	豆类	bean
17	pigeonpea	pige	Pulses	Pulses	豆类	bean
18	lentil	lent	Pulses	Pulses	豆类	bean
19	other pulses	opul	Pulses	Pulses	豆类	bean
20	soybean	soyb	Oilcrops	soybean	大豆	soyb
21	groundnut	grou	Oilcrops	groundnut	花生	grou
22	coconut	cnut	Oilcrops			
23	oilpalm	oilp	Oilcrops			

ID	SPAM_longName	SPAM_shortName	Group	CHN Stat Name	CHN Name	CHN shortName
24	sunflower	sunf	Oilcrops			
25	rapeseed	rape	Oilcrops	rapeseed	油菜籽	rape
26	sesameseed	sesa	Oilcrops			
27	other oil crops	ooil	Oilcrops			
28	sugarcane	sugc	Sugar Crops	sugarcane	甘蔗	sugc
29	sugarbeet	sugb	Sugar Crops	sugarbeet	甜菜	sugb
30	cotton	cott	Fibres	cotton	棉花	cott
31	other fibre crops ofib	ofib	Fibres	bast fiber	麻类	ofib
32	arabica coffee	acof	Stimulates			
33	robusta coffee	rcof	Stimulates			
34	cocoa	coco	Stimulates			
35	tea	teas	Stimulates			
36	tobacco	toba	Stimulates	tobacco	烤烟	toba
37	banana	bana	Fruits			
38	plantain	plnt	Fruits			
39	tropical fruit	trof	Fruits			
40	temperate fruit	temf	Fruits			
41	vegetables	vege	Vegetables	vegetables	蔬菜	vege
42	rest of crops	rest	Rest			

Table S2-4. SPAM product crop categories (corresponding to GAEZ crop categories)

ID	SPAM_longName	SPAM_shortName	Group	GAEZ_longName	GAEZ_shortName
1	wheat	whea	Cereals	Wheat	whe
2	rice	rice	Cereals	Wetland rice,Dryland rice	rcw,rcd
3	maize	maiz	Cereals	Maize	mze
4	barley	barl	Cereals	Barley	brl
5	pearl millet	pmil	Cereals	Pearl millet	pml
6	small millet	smil	Cereals	Foxtail millet	fml
7	sorghum	sorg	Cereals	Sorghum	srg
8	other cereals	ocer	Cereals	Oat	oat
9	potato	pota	Roots & Tubers	White potato	wpo
10	sweet potato	swpo	Roots & Tubers	Sweet potato	spo
11	yams	yams	Roots & Tubers	Yam	yam
12	cassava	cass	Roots & Tubers	Cassava	csv
13	other roots	orts	Roots & Tubers	Yam	yam
14	bean	bean	Pulses	Phaseolus bean	phb
15	chickpea	chic	Pulses	Chickpea	chk
16	cowpea	cowp	Pulses	Cowpea	cow
17	pigeonpea	pige	Pulses	Pigeonpea	pig
18	lentil	lent	Pulses	Chickpea	chk
19	other pulses	opul	Pulses	Chickpea	chk
20	soybean	soyb	Oilcrops	Soybean	soy
21	groundnut	grou	Oilcrops	Groundnut	grd
22	coconut	cnut	Oilcrops	Coconut	con
23	oilpalm	oilp	Oilcrops	Oil palm	olp

ID	SPAM_longName	SPAM_shortName	Group	GAEZ_longName	GAEZ_shortName
24	sunflower	sunf	Oilcrops	Sunflower	sfl
25	rapeseed	rape	Oilcrops	Rapeseed	rsd
26	sesameseed	sesa	Oilcrops	Rapeseed	rsd
27	other oil crops	ooil	Oilcrops	Olive	olv
28	sugarcane	sugc	Sugar Crops	Sugarcane	suc
29	sugarbeet	sugb	Sugar Crops	Sugarbeet	sub
30	cotton	cott	Fibres	Cotton	cot
31	other fibre crops ofib	ofib	Fibres	Flax	flx
32	arabica coffee	acof	Stimulates	Coffee	cof
33	robusta coffee	rcof	Stimulates	Coffee	cof
34	cocoa	coco	Stimulates	Cocoa	coc
35	tea	teas	Stimulates	Tea	tea
36	tobacco	toba	Stimulates	Tobacco	tob
37	banana	bana	Fruits	Banana	ban
38	plantain	plnt	Fruits	Banana	ban
39	tropical fruit	trof	Fruits	Banana	ban
40	temperate fruit	temf	Fruits	Maize	mze
41	vegetables	vege	Vegetables	Onion	oni
42	rest of crops	rest	Rest	Maize	mze

S3. Input spatial data

S3-1 Base map

In China, there is still not an integrated multi-type crop map with medium-high spatial resolutions (10-30m). Therefore, we collected multi-source base maps of 8 crop types to produce more accurate and timely references (Table S3-1), as for the rest crop types and the regions that are not covered, we still used SPAM2010 as the base map.

Table 3-1. China crop-type base maps used in this study

Crop Type	Dataset	Year	Resolution	Reference
wheat	CHN_winter_wheat_16-20	2016-2020	30m	(Dong et al., 2020)[39]
rice	CHN_double_rice_16-20	2017-2020	10m	(Pan et al., 2021)[45]
	CHN_single_rice_17-22	2017-2020	10m	(Shen et al., 2023)[59]
maize	CHN_maize_10m_17-21	2017-2021	10m	(Li et al., 2023)[58]
soybean	CHN_NE_10m_17-19	2017-2018	10m	(You et al., 2021)[41]
	CHN_soybean_10m_19	2019	10m	(Li et al., 2023)[53]
rapeseed	CHN_rapeseed_00-22	2000-2022	30m	(Liu et al., 2024)[60]
sugarcane	CHN_sugarcane_16-20	2016-2020	30m	(Zheng et al., 2022)[48]
cotton	CHN_cotton_XinJiang	2018-2021	10m	(Kang et al., 2023)[56]
rest	SPAM2010	2010	5 arcmin	(Yu et al., 2020)[6]

S3-2 Climate variables

ERA5-Land is a reanalysis dataset providing a consistent view of the evolution of land variables over several decades at an enhanced resolution compared to ERA5. Climate variables used in this study were calculated by certain aggregate methods based on ERA5 variables (Table S3-2). Among them, growing degree days (gdd) is calculated by the following formula, while others were aggregated by summation or average in year series.

$$gdd_{daily} = \min(\frac{\min(T_{max},T_{cap})+\max(T_{min},T_{base})}{2} - T_{base}, 0) \quad (1)$$

$$\mathrm{gdd} = \sum gdd_{daily} \quad (2)$$

Where T_{max} is the daily maximum temperature, T_{min} the daily minimum temperature, T_{base} the baseline temperature, and T_{cap} the temperature at which the daily maximum is capped. By setting the standard baseline temperature T_{base} = 10 °C and cap temperature $T_{cap} = 30$ °C, we summed gdd_{daily} in a year to obtain the final amount of annual accumulated heat (gdd). Growing degree days (gdd) is used to measure the accumulated heat experienced by plants in a year, which could be useful in predicting temperature suitable areas for certain crops [63].

Table S3-2. Descriptions of climate variables

Variable	**Input ERA5 variable**	**Aggregate method**
prec	total_precipitation_sum	Annual summation
temp	temperature_2m	Annual average
gdd	temperature_2m_min, temperature_2m_max	Equation (1), (2).
radi_down	surface_solar_radiation_downwards_sum	Annual summation
evap_veg	evaporation_from_vegetation_transpiration_sum	Annual summation

S3-3 Terrain variables

The Global Multi-resolution Terrain Elevation Data 2010 (GMTED2010) dataset contains elevation data for the globe collected from various sources at 7.5 arc-seconds resolution. Slope variable was calculated by ee.Algorithms.Terrain() function using elevation data as input in Google Earth Engine.

S3-4 Soil variables

OpenlandMap contains soil properties global layers produced based on machine learning predictions from global compilation of soil profiles and samples. 6 variables were selected and 6 standard depths of each were aggregated by a certain method (Table S3-3).

Table S3-3. Descriptions of soil variables

Variable	**Input OpenlandMap variable**	**Aggregate method**
soil_water	Soil water content (volumetric %) for 33kPa and 1500kPa suctions predicted at 6 standard depths*	Average
soil_texture	Soil texture classes (USDA system) for 6 soil depths	Mode

Variable	Input OpenlandMap variable	Aggregate method
soil_sand	Sand content in % (kg / kg) at 6 standard depths	Average
soil_pH	Soil pH in H_2O at 6 standard depths	Average
soil_orgnC	Soil organic carbon content in ×5 g / kg at 6 standard depths	Average
soil_clay	Clay content in % (kg / kg) at 6 standard depths	Average

*6 standard depths: 0, 10, 30, 60, 100, and 200 cm, the same below.

S3-5 Suitability

GAEZv4.0 produces a gridded suitability assessment for 48 major crops in two input levels (i.e., high, low), and two water supply regimes (i.e., irrigated or rainfed) at 5 arcmin resolution. The correspondence between GAEZ v4.0's crop categories and SPAM is presented in the Supplement (Table S2-4). Most of the SPAM2010 crops are included in GAEZ's crop categories, those not included are assigned values from similar crops. The suitability index in three regimes (irrigated (suit_i), rainfed and high input (suit_h), rainfed and low input (suit_l)) were selected as input indicators. GAEZ layers are provided by time periods in a 30 years' interval, including time period (1961-1990, 1971-2000, 1981-2010). These data layers were aggregated in coincidence year according to Table S3-4. Some crop types which have missing values in irrigated regimes use maximum value of high input regime and low input regime as a substitute.

Table S3-4. Aggregation process of GAEZ variables from multiple time periods

Time period	Input GAEZ layers	Aggregate method
1961-1970	Time Period (1961-1990)	Average
1971-1980	Time Period (1961-1990, 1971-2000)	Average
1981-1990	Time Period (1961-1990, 1971-2000, 1981-2010)	Average
1991-2000	Time Period (1971-2000, 1981-2010)	Average
2001-2022	Time Period (1981-2010)	Average

S3-6 Potential yield

Potential yield has a greater impact on farmer decisions when multiple crops are suitable to cultivate, this variable could also be accessed by GAEZv4.0 product in two input levels and two water supply regimes. GAEZv4.0 produces a gridded potential yield assessment for 48 major crops in two input levels (i.e., high, low), and two water supply regimes (i.e., irrigated or rainfed) at 5 arcmin resolution. The potential yield in three regimes (irrigated (potYield_i), rainfed and high input (potYield_h), rainfed and low input (potYield_l)) were selected as input indicators. GAEZ layers are provided by time periods in a 30 years' interval, including time period (1961-1990, 1971-2000, 1981-2010). These data layers were aggregated in coincidence year according to Table S3-4. Some crop types which have missing values in irrigated regimes use maximum value of high input regime and low input regime as a substitute.

S3-7 Cropland extent

Firstly, cropland maps determine where and to which extent crops could be cultivated (also in Section 2.3). Here, we used FROM-GLC Plus Global Land Cover Products (1982-2021, 1km subpixel) to extract cropland extent from 1982 to 2021 [64]. In periods where there are rarely remotely sensed images (before the 1980s), GCD (Global Cropland Dataset) which is produced by spatially allocating cropland statistics was used as extent [65] (Table S3-5).

Table S3-5. Cropland layers used in different time periods

Time period	Cropland layers
1961-1969	GCD (1960AD)
1970-1979	GCD (1970AD)
1980-1981	GCD (1980AD)
1981-2020	FROM-GLC Plus (Corresponding year)
2021-2022	FROM-GLC Plus (2021)

Given that crop production may take place over several seasons within a year, we also multiplied the cropland extent by the cropping intensity to get the annual maximum harvested area. Annual global cropping intensity datasets (GCI) cover periods from 2001 to 2019 [66]. For the remaining years, data from the nearest year is used as a substitute (Table S3-6).

Table S3-6. Cropping intensity datasets used in different time periods

Time period	**Cropping intensity datasets**
1961-2000	GCI (2001)
2001-2019	GCI (Corresponding year)
2020-2022	GCI (2019)

S3-8 Irrigation area

we integrated two datasets (HID and SPAM) to extract irrigation area proportion in a long time series. HID (historical irrigation data set) provides estimates of the temporal development of the area equipped for irrigation from 1900 to 2005 at 5 arcmin resolution [67], while SPAM contains irrigation area proportion information in year 2000, 2005 and 2010. Therefore, we adopted SPAM as a source of irrigation area after 2000, and adopted HID before 2000. For the remaining years which are not included in the periods of these two datasets, data from the nearest year is used as a substitute (Table S3-7). We divide the area of irrigated land by the area of cropland to get the proportion of irrigated land, and the proportion of rainfed cropland is defined as the remaining proportion (the sum of the two equals 1). Since the input cropland area data set may be inconsistent with the irrigated area, when the cropland area is less than the irrigated area, the cropland area is increased to equal to the irrigated area.

Table S3-7. Irrigation area datasets used in different time periods

Time period	Irrigation area datasets
1961-1964	HID (1960)
1965-1974	HID (1970)
1975-1982	HID (1980)
1983-1987	HID (1985)
1988-1992	HID (1990)
1992-1997	HID (1995)
1998-2002	SPAM (2000)
2003-2007	SPAM (2005)
2008-2022	SPAM (2010)

S3-9 Field size

Global field size map was produced by visual interpretation and sample interpolation, which estimated the percentage of different field sizes, ranging from very small to very large. Samples of 130K unique locations were collected by visually interpreting very high-resolution satellite imagery from Google Maps and Bing using the Geo-Wiki application in June 2017. In this study, we used this dominant field size map as input of field size which divides field size into 5 classes: Very large, Large, Medium, Small, and Very small (Table S3-8).

Table S3-8. Field size classes and definitions

Field size	Definitions
Very large	fields with an area of >100 ha
Large	fields with an area between 16 and 100 ha
Medium	fields with an area between 2.56 and 16 ha
Small	fields with an area between 0.64 and 2.56 ha
Very small	fields with an area <0.64 ha

S3-10 Rural population

Rural population is closely related to agricultural production, which can be considered as a measure of agricultural labor and also market accessibility. History Database of the Global Environment (HYDE version 3.2) is an internally consistent combination of historical population estimates and maps for land use. In this dataset, population is represented by maps of total, urban, rural population, population density, and built-up area. The period covered is 10 000 before the Common Era (BCE) to 2017 Common Era (CE). Estimates of rural population from HYDE v3.2 were selected as an indicator. For the remaining years which are not included in the periods of HYDE v3.2, data from the nearest year is used as a substitute (Table S3-9).

Table S3-9. Rural population layers used in different time periods

Time period	**Cropland layers**
1961-1969	HYDE (1960AD)
1970-1979	HYDE (1970AD)
1980-1989	HYDE (1980AD)
1990-1999	HYDE (1990AD)
2000-2017	HYDE (Corresponding year)
2018-2022	HYDE (2017AD)

S3-11 Location variables

We used functions in Google Earth Engine (ee.Image.pixelLonLat()) to extract longitude and latitude at each pixel at 10km resolution in degrees. They are used as location variables in the spatiotemporal dynamic modeling.

Table 3-10 spatial indicators used to generate probabilistic layers of crop-specific area

ID	Name	Year	Resolution	Group	Source
1	prec	1961-2022	0.1 degree	climate	ERA5-Land
2	temp	1961-2022	0.1 degree	climate	ERA5-Land
3	gdd	1961-2022	0.1 degree	climate	ERA5-Land
4	radi_down	1961-2022	0.1 degree	climate	ERA5-Land
5	evap_veg	1961-2022	0.1 degree	climate	ERA5-Land
6	Irrigation_prop	1960-1995 [1] 2000,2005,2010	5 arcmin 5 arcmin	agro-system	HID SPAM
7	Rainfed_prop	1660-1995 [1] 2000,2005,2010	5 arcmin 5 arcmin	agro-system	HID SPAM
8	suit_i	1961-2010 [2]	5 arcmin	suitability	GAEZ v4.0
9	suit_h	1961-2010 [2]	5 arcmin	suitability	GAEZ v4.0
10	suit_l	1961-2010 [2]	5 arcmin	suitability	GAEZ v4.0
11	potYield_i	1961-2010 [2]	5 arcmin	potYield	GAEZ v4.0
12	potYield_h	1961-2010 [2]	5 arcmin	potYield	GAEZ v4.0
13	potYield_l	1961-2010 [2]	5 arcmin	potYield	GAEZ v4.0
14	soil_water	1950-2017 [3]	250m	soil	OpenlandMap
15	soil_texture	1950-2017 [3]	250m	soil	OpenlandMap
16	soil_sand	1950-2017 [3]	250m	soil	OpenlandMap
17	soil_pH	1950-2017 [3]	250m	soil	OpenlandMap
18	soil_orgnC	1950-2017 [3]	250m	soil	OpenlandMap
19	soil_clay	1950-2017 [3]	250m	soil	OpenlandMap
20	rural_pop	1960-2017 [4]	5 arcmin	agro-system	HYDE
21	field_size	~2017	600m	agro-system	(Lesiv et al., 2019)[68]
22	slope	2010	7.5 arcsec	terrain	GMTED2010
23	elevation	2010	7.5 arcsec	terrain	GMTED2010
24	cropland	1960,1970,1980 1982-2021	1km 1km	agro-system	GCD FROM-GLC plus
25	longitude	/	/	location	/
26	latitude	/	/	location	/

[1] here refers to multiple periods from 1960 to 1995. More details in Supplement (Section S3-7).

[2] here refers to multiple periods from 1961 to 2010. More details in Supplement (Table S3-3).

[3] here represents the overall situation from 1950 to 2017.

[4] here refers to multiple periods from 1960 to 2017. More details in Supplement (Section S3-9).

S4. Results validation and analysis

S4-1 Data comparison

Table S4-1 Comparison between our results (2005) and SPAM2005 in Africa at the grid level.

Crop type	short name	RMSE(ha)	R^2
arabica coffee	acof	242.28	0.41
banana	bana	258.04	0.12
barley	barl	432.62	0.56
bean	bean	208.29	0.50
cassava	cass	254.71	0.51
chickpea	chic	102.28	0.30
coconut	cnut	358.48	0.27
cocoa	coco	649.86	0.48
cotton	cott	204.45	0.32
cowpea	cowp	252.59	0.74
groundnut	grou	155.00	0.44
lentil	lent	74.32	0.18
maize	maiz	359.99	0.49
other cereals	ocer	404.13	0.46
other fibre crops ofib	ofib	50.43	0.06
oilpalm	oilp	538.95	0.54
other oil crops	ooil	382.80	0.38
other pulses	opul	154.85	0.30
other roots	orts	179.34	0.25
pigeonpea	pige	258.49	0.38
plantain	plnt	446.98	0.25
pearl millet	pmil	459.42	0.61
potato	pota	136.65	0.19
rapeseed	rape	32.66	0.19
robusta coffee	rcof	148.83	0.41
rest of crops	rest	244.43	0.11
rice	rice	246.93	0.38
sesameseed	sesa	156.71	0.52
small millet	smil	188.21	0.47
sorghum	sorg	564.46	0.60
soybean	soyb	71.95	0.48
sugarbeet	sugb	242.72	0.15
sugarcane	sugc	205.37	0.28
sunflower	sunf	132.86	0.38
sweet potato	swpo	138.19	0.32

Crop type	short name	RMSE(ha)	R^2
tea	teas	81.37	0.67
temperate fruit	temf	69.64	0.27
tobacco	toba	36.72	0.38
tropical fruit	trof	170.41	0.15
vegetables	vege	192.27	0.17
wheat	whea	448.33	0.66
yams	yams	174.55	0.62

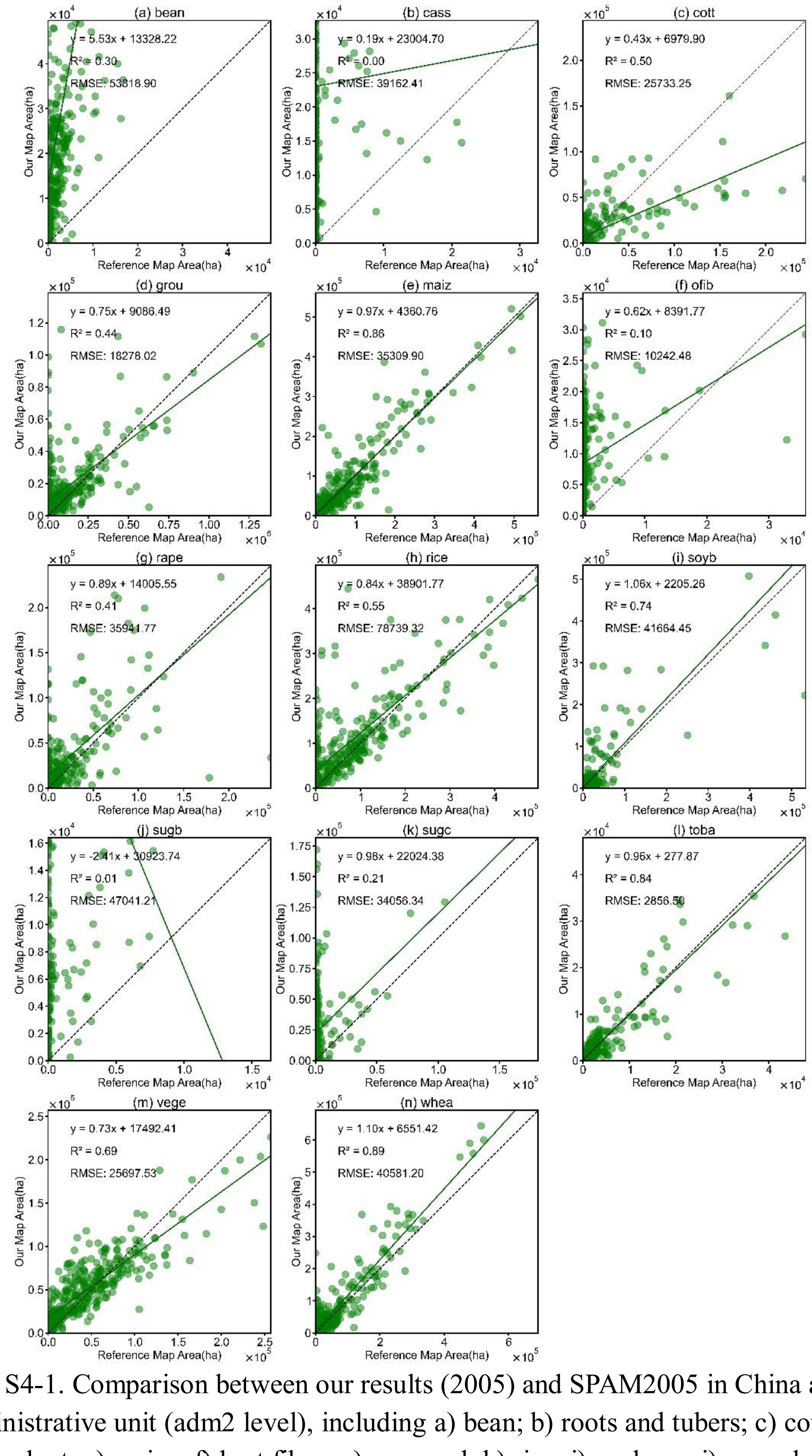


Fig S4-1. Comparison between our results (2005) and SPAM2005 in China at the Administrative unit (adm2 level), including a) bean; b) roots and tubers; c) cotton; d) groundnut; e) maize; f) bast fiber; g) rapeseed; h) rice; i) soybean; j) sugar beet; k) sugarcane; l) tobacco; m) vegetables; n) wheat.

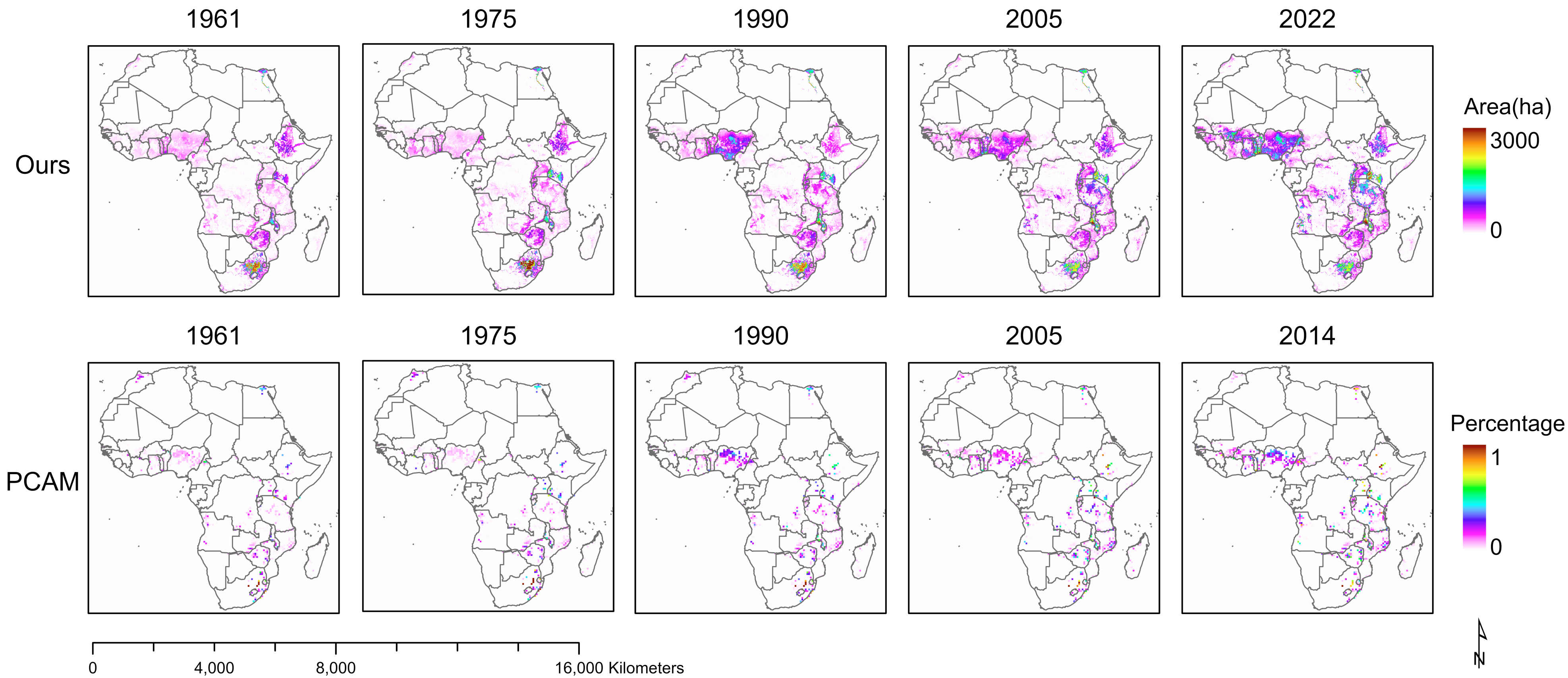


Fig 4-2. Visual comparison of our products with PCAM in Africa (Maize as an example).

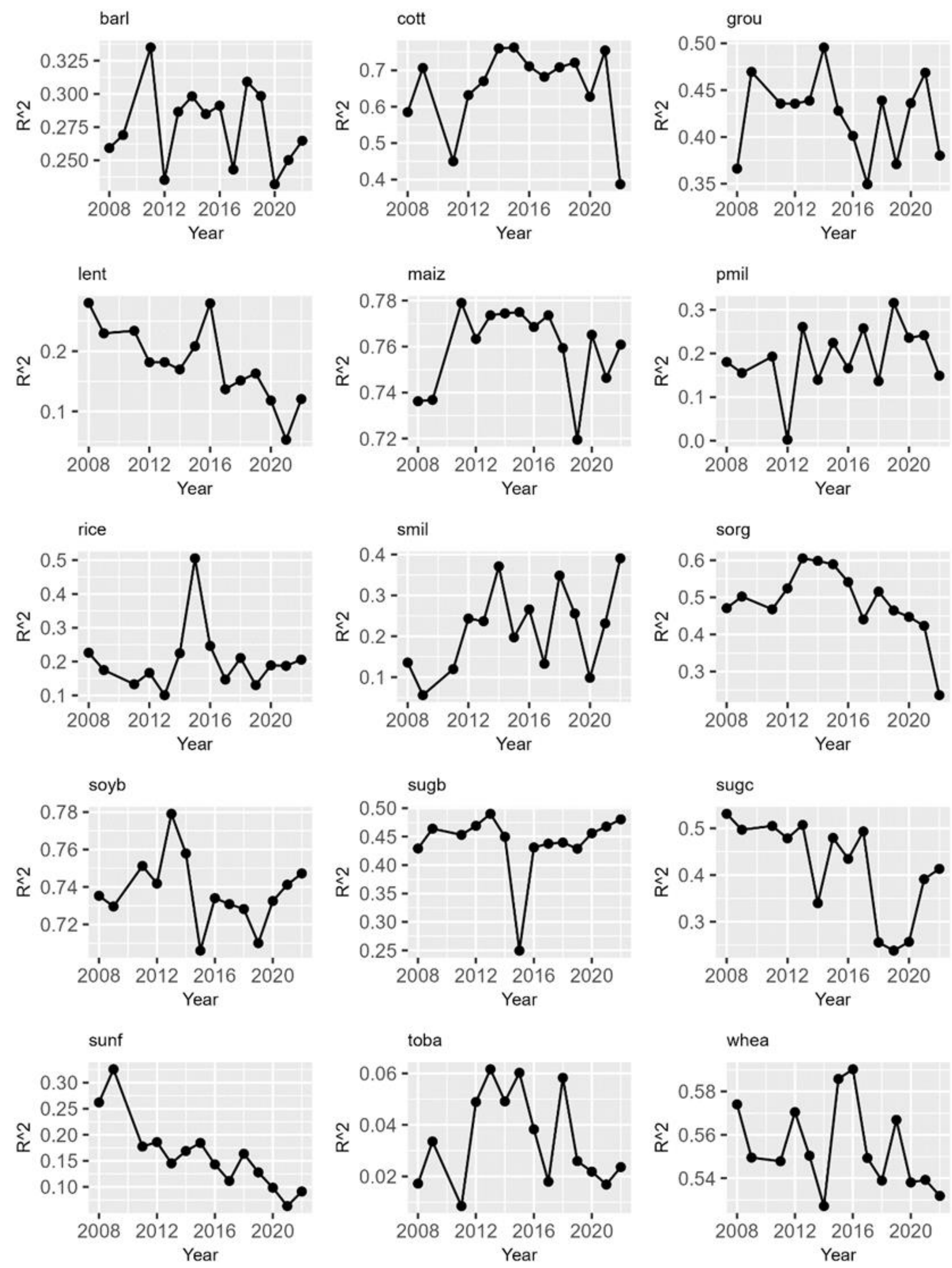


Fig S4-3. Comparison between our results (2008-2022) and CDL in USA at the grid level (R^2).

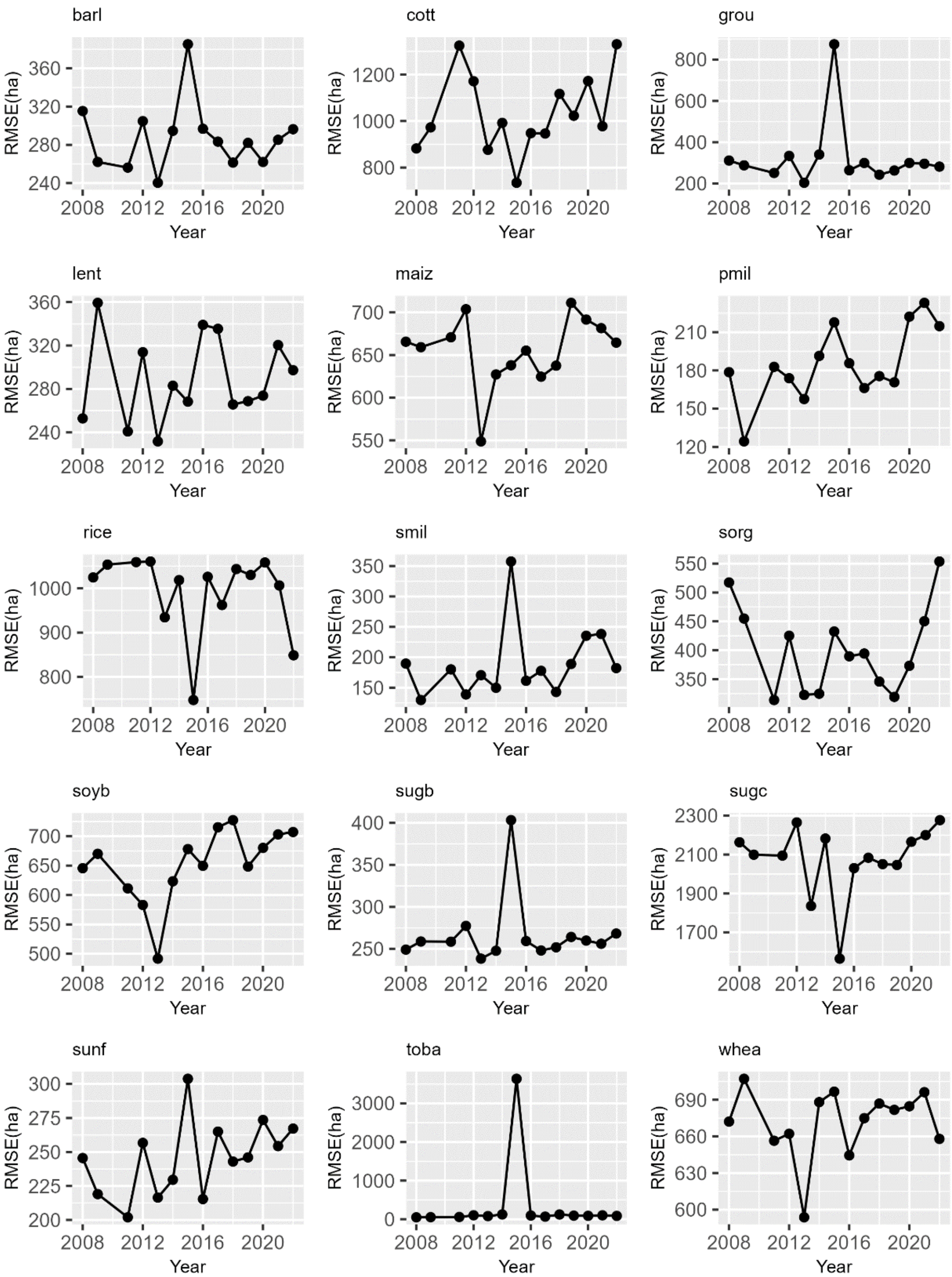


Fig S4-4. Comparison between our results (2008-2022) and CDL in USA at the grid level (RMSE).

S4-2 Model performance and interpretability

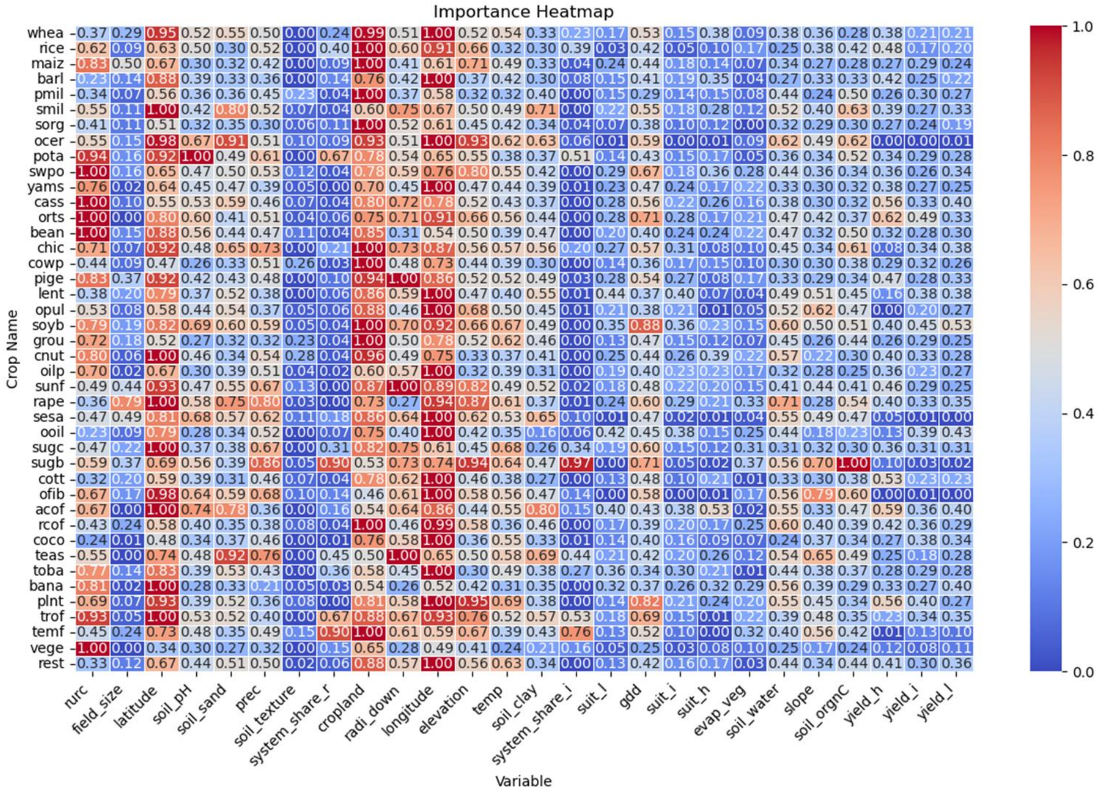


Fig S4-5. Importance analysis of spatial indicators used in RF models in Africa.

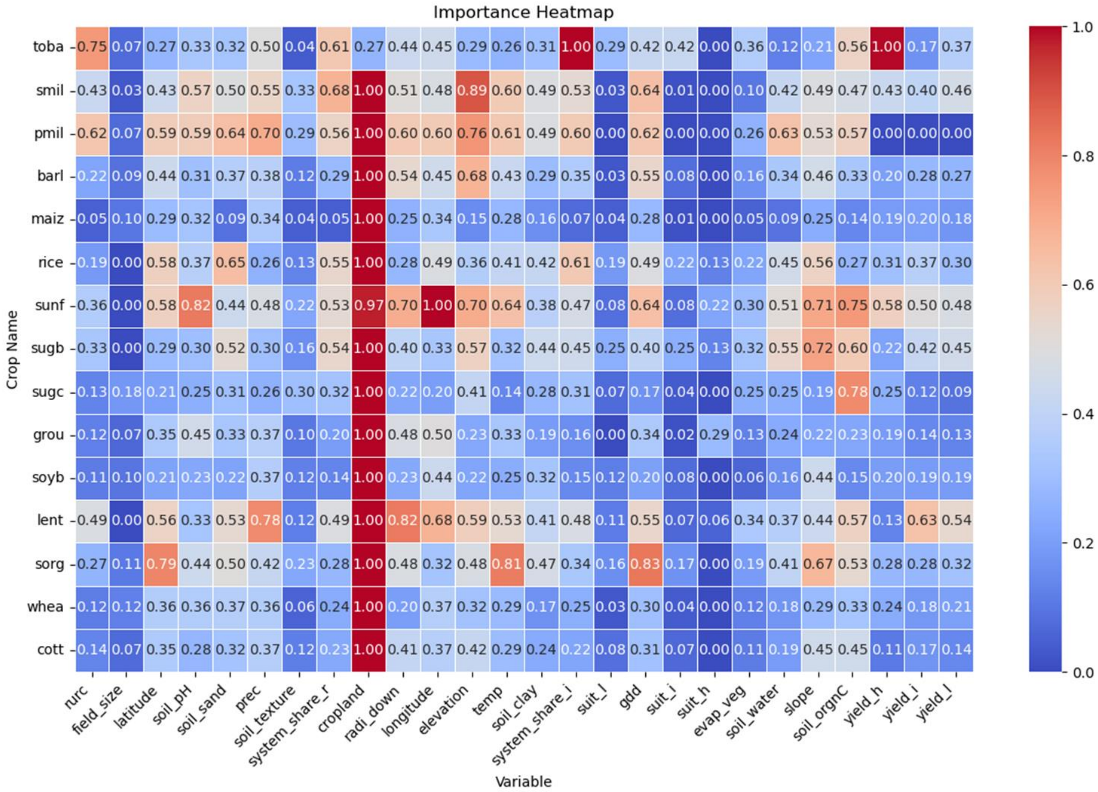


Fig S4-6. Importance analysis of spatial indicators used in RF models in USA

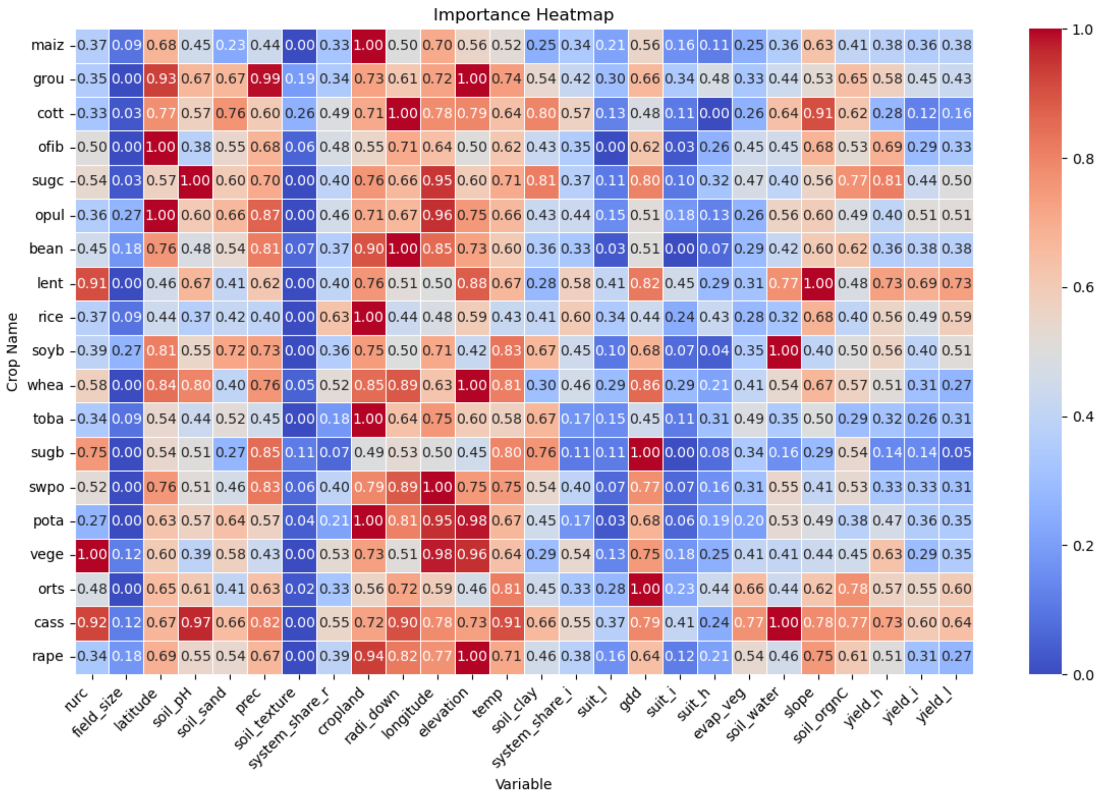


Fig S4-7. Importance analysis of spatial indicators used in RF models in China (using SPAM2010 as training data).

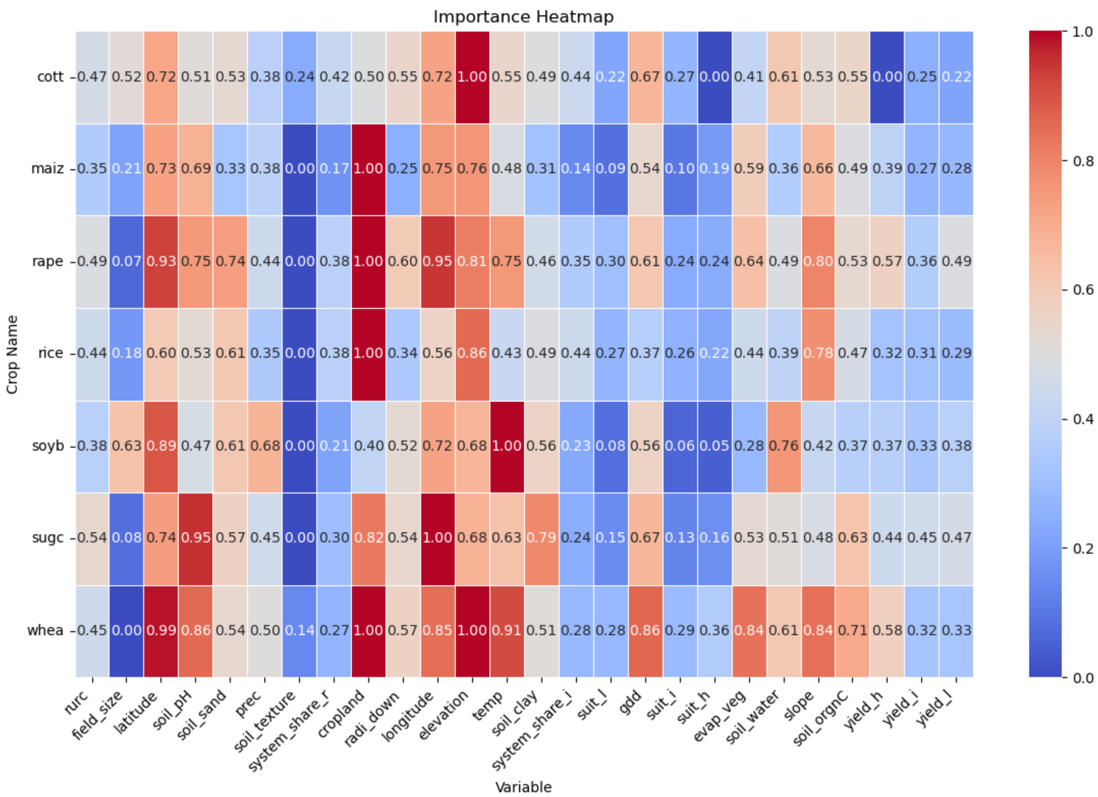


Fig S4-8. Importance analysis of spatial indicators used in RF models in China (using multi-year mapping results as training data).

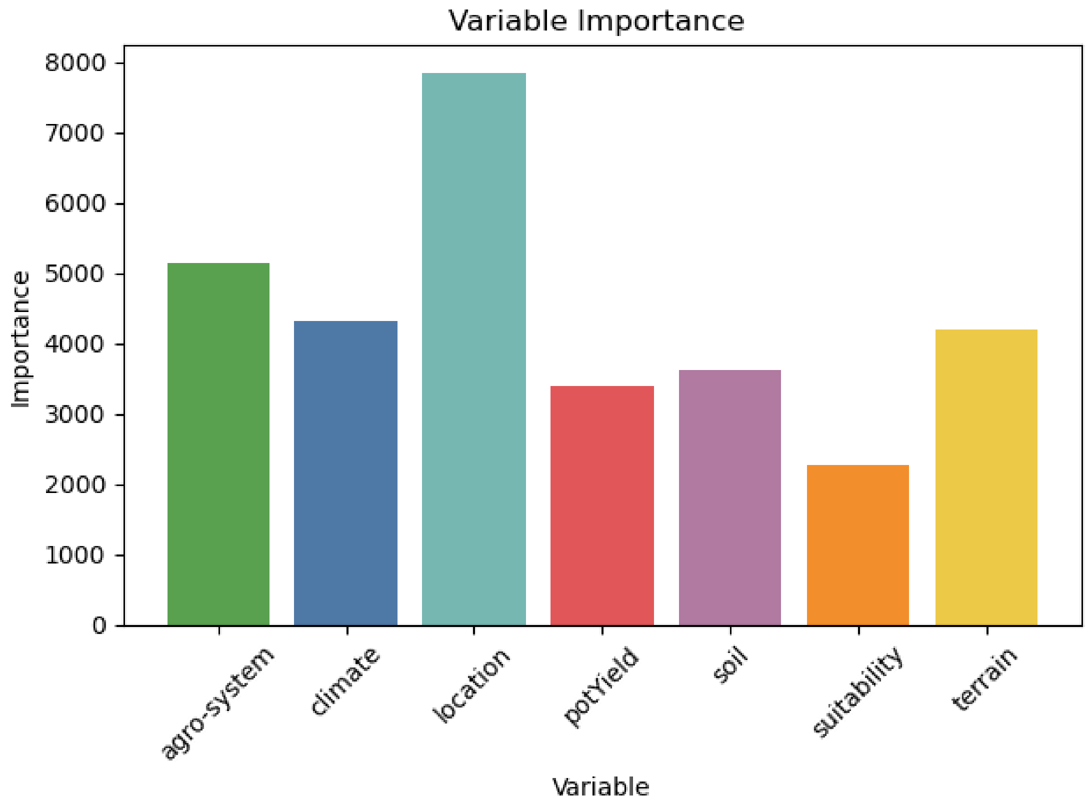


Fig S4-9. Importance of spatial indicators groups used in RF models in Africa.

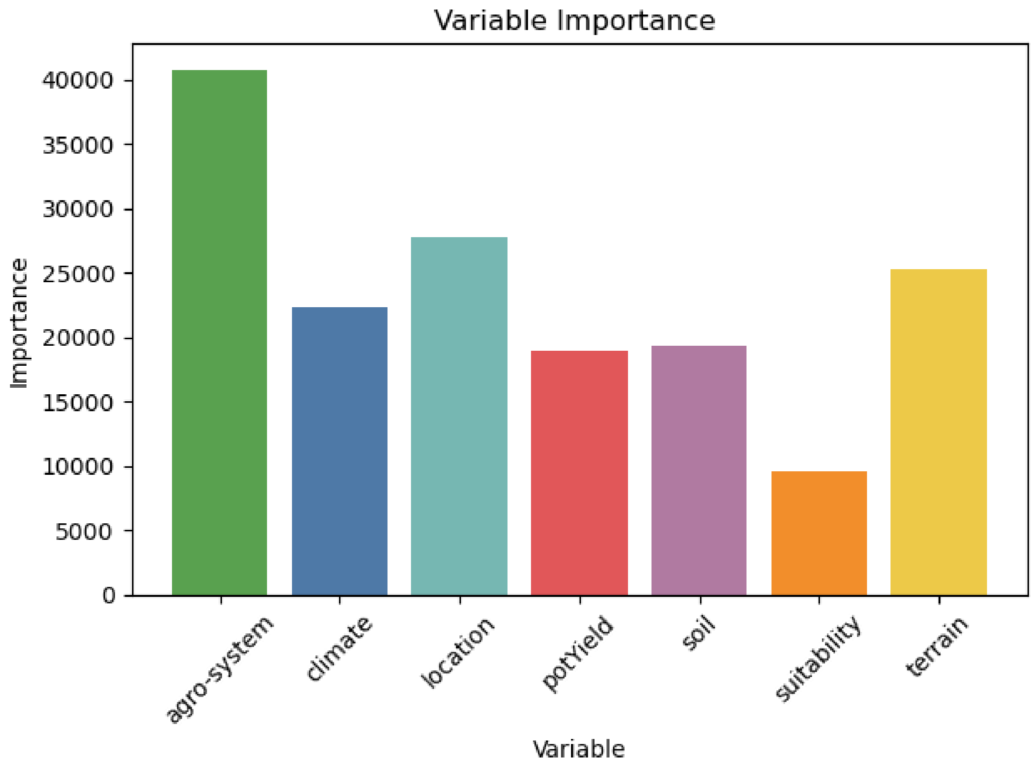


Fig S4-10. Importance of spatial indicators groups used in RF models in USA.

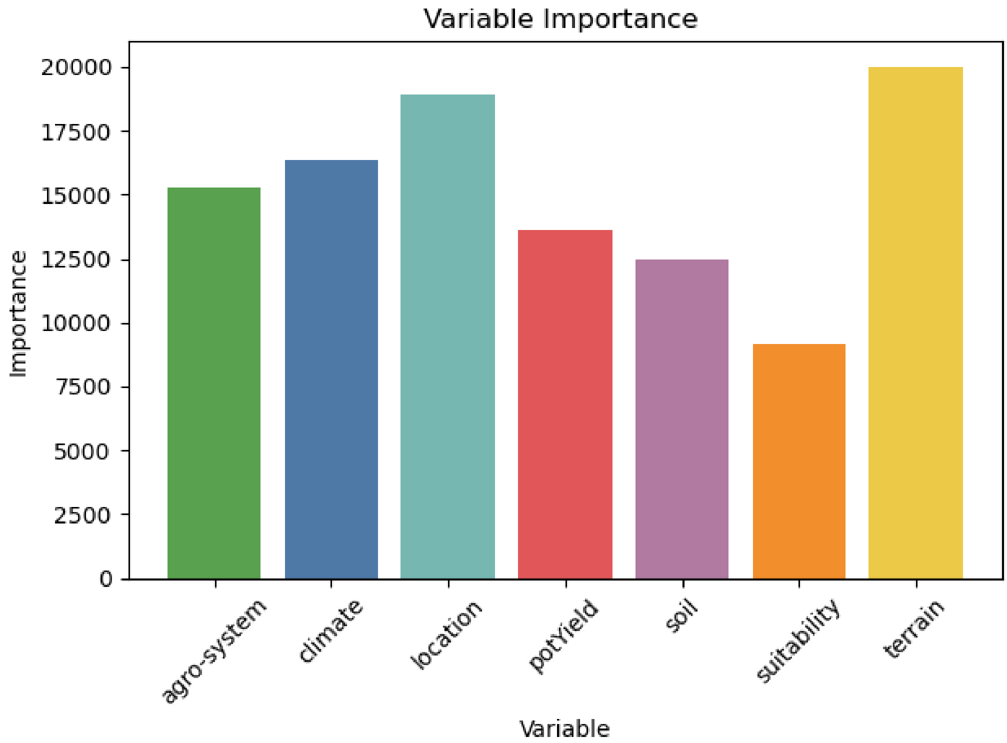


Fig S4-11. Importance of spatial indicators groups used in RF models in China (using SPAM2010 as training data).

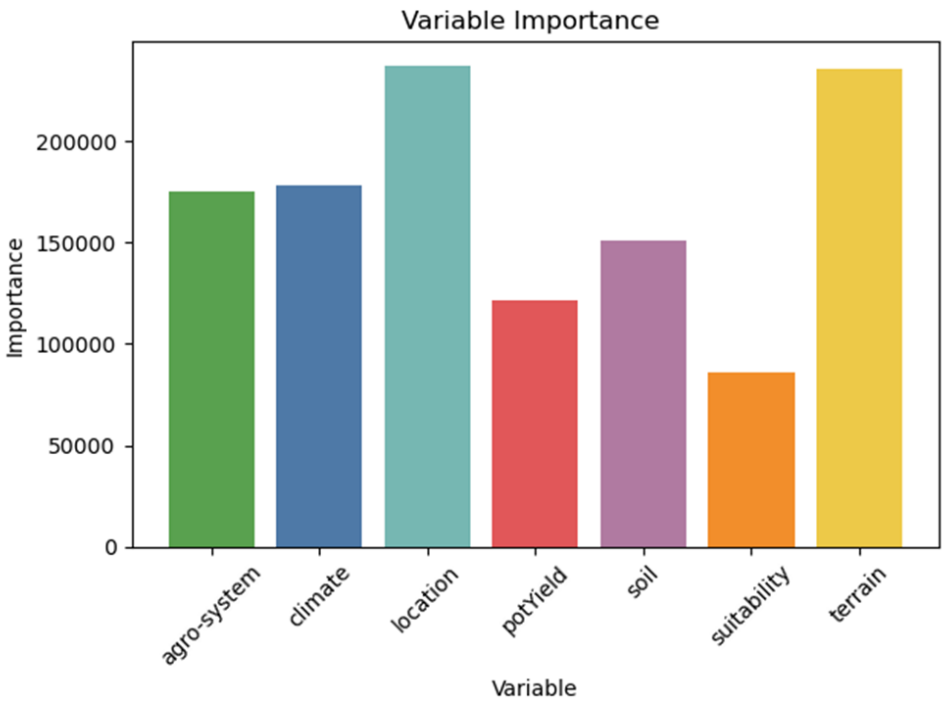


Fig S4-12. Importance of spatial indicators groups used in RF models in China (using multi-year mapping results as training data).

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