SUPPLEMENTARY MATERIALS

Supplementary Materials S1. Land use/cover data

Supplementary Materials S1.1. Classification classes

We applied our cropland abandonment mapping approach based on the land cover changes. In accordance with the GlobeLand30 classification scheme (http://www.globallandcover.com/, accessed 01 Nov 2022), we define ‘Cropland’ as an area for planting crops, such as paddy fields, irrigated drylands, vegetable fields and other crops with economic significance (e.g., orchard, forage). Our definition excludes non-tilled croplands, but given the prevalence of tilling, this omission should be minimal [1]). Our scheme defines 'Grassland' as perennial and steppe grasslands unused agriculturally. 'Forest' covers various forest types, riparian vegetation, and protective tree lines. Other classes include shrubs, bareland, impervious surfaces, wetlands, and water (Table S1).

Table S1. Descriptions of land use / land cover classes used in our time-series maps.

Code	Class	Descriptions
1	Cropland	Includes cultivated crops, described as areas used for the production of annual crops, such as corn, rice, soybeans, vegetables, and tobacco. This class also includes all actively tilled land and grass for grazing.
2	Grassland	Land covered by perennial natural herbaceous vegetation with a cover greater than 10%, including grasslands, meadows, savannas, desert grasslands.
3	Forest	Land covered by trees with more than 30% canopy cover,

		including deciduous broadleaf forest, evergreen broadleaf forest, deciduous coniferous forest, evergreen coniferous forest, mixed forest, and open forest land with a canopy cover of 10-30%.
4	Shrubs	Land with shrub cover and more than 30% scrub cover, including mountain scrub, deciduous and evergreen scrub, and desert scrub with more than 10% cover in desert areas.
5	Bareland	Natural cover land with less than 10% vegetation cover, including desert, sandy land, gravel land, bare rock, saline land.
6	Impervious surface	Includes developed open spaces with a mixture of some constructed materials, but mostly vegetation in the form of lawn grasses such as large-lot single-family housing units, parks, golf courses, and vegetation planted in developed settings for recreation, erosion control, or aesthetic purposes. Also included are lands of low, medium, and high intensity development with a mixture of constructed materials and vegetation, such as single-family housing units, multifamily housing units, and areas of retail, commercial, and industrial uses.
7	Wetland	Includes woody wetlands and herbaceous wetlands – Areas where forest or shrub land vegetation accounts for greater

		than 20% of vegetative cover and the soil or substrate is periodically saturated or covered with water. This class also includes areas where perennial herbaceous vegetation accounts for greater than 80% of vegetative cover and the soil or substrate is periodically saturated or covered with water.
8	Water	Land area covered by open water, including rivers, lakes, reservoirs, ponds.

Supplementary Materials S1.2. The number of training data and validation data

Yang and Huang [2] utilized 335,709 Landsat images on the GEE platform to classify land cover [2]. Their method, based on random forest algorithms, generated a continuous map of land-cover across China from 1990 to 2019, boasting a 30 m spatial resolution. This dataset captures various landscapes: cropland, woodland, shrub, grassland, bare land, impervious surfaces, water bodies, snow/ice, and wetlands. They further enhanced the temporal and spatial consistency of the China Land Cover Dataset (CLCD-30m) using a novel post-processing method that combined spatiotemporal filtering with logical reasoning, achieving a classification accuracy of approximately 79.31%. Another study assessed the CLCD's relevance to agriculture [3]. They validated the accuracy of the dataset's representation of 30 m cropland in China against six other datasets using 30,000 collected samples. Their findings indicated that the CLCD offers significant precision.

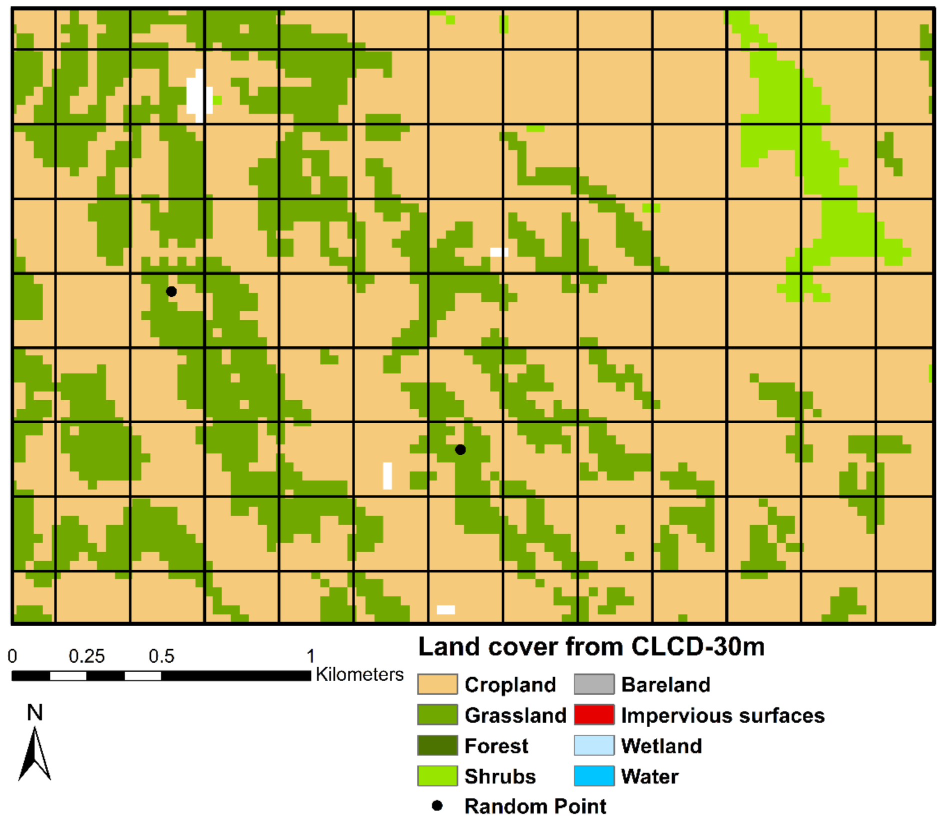

Figure S1. Sample point correction based on CLCD-30m. The black grid in the figure has a resolution of 250m, which reflects the resolution of the MODIS. The random points come from samples that we need to manually correct.

Table S2. The number of training samples for each land cover

Abbreviation: CL = Cropland; GRA = Grassland; FORE = Forest; SHR = Shrubs; BAR=Bareland; IM = Impervious surface; WET = Wetland; WAT = Water

Year	CL	GRA	FORE	SHR	BAR	IM	WET	WAT
2000	3027	905	4098	20	16	139	23	201
2001	2958	1092	4349	21	21	195	15	228
2002	2818	945	4183	39	19	94	13	281
2003	2866	1157	3703	35	17	119	41	241

2004	2861	1125	4151	29	25	120	32	304
2005	2863	1292	4178	39	20	114	11	204
2006	2834	1237	4999	34	16	129	56	234
2007	2824	1131	4365	21	27	121	46	221
2008	2627	992	4798	22	18	129	31	280
2009	2707	962	4654	23	29	60	36	240
2010	2537	924	3609	43	11	95	17	247
2011	3131	1260	4307	23	14	92	42	286
2012	2712	1006	3580	26	13	100	23	286
2013	2752	947	3864	26	14	100	26	286
2014	2767	987	3823	22	14	113	25	178
2015	2730	942	3768	20	12	142	29	286
2016	2844	1042	3786	20	18	127	14	286
2017	2811	1026	3998	15	17	143	20	286
2018	2907	986	4501	18	15	264	25	286
2019	2848	932	4654	18	17	262	26	201
2020	2649	985	4586	37	24	248	29	295

Table S3. The number of validation samples for each land cover

Abbreviation: CL = Cropland; GRA = Grassland; FORE = Forest; SHR = Shrubs; BAR=Bareland; IM = Impervious surface; WET = Wetland; WAT = Water

Year	CL	GRA	FORE	SHR	BAR	IM	WET	WAT
2000	1389	381	1717	12	6	27	8	57
2001	1240	548	1838	14	8	24	4	60
2002	1280	411	1797	15	5	23	3	70
2003	1343	462	1685	11	4	30	10	60
2004	1318	395	1585	18	9	32	11	69
2005	994	420	2032	12	9	32	4	69
2006	1013	408	1977	12	7	24	20	59
2007	1076	377	2121	14	12	28	15	58
2008	977	330	1934	7	6	22	10	73
2009	903	321	1887	7	9	20	12	41
2010	937	271	1780	14	4	32	6	44
2011	891	532	1958	7	5	31	4	54
2012	908	267	1830	8	4	27	8	46
2013	1001	316	1589	8	5	38	8	50
2014	921	411	1675	15	5	23	6	70
2015	931	314	1856	7	4	47	10	51
2016	927	347	1762	6	6	43	5	49
2017	937	343	1933	5	6	47	6	59
2018	816	328	2036	6	5	88	8	66

2019	884	311	2051	6	6	87	9	67
2020	882	328	1930	12	8	83	9	98

Supplementary Materials S2. Spatiotemporal dynamics of cropland abandonment and recultivation

Supplementary Materials S2.1. The effect of varying of abandonment definitions

Given the ecological pressures and food security issues within the study area, our research incorporated a two-year threshold to account for these aspects. Defining abandonment over a relatively short period could inadvertently lead to an overestimation of cropland abandonment, as fallow cycles of one year could be mistakenly classified as abandonment periods. In certain contexts, short-term abandonment might be more accurately interpreted as cyclical fallow periods, rather than true abandonment, in order to accurately represent the complexities of agricultural practices [4].

Moreover, our study delineates cropland abandonment as the transformation of cropland into natural vegetation types like grassland, shrubs, and bareland. It is unlikely that natural vegetation succession would develop into a tree-dominated landscape throughout the entire Yangtze River Basin within two years. The growth of naturally regenerating forests is a lengthy process that often spans many years, and the natural vegetation succession on abandoned land is influenced by a range of factors [5,6].

Our abandonment threshold also affected the proportion of abandoned croplands that were recultivated by the end of the study period. It is reasonable to infer a smaller recultivation area when applying a longer abandonment threshold.

Supplementary Materials S2.2. Comparing approaches to estimate cropland abandonment: time series imageries and two-timepoint imageries

Some studies estimate cropland abandonment merely comparing two cropland maps, identifying areas where land cover is classified as "cultivated" in one year but not in a subsequent year (for instance, comparing maps from 1992 and 2015)[7]. Such a method may overestimate abandonment by including short-term fallow periods and may even fail to account for subsequent recultivation. To illustrate this issue and examine the impact of using this simplified method versus our comprehensive annual time series approach, we estimated cropland abandonment by only identifying areas classified as "cropland" in 2000, and subsequently reclassified as either "woody vegetation (i.e., forest, shrubs)" or "herbaceous vegetation (i.e., grassland)" in 2020, excluding "non-vegetation" categories.

When we applied this two-timepoint method, we identified a total of only 19307×10^3 ha as "abandoned," which is a 10% underestimation as compared to the total 21490×10^3 ha of "abandonment" estimated for 2020 using our annual time series. This not only yielded differing area estimates but also pinpointed geographically distinct areas of abandonment. This underlines the importance of using a comprehensive and temporally rich methodology, such as an annual time series, for a more precise estimation of cropland abandonment.

Supplementary Materials S2.3. Flowchart in classifying cropland abandonment and recultivation

In our time series, we solely incorporated the progression from verifiable cropland to natural vegetation within our time series. Pixels that consistently displayed classifications of cropland or non-cropland (i.e., herbaceous or woody vegetation) throughout the time series were excluded. Since we lacked sufficient information about the previous cultivation status of non-cultivated land, determining the initial status in our time series was not feasible. Therefore, if pixels initially transitioned from non-cultivated into cultivated status and subsequently reverted to natural vegetation, we only considered the latter transformation of these pixels as abandonment (Figure 2).

To illustrate this, we considered the following time series, which represents twenty years beginning at the start of our time series (e.g. where 1 represents cropland and 2 represents grassland):

This represents five years of non-cropland to start the time series, followed by three years of cropland cultivation, followed by three years of non-cropland. Though this pixel experienced two periods of non-cropland classification of two or more years (from 2000 through 2004, and from 2008 through 2010), we only count the second, three-year period (2007 through 2009) as its first cropland abandonment, because it clearly followed cropland classification. As highlighted in the main text, pixels that transitioned from cropland to the non-vegetation land cover class (i.e. impervious surfaces, wetland, water) were not categorized as "abandonment." Consequently, we excluded all non-vegetation land cover pixels from our analysis, counting for less than 3% of the total area across all sites.

Supplementary Materials S2.4. Cumulative cropland abandonment area

Our analysis reveals that the majority of abandoned croplands did not remain idle. By 2020, about 74% of the total abandoned cropland area, corresponding to 15857×10³ ha, had been recultivated. Additionally, about 1294×10³ ha of the initially abandoned croplands were converted into impervious surfaces. These transformations resulted in a significant reduction in the total area of abandoned croplands. Specifically, by the end of the study period in 2020, the total area of land that remained abandoned was 4339×10³ ha. This figure represents a decrease of 51% compared to the total area that had been abandoned at least once during the time series.

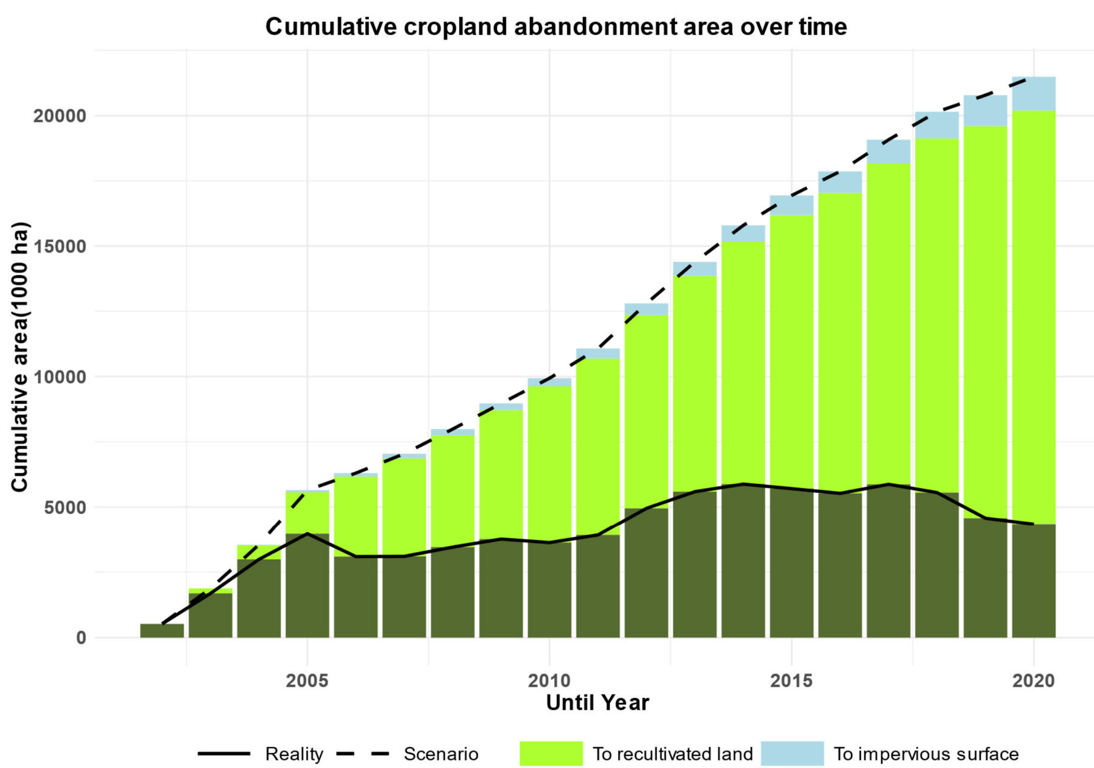

Figure S2. Cumulative cropland abandonment area. The solid black line represents the total cumulative reality area of abandoned cropland, and the dashed black line represents the cumulative scenario area of abandoned cropland, assuming a scenario without recultivation.

Supplementary Materials S2.5. Time-series analysis of cropland abandonment and recultivation

Cropland abandonment area trend: The regression analysis indicates a negative slope (<0), suggesting a decreasing trend in the cropland abandonment area over the years. However, the p-value for this trend is 0.48, which means that the observed trend is not statistically significant (Figure S3(a)).

Cropland abandonment rate trend: the trend in the cropland abandonment rate also shows a negative slope (< 0) with a p-value > 0.05, indicating that this decrease over time is neither statistically significant (Figure S3(b)).

Recultivation area trend: the trend in the recultivation area shows a positive slope > 0, with a p-value < 0.05, indicating a significant increase over time (Figure S4).

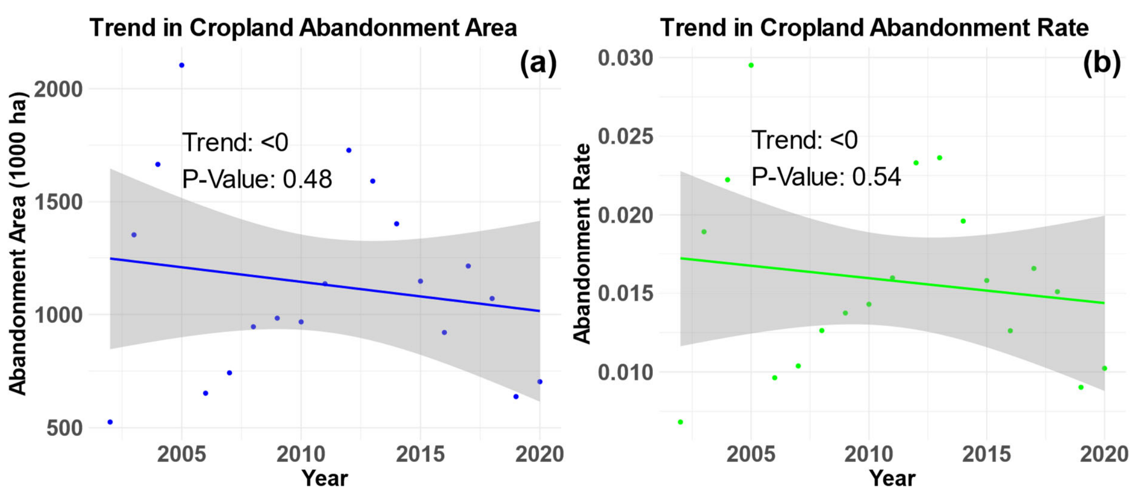

Figure S3. Trends in (a) cropland abandonment area and (b) rate (2002-2020). The blue and green lines respectively depict the trends in cropland abandonment area and rate over time. The gray shaded areas represent the 95% confidence intervals.

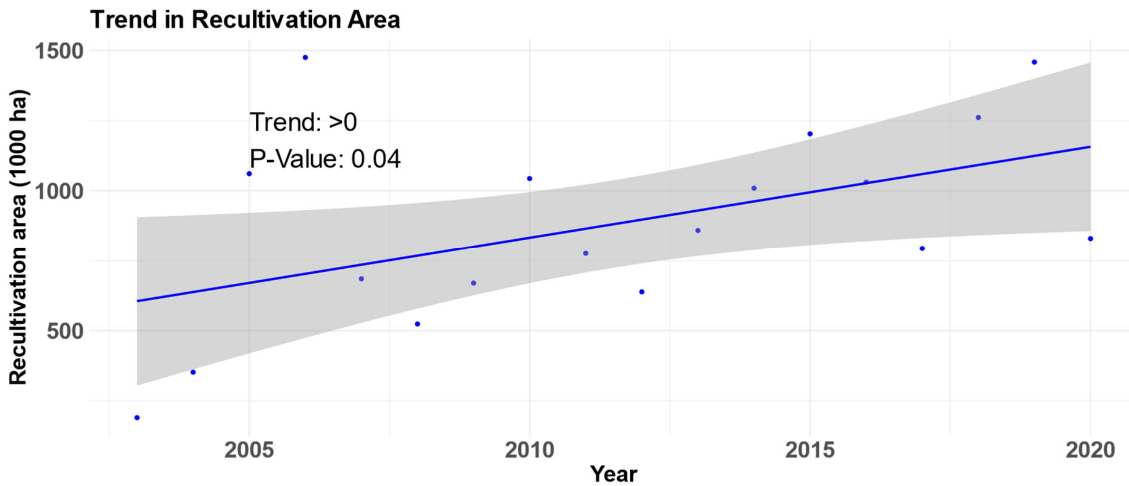

Figure S4. Trends in recultivation area (2003-2020). The blue line depicts the trends in recultivation area over time. The gray shaded areas represent the 95% confidence intervals.

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