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Supplement of

GLC_FCS30D: the first global 30 m land-cover dynamics monitoring product with a fine classification system for the period from 1985 to 2022 generated using dense-time-series Landsat imagery and the continuous change-detection method

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S3.2 **Detecting changes using the CCD algorithm and continuous Landsat imagery**

As previous studies have demonstrated that values of the parameters in CCDC affected the performance of land-cover change detection. One of the key step was to analyze the quantitative relationship between the parameter settings with the variability of the parameters. In this study, we make full use of the collected time-series validation datasets (LCMAP_Val and LUCAS) to implement the sensitive analysis. The reasons why we choose this two datasets as the reference because: 1) these two datasets were the third-party datasets which can ensure the objectivety of the analysis; 2) they covered the United States and European Union containing compolicated land-cover changes and environments, that is, the optimal parameter settings in these areas possibly were also suitable for other areas in land-cover change detection. In specific, the sensitive analysis between the omission error and commission error with the minObservations, chiSquareProbability and minNumOfYearScaler were independently analyzed in Figure S1, the results also showed the CCD is a parameter-sensitive algorithm and the optimal parameter values were 5, 0.95 and 2-year for minObservations, chiSquareProbability and minNumOfYearScaler.

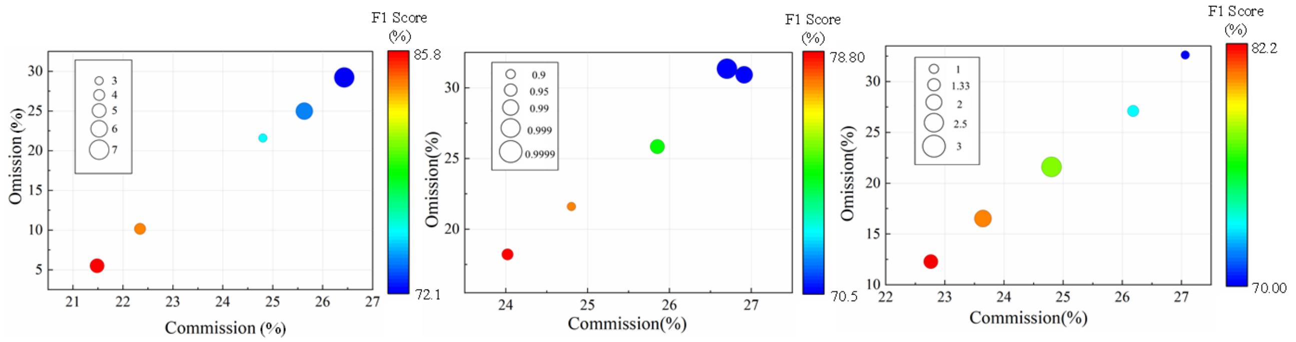

Figure S1. The sensitive analysis between the omission error and commission error with the minObservations, chiSquareProbability and minNumOfYearScaler using the time-series points from LCMAP_Val and LUCAS datasets after partly sampling.

Table S1 gave the uncertainty of the CCD algorithm (using the optimal parameter setting) at various land-cover change types based on the random sampling land-cover changed points from NLCD products over the United States. It should be noted that the wetland was independently generated, and the permanent snow ice and tundra were sparse distributed on the United States, the uncertainty analysis of CCD for these three classes were excluded.

Table S1. The uncertainty analysis of CCD algorithm for different land-cover change types using the random sampling land-cover changed points from NLCD products over the United States.

	To cropland	To forest	To shrubland	To grassland	To water	To bareland	To impervious surface
P.A. (±SE)	70.00(0.55)	45.64(0.49)	42.02(0.89)	66.13(0.33)	77.05(0.54)	42.86(1.32)	70.65(0.42)
U.A. (±SE)	46.10(0.48)	64.66(0.56)	23.81(0.56)	43.94(0.28)	58.02(0.55)	35.29(1.16)	57.33(0.42)

S3.3.3 Temporal-consistency optimization

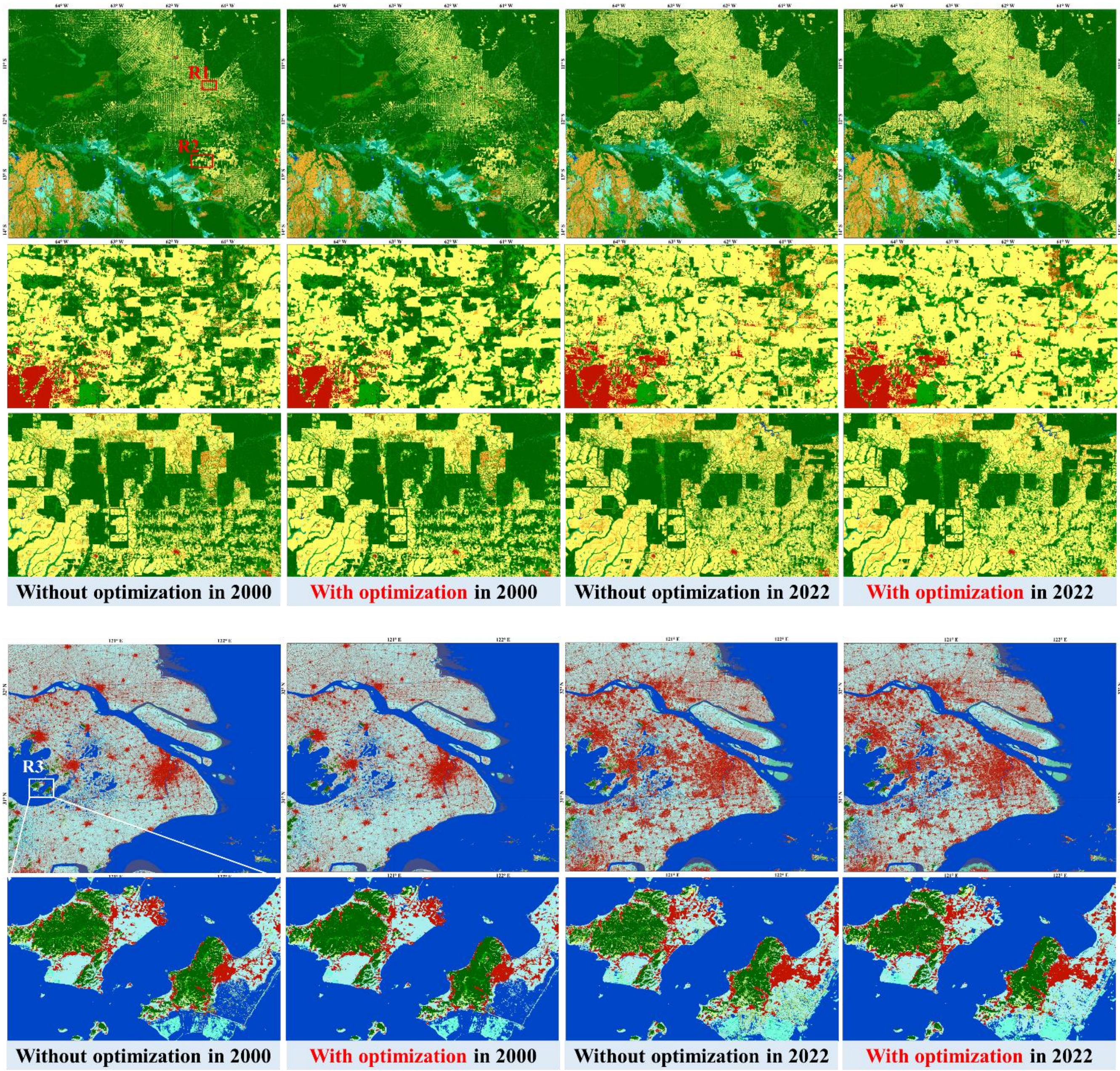

Figure S2. The comparisons before and after temporal consistency optimization in the Amazon's deforestation areas and urban rapid expansion area and their randomly enlargements.

S4.1 Overview of GLC_FCS30D maps and their changes

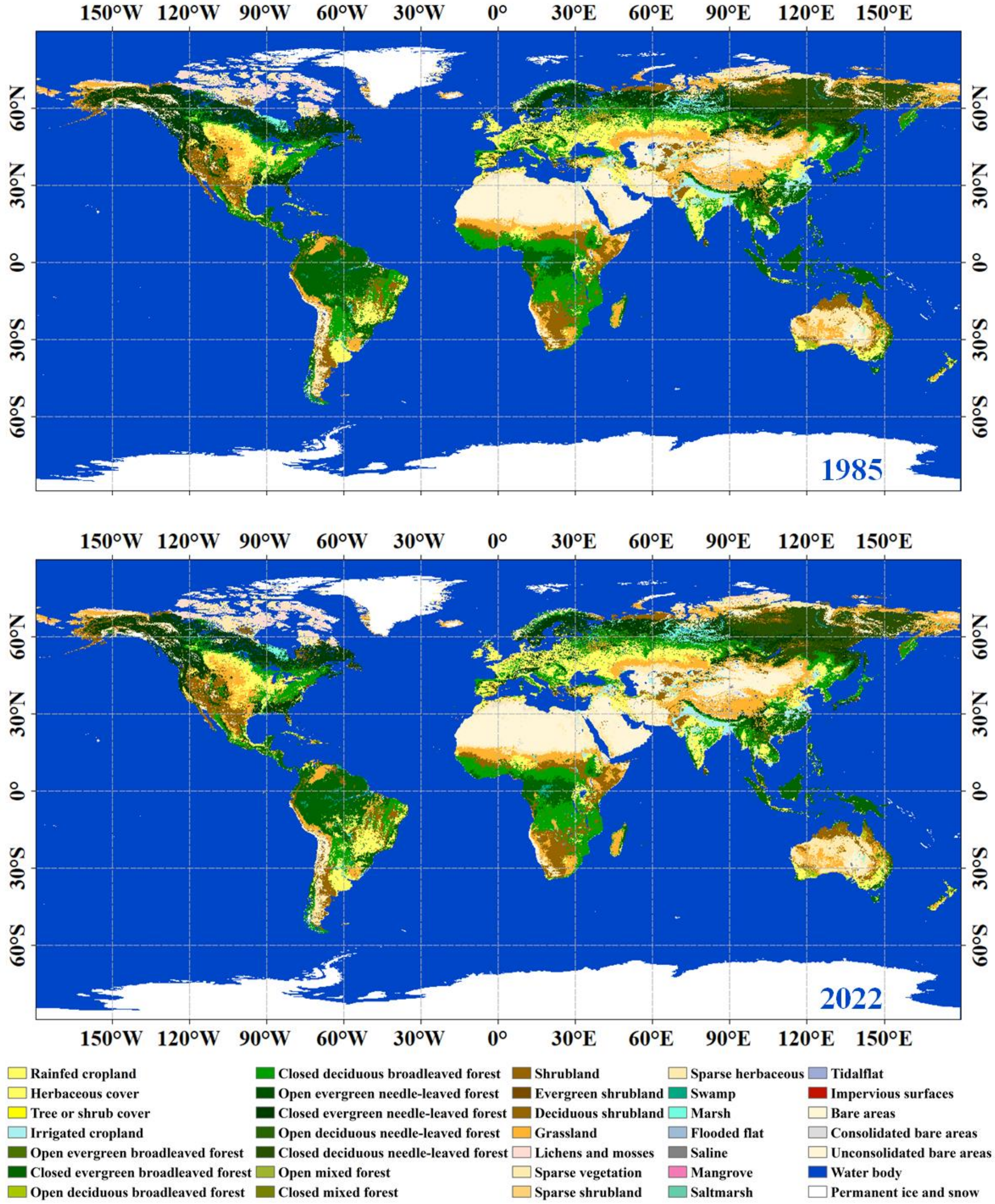

Figure S3. The overview of the GLC_FCS30D land-cover maps in 1985 and 2022.