



Correction

Correction: Xiong et al. Probabilistic Tracking of Annual Cropland Changes over Large, Complex Agricultural Landscapes Using Google Earth Engine. *Remote Sens.* 2022, 14, 4896

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References Correction

In the original publication [1], the reference list provided at the end is incorrect, refs. [48,84] should be removed. Therefore, we are replacing the reference list at the end, while the reference numbers in the text remain largely unaffected, except for the last sentence of Section 4.6, which the online version says “[103–106]”, but it should be “[103,104]”. The replaced reference list is attached below.

Text Correction

In the original publication, under Section 2.2.1, we reported an accuracy of “81”, which should be 81%.

References List

In the original publication, the reference list provided at the end is incorrect. Therefore, we are replacing the reference list at the end. References [16–22,48–57,59–72,75–104] have been modified:

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