compared with PRISMA (14%, 15%, 18%, 19%, and 23% for 1D-CNN, 3D-CNN, SVM, RF, and MNB, respectively). The results demonstrate that, when using the PRISMA time series and the 1D-CNN algorithm, early-season crop mapping in the northern Mediterranean agricultural sites is feasible at the appropriate time, which aids with decision making regarding food security and marketing.

These results show the way to use the hyperspectral time series, even though still timely discontinuous, with agricultural applications on a global scale. Moreover, it is expected that future algorithm development, especially in context of the feature selection in the combined temporal and spectral domains, will boost classification performance.

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