

This review concerns the manuscript entitled “The Cooling Efficiency Factor Index (CEFI): A New Satellite-Based Dataset for Research and Operational Monitoring of Land Surface Processes”. The authors produced a high-spatiotemporal-resolution cooling efficiency index with diurnal variation at a spatial resolution of 5 km for the period 2005–2025, based on geostationary satellite data. The authors find clear relationships between their index and the commonly used meteorological drought index, SPI, as well as with variations in vegetation and soil moisture. Several case studies are presented to demonstrate the integrative ability of the cooling efficiency index to represent land-surface properties at the large scale. I think the manuscript has a clear structure, with easily understandable text and figures. However, I have several comments to be addressed before I can recommend the manuscript for publication in Earth System Science Data.

Major points:

CEFI, the cooling efficiency index, is not purely a consequence of water availability; it also reflects the influence of energy availability that controls nonlinearly on the evaporation. I think this may explain why CEFI is decoupled from NDVI or evaporative fraction in some regions, such as the tropics and drylands (Fig. 5d,g). This decoupling may be particularly relevant when ecosystems experience stress that is not yet extreme and downregulates ET, or when land–atmosphere coupling strengths are changing. I suggest that the authors examine more deeply the joint roles of energy and water variability when interpreting the ecological and biophysical meaning of CEFI dynamics. One simple metric combining the energy and water controls on ET: correlation (ET, soil moisture) minus correlation (ET, net radiation), should be similarly valuable as evaporative fraction but more representing the land surface status, for the authors to have a better understanding of the derived cooling efficiency index.

We thank the Reviewer for the time devoted to reviewing our paper. Regarding the overall interpretation of the theoretical framework, we defined the CEFI as surface warming normalized by the integrated net radiation. This normalization should account for the energy input and remove most of its influence from the index. The remaining variability in the CEFI should therefore reflect mainly the partitioning of energy among sensible, latent, and ground heat fluxes. However, as the Reviewer correctly pointed out, this partitioning may be less relevant in some regions.

In desert regions, the correlation between the CEFI and NDVI or evaporative fraction weakens because of the extremely low plant cover, vegetation-mediated regulation is absent, and cooling efficiency is primarily determined by wind. Nevertheless, the CEFI captures even small vegetated areas surrounded by desert very well (see Zampieri et al., 2025).

In the humid tropics, one limitation of the CEFI that we have already identified is poor data availability due to cloudiness, resulting in very few valid detections per month.

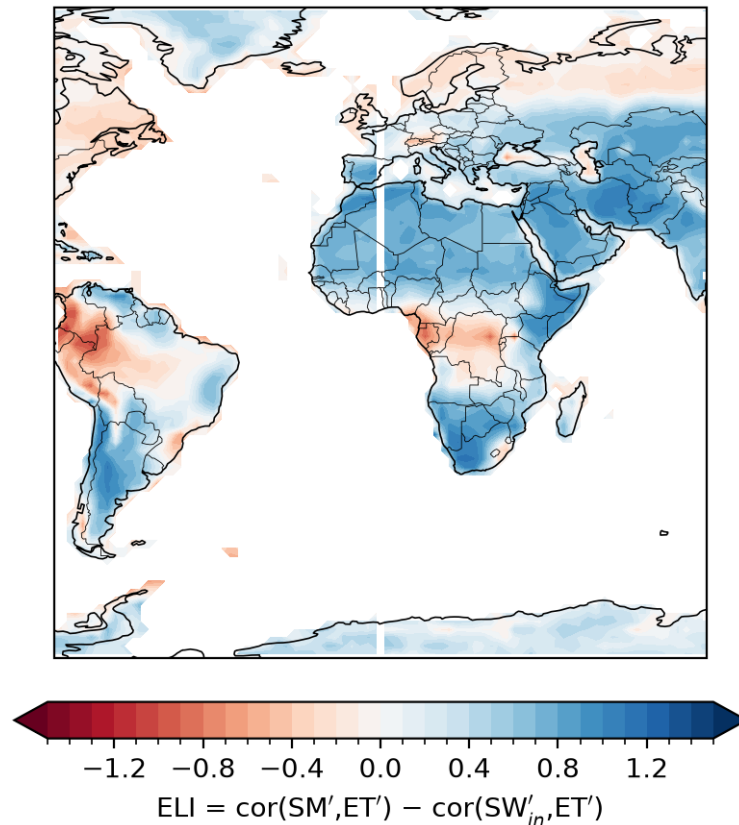


Figure 1: ecosystem limitation index (ELI) for period 2005-2025, adapted from Denissen et al. (2022).

The additional point raised by the Reviewer is also relevant. The indicator suggested by the Reviewer does indeed show some correspondence with the weaker correlations between the CEFI and the other indicators in rainforests, northern Europe, and the Alps (see Fig. 1). The Reviewer is therefore correct in noting that the CEFI is less relevant as a drought indicator in these regions, where evapotranspiration is limited more by energy availability (i.e. incoming solar radiation) than by water availability and vegetation stress. We will highlight this important point in the revised manuscript

I do not think the authors clearly explain the advantages of CEFI in the introduction or in the results sections, also when providing showcases regarding its applications. The authors may wish to clarify explicitly the advantages of CEFI relative to commonly used indices such as SPI in the introduction: does CEFI provide a more direct measure of land-surface cooling that goes beyond the atmospheric dryness conditions assessed by SPI? Does it provide a more accurate, near-real-time monitoring approach that could be applied in agricultural or urban studies? Does it lessen the need for ET observations from eddy-covariance measurements or ET and evaporative fraction derived from the satellite LST due to their model uncertainties (see ensemble ET models such as compiled in the OpenET project which also monitor ecosystem stress near-real time: <https://etdata.org/methods/>)?

We will improve the introduction by incorporating the Reviewer's constructive suggestions. An important distinction is that the SPI characterizes a driver of drought, whereas the CEFI reflects the signal of the specific impact of drought on vegetation. The CEFI can therefore complement

the SPI and other standard drought indicators in impact studies, including those focused on agriculture and urban environments. It also provides broader spatial coverage than eddy covariance measurements. Finally, the CEFI is derived directly from observations, without intrinsic modelling assumptions. By contrast, approaches such as those used in OpenET offer the advantage of providing direct evapotranspiration estimates but rely on modelling methods that require additional assumptions and parameterization.

OpenET models are generally based on Landsat LST and reflectance. However, DisALEXI (Disaggregation of the Atmosphere–Land Exchange Inverse model) also integrates other satellite data such as GOES and ALEXI. LE is calculated by residual of the surface energy budget and is therefore affected by errors in the estimate of the three other fluxes ($LE = R_n - G - H$). G is parameterized by empirical relationships. H uses aerodynamic resistance and a calibrated relationship between surface temperature and near-surface temperature difference.

eeMETRIC (Earth Engine implementation of Mapping Evapotranspiration at High Resolution with Internalized Calibration) also uses NDVI data. It is based on a similar method of DisALEXI, requiring calibration.

geeSEBAL (Google Earth Engine implementation of the Surface Energy Balance Algorithm for Land) Also calculates residual LE after estimating H and G and assumes constant daytime evaporative fraction

PT-JPL (Priestley–Taylor Jet Propulsion Laboratory model) does not independently solve aerodynamic H to obtain LE as residual. Instead it uses the Priestley–Taylor potential evaporation, reduced by functions representing vegetation activity, temperature, atmospheric humidity and moisture limitation. Radiation is partitioned among canopy and soil; G is still parameterized.

SIMS (Satellite Irrigation Management Support) does not explicitly solve all four fluxes. Derives an ET fraction from surface temperature relative to assumed theoretical relationships wet/cold and dry/hot limits, which depend on vegetation types, then multiplies it by reference ET computed with the Penman–Monteith equation (needing several meteorological data).

SSEBop (Operational Simplified Surface Energy Balance) is less focused on LST. It uses crop coefficients $\times$ reference ET, computed with the Penman–Monteith equation, with a soil water balance adding soil evaporation. It does not solve the actual surface energy balance. Its vegetation approach assumes well-irrigated crops and can overestimate ET during short-term water stress.

In addition to satellite observations, these models need additional meteorological data. NLDAS / NLDAS-2 weather inputs for models including eeMETRIC, geeSEBAL and PT-JPL. PT-JPL's documented default includes hourly air temperature, vapor pressure, wind and incoming shortwave/longwave radiation. SIMS uses a downscaled version of NLDAS-2 usign PRISM. Daymet air-temperature climatology and ERA5 net radiation are used in SSEBop boundary parameterization.

The nominal resolution of OpenET is 30 m, much higher than the CEFI, however, most of the supporting variables employed in the parameterization are derived from datasets at much lower resolution. The lack of validation of these datasets despite few isolated sites also question their validity in data poor regions.

For the applications presented in Figures 6 and 8, I would also expect to see comparisons between CEFI and other drought indices in relation to maize production and urban green space, respectively. In addition, the annual-scale maize-production case study may not adequately demonstrate the unique value of CEFI. An analysis at a finer spatial and temporal resolution would be more informative.

Regarding the agricultural application example, we do not have access to spatially distributed crop production data for Africa. Official FAOSTAT data are available at the national level and on an annual basis. We therefore followed a commonly used methodology, comparing FAOSTAT data with spatially aggregated climate indicators calculated over the crop's most sensitive phenological period (see, e.g., Lesk et al., 2016; Zampieri et al., 2017, 2019). Following the Reviewer's suggestion, we will add a comparison with the other drought indicators examined in the paper.

Figure 2 compares drought indicators with crop production for different countries and crops. For this example, we selected major African producers of four important crops: South Africa for maize, Algeria for wheat, Nigeria for rice, and Niger for millet. In these cases (as well as in numerous additional cases not shown here) the CEFI performs as well as or better than the SPI and SPEI. This is a striking result, considering that the CEFI is calculated on a monthly basis considering few days, whereas the SPI and SPEI integrate conditions over longer time windows. A predictive model combining the best-performing CEFI, SPI, and SPEI series could potentially explain an even greater proportion of the variance in crop production.

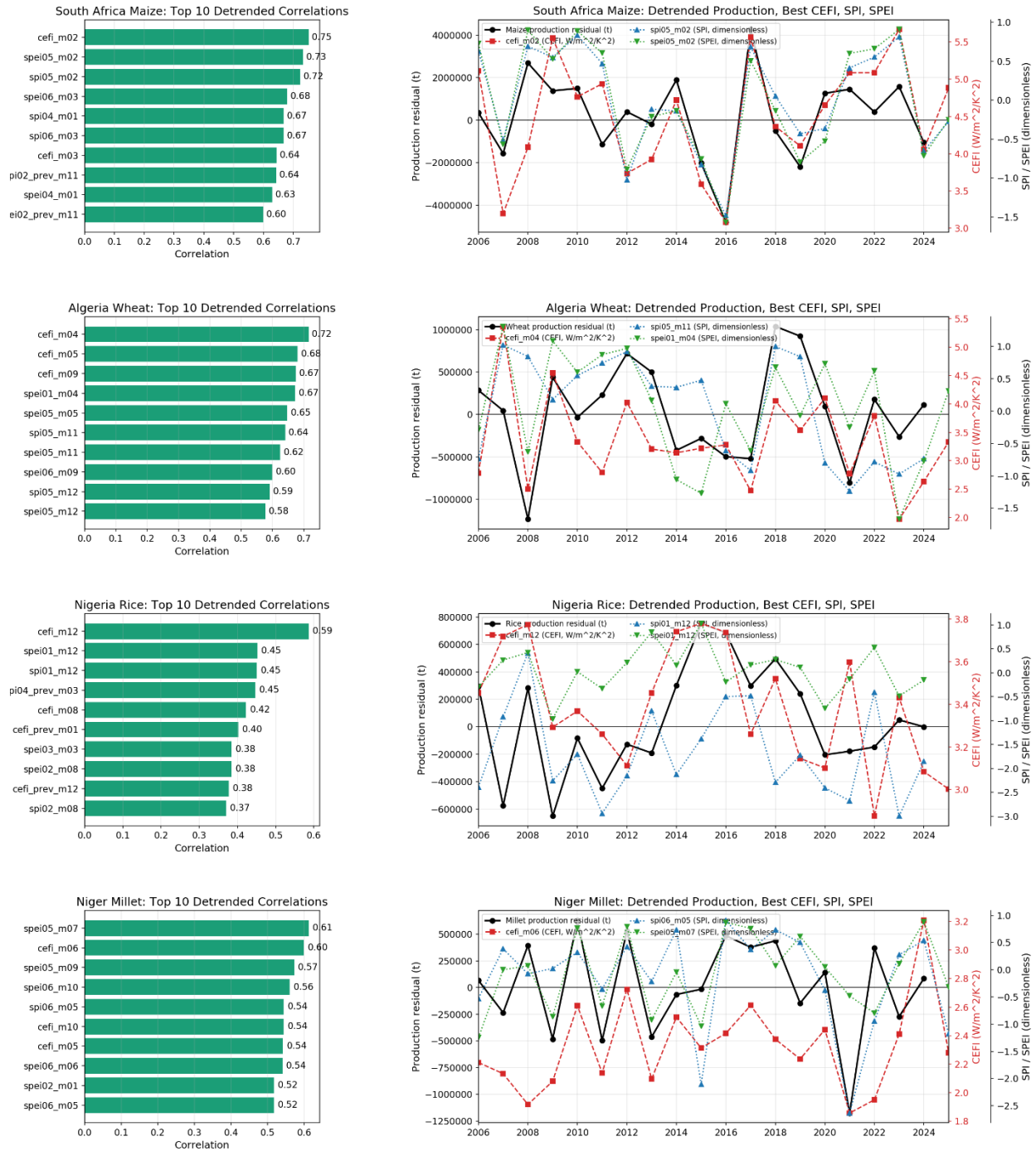


Figure 2: Left) Ranked correlations between annual crop production anomalies from FAOSTAT and CEFI, SPEI, and SPI, calculated for different months of the growing season and, for SPEI and SPI, different accumulation periods. Right) Time series of detrended crop production anomalies and the CEFI, SPEI, and SPI series with the highest correlations. The indicator time series were calculated as weighted averages of gridded data, using the MIRCA-OS spatial distribution of crop areas (Kebede et al. 2025) as weights, via the API available at www.cefiland.com.

For the dust-variation case study, can the authors explain how much of the dust variability is influenced by wind and how much is uniquely associated with cooling efficiency? What processes might link cooling efficiency to dust and air pollution? The authors may wish to control for wind speed when examining the relationship between CEFI and dust. It would also be useful to investigate how local cooling effects, as represented by CEFI, and external wind systems (incl. upwind influences and wind direction) jointly regulate dust formation.

Our interpretation is that wind is the main driver of the dust variability considered here. As the CEFI serves as a proxy for wind speed in desert regions, we present correlation maps suggesting that it may help identify dust source areas. We will clarify this interpretation in the revised manuscript. However, this application requires a more detailed analysis, which is beyond the scope of a data paper. Our aim here is to illustrate potential applications that will be investigated more thoroughly in follow-up studies.

Minor points:

In the introduction, it would be helpful to clarify the advances of this study relative to the previous literature Zampieri et al., 2025.

We reported the differences in the methodology and will mention them also in the Introduction.

Li et al., 2023 that is cited in the introduction is missing from the reference list.

Thanks for spotting this, we included the citation.

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