

The manuscript 'The Cooling Efficiency Factor Index (CEFI): A New Satellite-Based Dataset for Research and Operational Monitoring of Land Surface Processes' by Zampieri et al. presents a new satellite-based dataset of CEFI, which aims to quantify the lands capacity to dissipate heat. Although the authors show strong relations between the CEFI and several biophysical variables I believe several aspects of the manuscript should be improved before publication. Please find my comments below.

Major comments:

- Both the concept (what is CEFI exactly) and goal (why do we need it) of the dataset is lacking throughout the introduction. This makes it unclear what the CEFI adds to the existing drought products. At the same time, the first few paragraphs (L347-381) of the discussions describe this rather clear. Moving these lines to the introduction could provide a scientific and societal relevance that is currently missing. Also, could the authors mention how the CEFI data can be used and maybe give examples of potential applications? Could we use it as a drought index? Or more as a way to study land-atmosphere interactions?
- We have restructured the paper as suggested. Regarding its potential benefits, the CEFI has many applications that we have only begun to explore in this data paper. We consider drought monitoring a primary application, but the CEFI can also be used to quantify land-atmosphere interactions in process studies. We have added these considerations to the Introduction.
- The derivation of the CEFI in '2. Theory' is not clear without reading Zampieri et al. (2025). I understand that the authors do not want to repeat the earlier paper, but the derivation could be refined. For example:
 1. Equation 2 On one side there is a delta and on the other side the integral. Maybe make mathematically consistent. Also, it is not clear to me why the c_s term is brought to the other side of the equation, and put back in the next step.
 2. Equation 6: Maybe the authors could shortly explain how the linear approximation follows from $c_s = c_a - e_c$.
 3. How is ΔT_s exactly defined and calculated? In L74 the authors mention 'two different times of the day, after the sunrise and before the sunset', in L111 'monotonically increasing LST are used for linear regression'. Does this mean ΔT_s is calculated for each time step as the difference between the LST and LST at sunset, as long as LST is monotonically increasing? Also, is this the CEF calculated based on daily values and then averaged over the month?

We will provided clearer explanations in the new version. Regarding the aspects raised by the Reviewer:

- 1) Equation 2 is consistent and exact. Delta T represents a temperature difference which is given by the integral of the radiative term. Then both terms of the equation are divided by Delta T and multiplied by c_s , to express everything in terms of heat capacity dimensions.
- 2) The linear approximation does not follow from $c_s = c_a - e_c$ directly, it is suggested by the actual observations.
- 3) Yes, ΔT_s is calculated for each time step as the difference between the LST and LST at sunset, as long as LST is monotonically increasing. We will explain this better in the new version. And yes, CEF is calculated based on daily values and then averaged over the month. Actually we take the median

- *Could the authors comment on the uncertainty introduced by the satellite/model products used to compute R_n , and on the independence of these inputs from the variables against which CEFI is later validated? As I understand the methodology, $R_n = (1-\alpha) \cdot RS_{\downarrow} + RL_{\downarrow} - RL_{\uparrow}$, where:*
 1. *$LW_{\downarrow}$ is calculated from an LSASAF product*
 2. *$LW_{\uparrow}$ is calculated using Stefan-Boltzmann with LST (LSASAF) and emissivity (LSASAF)*
 3. *$SW_{\downarrow}$ is calculated from an LSASAF product*
 4. *$SW_{\uparrow}$ is calculated using the albedo (LSASAF) and $SW_{\downarrow}$.*
- *This makes me wonder two things: 1) LST is both used in the R_n and the LST to derive the slope of CEFI. This means errors in LST appear into both R_n and LST itself. Could the authors comment on how this coupling might affect the apparent near-linearity of the ca vs. ΔLST relationship? 2) Several R_n inputs are not directly measured, but are themselves model- or land-cover-derived and may not be independent of the variables used later to validate CEFI. For example, the emissivity is calculated based on look-up-tables which are derived from NDVI. In addition, the downwelling longwave radiation is derived from meteorological forecast fields. Could the authors clarify whether these dependencies were considered and how it affects the results?*

We thank the Reviewer for raising this important point.

- 1) The main driver of R_n at daytime is the incoming shortwave, the longwave component ($LW_{\uparrow}$ minus $LW_{\downarrow}$) being 10% or less, and less varying through the day. Therefore, while the LST is purely estimated from the thermal sensors, R_n is dominantly derived from solar radiation. Therefore, if there are errors in R_n and LST estimations, they are mostly uncorrelated.
- 2) Regarding these errors, we will include a discussion of the uncertainty in the new version, which was indeed missing: “MSG/SEVIRI land surface temperature (LST) and downward surface radiation products from LSA SAF have been evaluated against ground observations, with performance depending on surface conditions, sky state and temporal averaging. For LST, Trigo et al. (2008) combined validation against measurements at Évora, Portugal, with MODIS intercomparisons, highlighting the influence of surface heterogeneity and viewing geometry. Longer-term validation by Göttsche et al. (2016) over three African sites during 2009–2014 showed that, excluding rainy seasons, the highest site-level mean root-mean-square error (RMSE) was 1.6 K, within the product’s 2 K target accuracy; daytime and nighttime biases reached approximately 0.7 K with opposite signs, partly cancelling when combined. This aspect can have an impact on the CEFI, as morning temperature rise can be slightly overestimated or underestimated, depending on the locations. For downward shortwave radiation, Carrer et al. (2019) evaluated the MDSSFTD product against instantaneous observations from four Baseline Surface Radiation Network (BSRN) stations over seven months, reporting a mean bias of $+3.62 \text{ W m}^{-2}$ and a relative mean bias of 0.252%, and finding that the product met its all-sky target requirements of 20 W m^{-2} below 200 W m^{-2} and 10% at higher fluxes. For downward longwave radiation, Lopes et al. (2024) reported monthly-mean RMSEs for the operational LSA SAF MDSLFL product of 16.09 W m^{-2} against BSRN and 15.10 W m^{-2} against FLUXNET2015, with respective

biases of -4.61 and -2.44 W m^{-2} . Against BSRN, ERA5 achieved an RMSE of 9.51 W m^{-2} , while the newer MARS approach combining MSG cloud information with ERA5 predictors reduced RMSE to 7.10 W m^{-2} .”

- *In the results, the authors present that CEFI correlates with several biophysical variables, including soil moisture, NDVI, Wind speed. From the CEFI calculation this makes sense, as both sensible and latent heat flux are included, which depend on things like water availability, vegetation type, atmospheric conditions etc. These correlations seem highly variable in space and time. So how can a user interpret whether a certain CEFI anomaly is due to vegetation stress, or land cover change, or wind conditions etc?*

The Reviewer is correct that the CEFI can depend on all these factors. It should therefore be interpreted alongside other indicators to provide additional information. We have shown, however, that the relative importance of the drivers of CEFI variability changes throughout the year, which can help the interpretation. The CEFI is strongly associated with vegetation drought during the hot, dry part of the year and with wind during the cold, wet part, although these influences can admittedly overlap. Although not discussed in the manuscript, this is why we included wind information in the published dataset: it could help isolate and remove the wind-driven component of the CEFI to derive an indicator more specifically related to drought. The CEFI may also be affected by land-use change. We did not discuss this influence because it is generally more localized and/or varies more slowly, but it is indeed a possible source of uncertainty. We will acknowledge it in the revised manuscript.

- *Did the authors consider looking at anomalies in CEFI? As the CEFI value is highly variable in space and time, looking at (relative) anomalies would provide insight into whether CEFI is different from ‘normal’ conditions. Maybe this would provide more information on drought stress than the actual value?*

All the correlation analyses presented are based on anomalies. The correlation coefficients do not distinguish between absolute and relative anomalies. For visualization purposes, we have so far used absolute anomalies rather than relative or standardized anomalies, as we are still seeking a more physically grounded interpretation of the CEFI. However, the Reviewer’s suggestion is sensible, and we will take it into account in the revised manuscript.

Minor comments:

- *In Figure 1: adding the variable names in the axis labels rather than in the title would improve readability. Also, maybe the exact definition of ΔT_s can be added to the figure (i.e. the temperature differences between which hours).*

We will improve Figure 1. However, we cannot add the hours as the detection window of the CAFI can vary day by day. We implemented this feature to maximize valid detections. This was not explained in the old version of the paper, but we will in the new one.

- *L103: how do the authors match the different temporal resolutions of the different datasets?*

All datasets are interpolated in a common grid of 0.1° resolution of GLEAM.

- *L112: ‘rejecting regressions with $r^2 < 0.7$ ’. Why were these rejected? How many were rejected based on this criterium? Why do some days have a low r^2 ?*

We will compute the rejection rate. However, it is difficult to attribute a specific reason for that just on the basis of geostationary satellite data (spurious impact of cloud, wind burst, errors in the data, etc.)

- *Line 140-145: if the results are not shown in this paper or elsewhere, adding the information on the PDP does not add anything here.*

We will remove this part

- *L177: NDVI is also strongly dependent on the precipitation regime, right? So how are these impacts separated?*

We will acknowledge that these features share predictive information.

- *Figure 3: over which period is the CV calculated? For each month separately?*

CV is calculated from 2005 to 2025, for each month separately and the averaged together.

- *Figure 4: it is not clear to me what is meant by 'mean correlation' or 'max correlation'. Does this mean the correlation is calculated per year, for example, and then take maximum value over the years?*

Correlations are calculated separately for each calendar month. The “mean” is the average of these monthly correlation coefficients, whereas the “max” is the highest correlation coefficient obtained across the months. We acknowledge that this distinction was not clearly explained in the manuscript and will clarify it in the revised version.

- *Figure 6: why was 2006 removed? How do you determine it is an outlier? What is the correlation when this outlier would be included? Also, why were other countries not included?*

We added a more general analysis of crop production variability in the new version of the manuscript, where no outlier will be removed. Figure 1 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.

- *Add a unit and variable description to the NetCDF files. It would also be useful to add a readme file to the folder.*

We'll improve the NetCDF files and add a readme file.

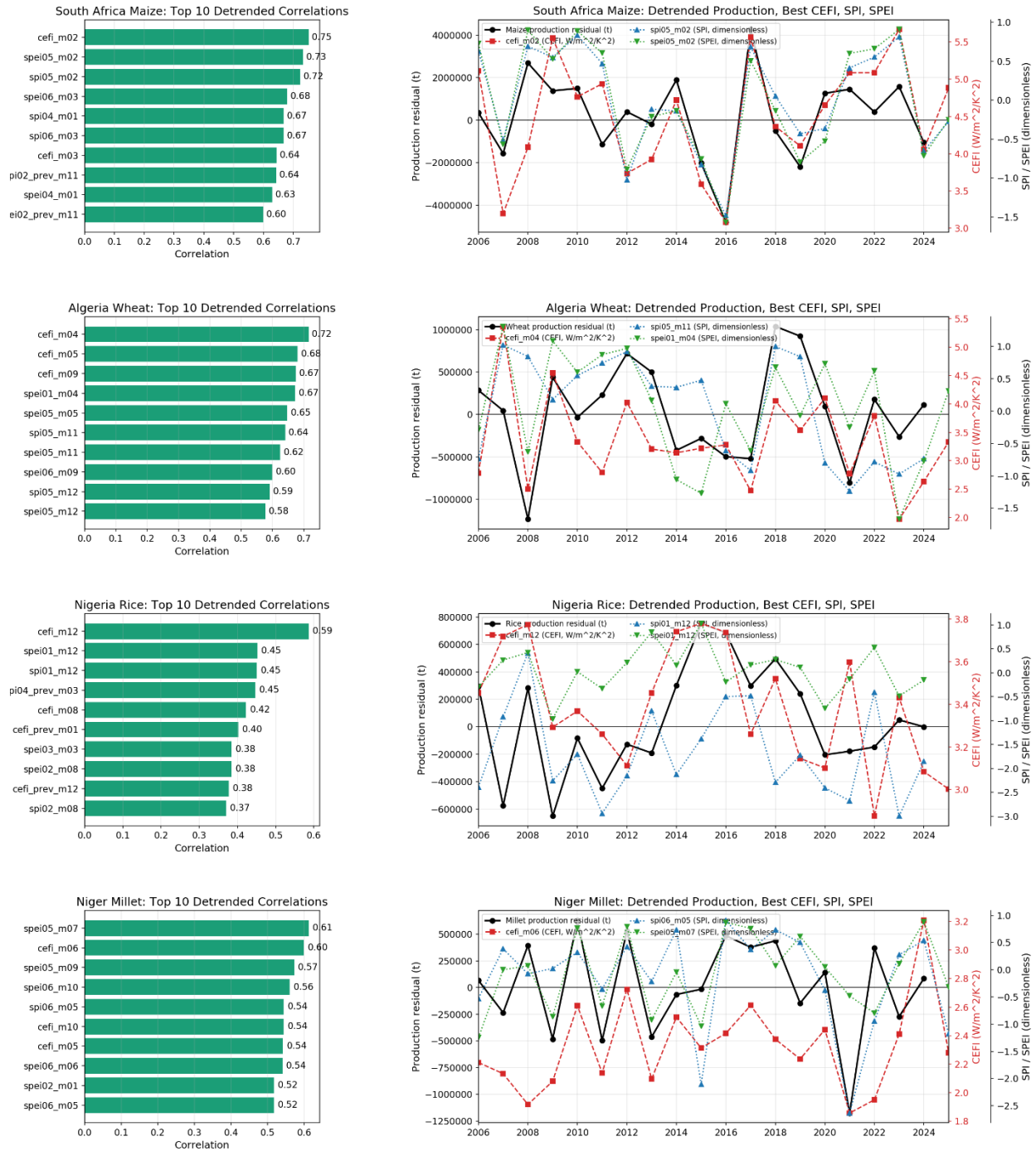


Figure 1: Left) Ranked correlations between annual crop production anomalies from FAOSTAT and CEFI, SPEI, and SPI, calculated for different months of the growing season and, for SPEI and SPI, different accumulation periods. Right) Time series of detrended crop production anomalies and the CEFI, SPEI, 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.

REFERENCES:

Göttsche et al. (2016), Long Term Validation of Land Surface Temperature Retrieved from MSG/SEVIRI with Continuous in-Situ Measurements in Africa. Remote Sensing, 8, 410.

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