LETTER

Enhancing the fire weather index with atmospheric instability information

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Abstract

The Fire Weather Index (FWI) is widely used to assess the meteorological fire danger in several ecosystems worldwide. One shortcoming of the FWI is that only surface weather conditions are considered, despite the important role often played by atmospheric instability in the development of very large wildfires. In this work, we focus on the Iberian Peninsula for the period spanning 2004–2018. We show that atmospheric instability, assessed by the Continuous Haines Index (CHI), can be used to improve estimates of the probability of exceedance of energy released by fires. To achieve this, we consider a Generalized Pareto (GP) model and we show that by stepwisely introducing the FWI and then the CHI as covariates of the GP parameters, the model is improved at each stage. A comprehensive comparison of results using the GP with the FWI as a covariate and the GP with both the FWI and CHI as covariates allowed us to then define a correction to the FWI, dependent on the CHI, that we coined enhanced FWI (FWIe). Besides ensuring a better performance of this improved FWI version, it is important to stress that the proposed FWIe incorporates efficiently the effect of atmospheric instability into an estimation of fire weather danger and can be easily incorporated into existing systems.

1. Introduction

Wildfires are an important natural hazard with significant impact on ecosystems and human populations (Amraoui et al 2015). The Iberian Peninsula, and in particular Portugal and the northwestern Spanish province of Galicia, are the regions in Southern Europe most affected by wildfires (Pereira et al 2011). According to the European Forest Fire Information System (EFFIS, San-Miguel-Ayanz et al 2012), Portugal and Spain rank in 1st and 2nd place, respectively, for the European countries with the highest burned area during the period of 2008–2018. Portugal with a figure of 115736 ha yr⁻¹, corresponding to 1.2% of the country area, and Spain with 62844 ha yr⁻¹, corresponding to about 0.1% of the country area. Together, Portugal and Spain account for about 44% of the total burned area in Europe. Furthermore, future climate scenarios predict an increase in fire-prone weather conditions making this problem even more relevant (Amatulli et al 2013, Pereira et al 2013, Bedia et al 2014, Abatzoglou et al 2019).

Wildfires can be categorized into three types: convective, wind-driven and topographic (Lecina-Diaz et al 2014). Atmospheric instability plays an important role in convective fires in which the hot air rising above the fire can, in the right conditions, generate pyrocumulonimbus and result in extreme fire intensity and unpredictable fire behavior, particularly if high amounts of dry fuel is available. In the case of wind-driven fires, the strong wind is the main factor driving the fire propagation that occurs in the direction of the wind. For the topographic fires, slope winds are the main force and fire progression will be strongly dependent of the topography.

Over the years, several methods have been proposed to assess the meteorological fire danger over Europe (e.g. San-Miguel-Ayanz et al 2012, Dacamara...
et al 2014, Pinto et al 2018a). These methods are usually based on the Fire Weather Index (FWI), one of the components of the Canadian Fire Weather Index (CFWIS, van Wagner 1974, 1987), and, therefore, the limitations of the FWI may affect the accuracy of fire danger estimates. Other indices exist for similar purposes, for example, the Forest Fire Danger Index (FFDI, McArthur et al 1967) is commonly used over Australia. These indices are based on surface meteorological information and drought/fuel moisture, without taking into consideration atmospheric instability conditions that can play an important role in the development of very large fires (Fernandes et al 2016). The Haines Index (Haines 1988) has been proposed to measure fire-prone atmospheric instability conditions over the United States of America, and has since then been used over several regions of the globe such as the United States (e.g. Werth and Ochoa 1993, Trouet et al 2009), New Zealand (Simpson et al 2014), the Mediterranean basin (Tati and Turkes 2014) and Australia (McCaw et al 2007). However, the original formulation of the Haines Index presents some limitations that need to be addressed (Potter 2018). The Continuous Haines Index (CHI, Mills and McCaw 2010) has been proposed to address some of these limitations and has been used mainly over Australia (e.g. McRae et al 2013, Sharples et al 2016).

The main goal of this work is to provide an enhanced version of the widely used FWI to take into account atmospheric instability. We choose the CHI as it provides a simple large-scale measure of instability that has been shown to be useful to evaluate extreme convective fires in conjunction with the FWI (e.g. Pinto et al 2018b) or with the FFDI over Australia (e.g. Ndalla et al 2020). We first show that the logarithm of energies released by fires, as derived from remote sensing observations, follow a Generalized Pareto (GP) distribution. Then, we show that by incorporating the FWI and CHI as covariates of the GP parameters, the model is better at explaining the observations of released energy. The resulting model allows us to estimate the probability of exceedance of a predefined energy threshold, dependent on the FWI and CHI. Moreover, this probability of exceedance may be expressed in terms of an enhanced FWI, i.e. FWLe, which incorporates the effect of atmospheric instability into an estimation of fire weather danger. Finally, we show two case studies to exemplify the practical use of the FWLe.

2. Data and methods

This study focuses on the Iberian Peninsula, spanning the period of 2004–2018. The data to compute the FWI and CHI were obtained from ERA5 reanalysis, available at https://cds.climate.copernicus.eu. ERA5 is the latest reanalysis produced by the European Center for Medium-range Weather Forecast (ECMWF), featuring a spatial resolution of 0.25° and 37 pressure levels. The data obtained for the period and region of study comprise temperature and dew point at 2 m, 700 hPa and 850 hPa, U and V components of the wind at 10 m and 24 h accumulated precipitation; all fields are daily, referring to 12 h UTC.

2.1. Fire weather index

The CFWIS consists of six indices: three fuel moisture codes that have a memory component, allowing us to capture the effect of drought; and three behavior indices, including the FWI. The weather inputs required to compute the CFWIS indices are 2 m temperature and relative humidity, 10 m wind speed and 24 h accumulated rain. The relative humidity is computed using the temperature and dew-point temperature according to the Magnus expression (Lawrence 2005). The code for the computation of the CFWIS indices can be found in Wang et al (Wang et al 2015) and an in-depth interpretation of the CFWIS indices can be found in Wotton (Wotton 2009). The CFWIS indices are therefore computed for each ERA5 grid cell covering the study region and for each day of the study period (2004–2018).

2.2. Continuous Haines Index

The CHI is designed to assess the instability that favours convective fires and is composed of two terms: (1) an instability term that is based on the difference in temperature at two atmospheric levels (CA), and (2) a moisture term that is given by the difference between temperature and dew point at the lower level (CB). This is an important feature, since a very high CHI requires dry atmosphere at the lower level and a steep lapse rate. If instead the air is moist at the lower level, a rising parcel of air will result in a low lifting condensation level that is favorable to the development of storms with heavy rainfall. A dry atmosphere and high cloud base are favorable to dry thunderstorms and severe wind phenomena such as downbursts that can also play a role in the ignition and spread of fire. In this sense, the CHI is, by design, more suitable for measuring conditions favorable to convective fires in comparison to the traditional instability indices. Furthermore, the CHI can be computed at different height levels depending on the average topography of the region (Haines 1988, Mills and McCaw 2010). We selected the level 850–700 hPa, referred to as the middle level, which is more suitable for the average topography over the Iberian Peninsula (Winkler et al 2007). The CHI is then defined as,

\[ CA = \frac{(T_{850} - T_{700})}{2} - 2, \]  

\[ CB = \min (T_{850} - DP_{850}, 30) / 3 - 1, \]  

if \( CB > 5 \), then \( CB = 5 + (CB - 5) / 2 \)

\[ CHI = CA + CB, \]
where the T700 and T850 are the temperature at 700 and 850 hPa, DP850 is the dew-point temperature at 850 hPa and the min (T850 - DP850, 30) term in equation (2) indicates that an upper bound of 30 °C is set to the difference between the temperature and dew-point at 850 hPa. Using equations (1)–(3), the CHI is then computed for each ERA5 grid pixel covering the study region and for each day during the study period (2004–2018).

### 2.3. Daily energy released by fires

Daily energy values were derived from Fire Radiative Power (FRP) product produced and disseminated by the Satellite Application Facility for Land Surface Analysis (LSA SAF) (Trigo et al 2011, Wooster et al 2015). To derive the daily energy values from the FRP data with a periodicity of 15 min, we convert the radiative power to energy by assuming a constant power over the 15 min period (Pinto et al 2018a) and limiting to FRP events with fire confidence (Roberts and Wooster 2014, Wooster et al 2015) greater than 70%. We then sum the energy values for each day over each ERA5 grid cell in order to have triplets of (FWI, CHI, energy) for each day and each ERA5 cell covering the study region.

### 2.4. Generalized Pareto models and FWIe

The GP distribution has been shown to be useful for modeling fire duration (Dacamara et al 2014) and fire released energy (Pinto et al 2018a). The cumulative distribution function (CDF) of the GP for an exceedance of $x$ above a predefined minimum threshold is defined as,

$$G(x|\alpha, \sigma) = 1 - (1 + \frac{\alpha}{\sigma}x)^{-1/\alpha}, \quad (4)$$

where $\alpha$ and $\sigma$ are the shape and scale parameters of the distribution, respectively.

To test for the goodness of fit of the samples to the GP distribution, the $A^2$ test is used (Anderson and Darling 1952) and the confidence level is obtained by generating 5000 data samples from the GP distribution with the estimated shape and scale parameters (Dacamara et al 2014, Pinto et al 2018a).

We then consider two models, one with the FWI as a covariate of shape and scale parameters of the GP and another with both the FWI and CHI as covariates. The shape and scale parameters for the first model ($GP_{FWI}$) are defined as,

$$\alpha (FWI) = a + b \times FWI, \quad (5)$$

$$\sigma (FWI) = c + d \times FWI, \quad (6)$$

where $a$, $b$, $c$ and $d$ are the new model parameters. For the $GP_{FWI, CHI}$ model, the shape and scale parameters are defined as,

$$\alpha (FWI, CHI) = e + f \times FWI + g \times CHI + h \times FWI \times CHI, \quad (7)$$

$$\sigma (FWI, CHI) = i + j \times FWI + k \times CHI + l \times FWI \times CHI, \quad (8)$$

where $e$, $f$, $g$, $h$, $i$, $j$, $k$ and $l$ are the new parameters.

We find the parameters for each model using maximum likelihood estimation (MLE) and we test if the more complex models are better than the previous one using the likelihood ratio test (Neyman and Pearson 1933). We implement this procedure in Python using the SciPy library (Virtanen et al 2020).

As the use of the FWI in practical applications is more widespread than the concept of probabilities of exceedance of energy released by fires, we then determine the FWI value, i.e. FWIe, that yields $GP_{FWIe} = GP_{FWI, CHI}$ for a given threshold. The FWIe is therefore a function of the FWI and CHI, calibrated so that the probability of exceedance of a predefined threshold of released energy on the $GP_{FWI}$ model is identical to the one given by the more complex $GP_{FWI, CHI}$ model.

In order to test for the generalization of the method for years not used to estimate the parameters, we use a 15-fold cross-validation (CV) scheme, leaving one year out for validation on each fold and estimating the parameters with the remaining years (Wilks 2011). To present the results, we then consider the average of the 15 models. The standard deviation of the 15 models is used to assess the uncertainty of the estimates.

### 3. Results and discussion

#### 3.1. GP model for all data

In order to show that the GP model is appropriate to model the distribution of the natural logarithm of energy (ln(E)) released by fires, we consider all ERA5 grid cells, over the study region and period, for which the natural logarithm of daily released energy is greater than 5 (about 150 GJ) and we subtract 5 to have values starting at zero. The threshold of 5 is chosen empirically based on visual inspection of the histogram of the natural logarithm of energy (figure 1, left panel) as the start of the right tail of the distribution. Figure 1 also shows the histograms for the FWI and CHI where the histograms in gray correspond to all 28 709 events, whereas the histograms in blue represent the corresponding distributions for events with ln(E) > 5, resulting in 17 573 events. It is worth noting that for the FWI histograms (figure 1, central panel) the distribution is bimodal, the lower mode corresponding to a smaller peak of fire activity usually occurring in March, more prominent in the north of the Iberian Peninsula (Trigo et al 2016).
The optimal shape and scale parameters of the GP are then obtained for the given distribution of ln(E) using MLE, resulting in a shape parameter of $-0.33$ and a scale parameter of 2.62. The quantile-quantile plot (figure 2) provides an indication of the goodness of fit of the model, revealing that observed quantiles plotted against theoretical ones are very close to the 1:1 line. Following the Anderson–Darling test and corresponding computation of the $A^2$ statistic, we can conclude that samples follow a GP distribution with a confidence level above 97%. The GP model with the obtained shape and scale parameters provides the probability of an event exceeding any given threshold, assuming that it has already exceeded the threshold of 5 as mentioned above (i.e. that its total released energy is higher than $e^5$ GJ). As an example, an exceedance of 2.6 corresponds to the probability of exceeding 5 + 2.6 (about 2000 GJ) given that 5 (about 150 GJ) was already surpassed. We represent this conditional probability as $P(2000|150)$.

### 3.2. GP model dependent on FWI

Following the procedure described in section 2.4, we now define the shape and scale of the GP as functions of the FWI according to equations (5) and (6) and we find the parameters $a$, $b$, $c$, and $d$, using MLE. Table A1 in the appendix shows the average and standard deviation of the four parameters for the 15 CV folds. Using an exceedance threshold of 2000 GJ we can now compute the probability of exceedance of 2000 GJ given 150 GJ—$P(2000|150)$—for successive values of the FWI. We repeat this procedure for each of the 15 CV folds. Figure 3 shows the average of the CV folds and the 95% confidence interval (95% CI), represented by the shaded region. We can see that as expected the $P(2000|150)$ increases with the FWI, starting at about 0.1 for FWI of 0 and rising up to more almost 0.6 for an FWI of 100. This result is in line with results obtained by Pinto et al (Pinto et al 2018a) for the Mediterranean Europe, although it should be noted that here we also introduce the FWI as a covariate of the shape parameter. This differs from previous works where the FWI was only used as a covariate of the scale parameter (DACAMARA et al 2014, Pinto et al 2018a). To assess the statistical significance of introducing the FWI also as a covariate of the shape parameter, we compared a model with the
FWI as the covariate of the scale parameter with the one with the FWI as the covariate of both shape and scale parameters, using the negative log-likelihood (NLL) ratio test. We obtained a p-value < 0.0001 suggesting that including the covariate in the shape parameter improves the performance of the model. Furthermore, the small spread of the model (even for high values of the FWI), as depicted by the small difference between the 15 CV folds, is a good indication of the robustness of the approach.

3.3. GP model dependent on FWI and CHI
Following the same procedure as the one adopted in the previous section, we now consider both the FWI and CHI as covariates of the shape and scale parameters according to equations (7) and (8) and the eight parameters are again obtained using MLE. Table A2 in the appendix shows the average and standard deviation of the parameters. Using the 15 CV models and fixing an exceedance of 2.6, similar to section 3.2, we now compute $P(2000|150)$ for successive values of the FWI and CHI for each model and we show the mean (figure 4, left panel) and twice the standard deviation (figure 4, right panel) of the 15 models. As mentioned before, the $P(2000|150)$ increases significantly for higher values of the FWI. This increment, however, is not constant as it depends on the magnitude of the CHI. Indeed, higher (lower) values of the CHI translate to an increase (decrease) in the probability of exceedance. Finally, considering the amplitude of values depicted on the right panel of figure 4, we can confirm that the variation among the 15 models is in general small, being the highest for very low CHI and very high FWI. This corresponds to a region of the (FWI, CHI) domain with a low number of fire events, as shown by the black contours in figure 4 right panel, corresponding to the Gaussian kernel density estimation for all fire events, scaled to the interval (0, 1).

In order to evaluate the GP model with FWI and CHI as covariates in respect to the GP model with only FWI as the covariate, the NLL ratio test is used. Once again, the obtained p-value < 0.0001 is a good indication that including the CHI translates to a model that explains better the observed values of released energies by the fires.

3.4. FWIe
Comparing the CDF for low/high values of the FWI and CHI (figure 5, left panel), it can be seen that for an FWI of 10 (gray dashed line, disregarding in this case the CHI), fires with lower energy are more common whereas for an FWI of 80 (black dashed line, also disregarding the CHI) the CDF increases at a slower pace, meaning that large fires are much more likely. When evaluating the results for the same values of the FWI, but considering the model of section 3.3, i.e. with both the FWI and CHI as covariates, and selecting extreme values for the CHI (1 and 12, respectively), we see that for a CHI of 12 (1), the CDFs shift downwards (upwards), meaning that, as discussed before, the probability of large fires increases (decreases) for higher (lower) CHI. Furthermore, it is worth noting that the effect is more prominent for higher values of the FWI.

Using the $GP_{(FWI)}$ model and $GP_{(FWI, CHI)}$ model, we can now use the threshold of exceedance of 2.6 (i.e. the $P(2000|150)$) to find the FWI value in the $GP_{(FWI)}$ model, i.e. the FWIe, which yields $GP_{(FWIe)} = GP_{(FWI, CHI)}$ for the selected threshold of 2.6. Figure 5 (right panel) shows that the CDFs for the $GP_{(FWIe)}$ model using the FWIe (represented by the dashed black lines), hereafter referred to as $GP_{(FWIe)}$, are very close to the ones of the $GP_{(FWI, CHI)}$ model. Note that by the definition of FWIe, they must be equal for an exceedance of 2.6 (~2000 GJ). One advantage of using the FWIe instead of a model with the FWI and CHI is that the FWI is widely used and for practical applications it is usually easier to introduce a modification to an already widespread index.

Figure 6 shows the values of the FWIe for each (FWI, CHI) pair (left panel) and their respective differences in respect to the baseline FWI (right panel). Table A3 in the appendix shows the FWIe values for fixed values of the FWI and CHI. It can be observed
Figure 5. Cumulative distribution functions for several values of the FWI and CHI (left panel) and comparison of CDFs of the $GP_{(FWI,CHI)}$ model and $GP_{(FWI)}$ model (right panel).

Figure 6. FWIe for successive values of the FWI and CHI (left panel) and differences with respect to the FWI. Black contours in the left panel correspond to twice the standard deviation of the 15 CV models.

(figure 6, right panel) that for higher values of the FWI, the contribution of the CHI is stronger, translating into differences exceeding ±20. This suggests that the fire danger based only on the FWI underestimates (overestimates) the probability of large fires for the CHI values above (below) about 7, being the effect less pronounced when the FWI is low.

To further validate the model and understand how well it generalizes to years not used for the estimation of the parameters, we compare probabilities of exceedance provided by the two GP models ($GP_{(FWI)}$ and $GP_{(FWIe)}$) with actually observed fire released energy, as computed from the LSA SAF FRP product (see section 2.3). We consider a sliding window of probabilities estimated by the model (for the threshold of 2.6), starting at the probability interval (0–0.2) and then increasing in steps of 0.05, considering only the windows that include at least 200 observations. Then, for each window, we plot the average model estimates against the fraction of events exceeding 2.6. The procedure is repeated for the $GP_{(FWI)}$ and $GP_{(FWIe)}$ models both for the mean of the 15 CV models and for out-of-fold (OOF) prediction, i.e. the probability for each event is assigned using the model that did not use that year for the estimation of the parameters. The results (figure 7) indicate that the model estimates agree on average with the observed fractions of exceedance. Most importantly, the difference between the 15 CV mean and the OOF estimates is very small, indicating that the model generalizes well for ‘unseen’ years, giving therefore some confidence to use the model for forecasting over the next few years.

Figure 7. Model estimates of $P(2000|150)$ versus observed fractions of exceedance.
Table 1. Number of occurrences for groups of released energy (E) and FWI. Values in square brackets show the percentage of occurrences with respect to the total of each group of released energy.

| E (GJ) - FWI / FWIe | 0–10 (%) | 10–30 (%) | 30–50 (%) | 50–70 (%) | >70 (%) | Total |
|---------------------|----------|-----------|-----------|-----------|---------|-------|
| 148–2000            | 2577 (21.0) / 2633 (21.4) | 4877 (39.7) / 5155 (41.9) | 4142 (33.7) / 3613 (29.4) | 664 (5.4) / 792 (6.4) | 40 (0.3) / 107 (0.9) | 12 300 (100) |
| 2000–10 000         | 349 (9.9) / 341 (9.7) | 1284 (36.6) / 1355 (38.6) | 1568 (44.7) / 1406 (40.1) | 273 (7.8) / 345 (9.8) | 35 (1.0) / 62 (1.8) | 3509 (100) |
| >10 000             | 49 (2.8) / 50 (2.8) | 429 (24.3) / 456 (25.9) | 989 (56.1) / 862 (48.9) | 262 (14.9) / 325 (18.4) | 35 (2.0) / 71 (4.0) | 1764 (100) |
| Total               | 2975 (16.9) / 3024 (17.2) | 6590 (37.5) / 6966 (39.6) | 6699 (38.1) / 5881 (33.5) | 1199 (6.8) / 1462 (8.3) | 110 (0.6) / 240 (1.4) | 17 573 |
To better discuss the effect of the FWIe, table 1 shows the number of events for groups of released energy and FWI/FWIe (top and bottom row on each cell, respectively). Comparing the FWI with the FWIe rows, we can see that for the FWIe there is an overall decrease in the number of events for the FWIe in the range 30–50 and an increase for other groups of the FWIe. However, if we look for the individual groups of fire-released energy, we can see that for values below 2000 GJ, 60.7% (63.3%) of the events occur with an FWI (FWIe) of less than 30. Conversely, for energy values above 10 000 GJ, 16.9% (22.4%) of the events occur with an FWI (FWIe) greater than 50. This difference is even more noticeable for FWI and FWIe greater than 70 where the fraction of events with released energy greater than 10 000 GJ doubles from 2% to 4%. This is a good indication that the FWIe can discriminate better the conditions favoring large fires, which especially in the case of extreme fire events, are often enhanced by atmospheric instability.

4. Case studies

4.1. Monchique fire—August 2018

The fire of Monchique 2018 took place during 3–10 of August in the southwest of the Iberian Peninsula, leading to a burned area of about 27 000 hectares (Dacamara et al 2019). The left panel of figure 8 shows the evolution of the FWI, FWIe and CHI, for the month of August, considering for each day the maximum value over the two ERA5 grid cells where the fire was severe. The colored bars in the same panel correspond to the natural logarithm of the total energy released by the fire on each day, with colors corresponding to the legend in figure 8 (right panel) where a high-resolution reference map of the burned area is shown (Rego et al 2019). It is interesting to note that on day 5 when the fire reached extreme values of released energy and was burning an extensive region, the FWI was 51.9. However, the CHI was 11.8, indicating a high level of instability that can translate into extreme fire behavior. The resulting FWIe of 61.9 is significantly higher than the corresponding FWI. This is a good example of a case where...
4.2. Guadalajara fire—July 2005
The Guadalajara fire that took place during 16–19 July 2005 lead to a burned area of more than 8000 ha and with a high cost in human lives, being responsible for the death of 11 forest agents (Cardil and Molina 2015). The analysis of the FWI, FWIe and CHI together with the natural logarithm of released energy (figure 9) shows that the fire started on 16 July, a day with an extreme FWI value of 74.0. However, we argue that the fire risk for that day was not entirely encapsulated by the FWI metric alone, as the associated CHI value reached 12.8, translating to an extreme FWIe of 92.6. The fire was only extinguished 3 d later when the FWI/FWIe were both close to a milder value of 40. Once again, this is a good example of how the use of the CHI provides additional relevant information that is well incorporated in the FWIe.

5. Conclusions
Understanding and assessing the meteorological fire danger is of paramount importance to fire management. To this end, the FWI is widely used, being the basis for several operational fire danger rating systems. The FWI, however, does not account for the atmospheric instability, assessed by the CHI, which is shown to play a role in the energy released by fires. The use of the CHI alone is not straightforward, since atmospheric instability conditions can be observed throughout the year, even when the fire danger, as measured by the FWI, is low. Therefore, to address these problems, we demonstrated that the FWI can be improved by incorporating relevant information related to vertical instability through the CHI. It is worth noting that we are not suggesting that one disregard the historical know-how associated with the FWI metric, but basically an upgraded version be adopted, as the proposed FWIe can be easily incorporated into existing FWI-based systems.

The analysis of two case studies shows the practical application of the FWIe aiming towards an improved reliability of fire danger estimates that can be particularly important for days with a mild FWI, but a very high CHI where the fire danger can be underestimated. The opposite situation can also be true, i.e. days that present a very high FWI value can be in fact associated to a more moderate fire risk due to the presence of a very stable atmosphere (CHI values close to zero), leading to lower values of the FWIe, which in some cases can be significantly smaller than the original FWI.

Climate change in recent decades has warmed continents faster than the ocean and such asymmetric trends are bound to continue in the coming decades (IPCC 2014). In semi-arid regions already prone to wildfires, such as the Mediterranean, the rise of temperature must be considered together with the increasing dryness, both concurring to increasing values of sensible heat fluxes at the surface. In fact some of the most recent notorious events, with a significant number of human casualties, have been amplified by vertical atmospheric instability, such as the Portugal event in June 2017 (Viegas 2018, Turco et al 2019), California 2018 (Brown et al 2020), Greece 2018 (Lagouvardos et al 2019) and Australia 2019 (Bureau of Meteorology 2019). In this context, we argue that our enhanced FWI scale is particularly suitable to account for the likely increase in dry vertical instability of such continental areas.

Code to compute the FWIe is available at https://github.com/mnpinto/FWIe.

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Appendix

Table A1. 15-fold average and standard deviation (in square brackets) for the parameters a, b, c and d of equations (5) and 6.

| Parameter | 15-fold average (standard deviation) |
|-----------|--------------------------------------|
| a         | −0.236 (0.006)                       |
| b         | −0.0049 (0.0003)                     |
| c         | 1.46 (0.02)                          |
| d         | 0.045 (0.001)                        |

Table A2. As in table 1, but for parameters e, f, g, h, i, j, k and l of equations (7) and 8.

| Parameter | 15-fold average (standard deviation) |
|-----------|--------------------------------------|
| e         | −0.188 (0.009)                       |
| f         | −0.0038 (0.0005)                     |
| g         | −0.008 (0.001)                       |
| h         | −0.00013 (0.00004)                  |
| i         | 1.36 (0.04)                         |
| j         | 0.031 (0.003)                       |
| k         | 0.021 (0.004)                       |
| l         | 0.0018 (0.0002)                     |
Table A3. FWIe values for the FWI/CHI pairs.

| FWI | CHI | 1   | 3   | 5   | 7   | 9   | 11  | 13  |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 0   |     | 0.0 | 0.2 | 0.5 | 1.0 | 1.6 | 2.1 | 2.7 |
| 20  |     | 13.8| 16.0| 18.3| 20.5| 22.8| 25.0| 27.2|
| 40  |     | 28.3| 32.2| 36.1| 40.0| 43.9| 47.8| 51.7|
| 60  |     | 42.7| 48.3| 53.9| 59.5| 65  | 70.6| 76.2|
| 80  |     | 57.2| 64.4| 71.7| 78.9| 86.2| 93.4| 100.7|
| 100 |     | 71.6| 80.6| 89.5| 98.4|107.3|116.2|125.1|

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Data availability

Pre-processed data used for this study are openly available at https://github.com/mmpinto/FWIe.

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