climatrends: Precipitation and temperature indices for climate variability analysis in R

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Introduction

Abiotic factors plays an important role in most ecological and crop systems that depends on certain levels of temperature, light and precipitation (and their interplay) to initiate important physiological events (Schulze et al. 2019). In the walk of climate change, understand how these factors drives the physiological processes is a key approach to provide recommendations for adaptation and biodiversity conservation. If translated to stress

Raw temperature and precipitation values are … to describe how organisms interacts with the enviroment

climatrends aims to provide the R (R Core Team 2020) toolkit to compute extreme precipitation and temperature indices that serves as input for climate and crop models (van Etten et al. 2019; Kehel, Crossa, and Reynolds 2016), trends in climate change (Aguilar et al. 2005; de Sousa et al. 2018) and applied ecology (Prentice et al. 1992; Liu and El-Kassaby 2018).

[…continue…]

Methods and features

Implementation

Six main functions are provided, `crop_sensitive()`, `ETo()`, `GDD()`, `late_frost()`, `rainfall()` and `temperature()` with a default method for numeric 'vector's and additional methods (R Core Team 2020) for classes 'matrix' (or array), 'data.frame', and 'sf' (of geometry POINT or POLYGON) (Pebesma 2018). The later two are designed to fetch data from cloud sources.

say that the idea for the functions started with citizen science projects that is why `day.one` and `span` may be variable across locations. For time series analysis where fixed periods are defined across many locations the indices can be adjusted with last.day.

[…continue…]

Growing degree-days

Growing degree-days (gdd) is an heuristic tool in phenology that measures heat accumulation and is used to predict plant and animal development rates (Prentice et al. 1992). Growing degree-days are calculated by

Table 1: Main functions available in climatrends.

Name	Function	Input	Output
crop_sensitive()	Compute crop sensitive indices	According to each method that can be a numeric vector (default), an array, data.frame or sf (POINT or POLYGON), the later two designed to fetch data from cloud sources	A dataframe with crop sensitive indices with n colunms depending on the number of thresholds passed to each index
Eto()	Reference evapo-transpiration	According to each method that can be a vector (default), an array, data.frame or sf (POINT or POLYGON), the later two designed to fetch data from cloud sources	The reference evapotranspiration
GDD()	Compute growing degree-days	According to each method that can be a numeric vector (default), an array, data.frame or sf (POINT or POLYGON), the later two designed to fetch data from cloud sources	Either the cumulative sum of gdd across time (the default), or the gdd obtained in each day, or the number of days required to reach a certain amount of gdd
late_frost()	Compute the occurrence of late-spring frost	According to each method that can be a numeric vector (default), an array, data.frame or sf (POINT or POLYGON), the later two designed to fetch data from cloud sources	A data.frame with the duration and gdd accumulated during the events of frost, latency (where there is no frost event, but also there is no gdd), and warming (where gdd is accumulated)
rainfall()	Precipitation indices	According to each method that can be a numeric vector (default), a matrix, data.frame or sf (POINT or POLYGON), the later two designed to fetch data from cloud sources	Either the indices considering the series as a whole, or time series indices splitted into equal intervals of days
temperature()	Temperature indices	According to each method that can be a numeric vector (default), an array, data.frame or sf (POINT or POLYGON), the later two designed to fetch data from cloud sources	Either the indices considering the series as a whole, or time series indices splitted into equal intervals of days

taking the integral of warmth above a base temperature (T_0). The function `GDD()` applies by default the following equation.

Equation [1]

$$GDD = \frac{T_{max} + T_{min}}{2} - T_0$$

Where T_{max} is the maximum temperature in the given day, T_{min} is the minimum temperature in the given day and T_0 is the minimum temperature for growth (as per the physiology of the focal organism or ecosystem averages).

Additionally, the function `GDD()` offers three modified equations (two) designed for cold environments and (one) for tropical environments. For cold environments, where T_{min} may be lower than T_0, there are two variants of the previous equation to adjust either T_{mean} (variant a) or T_{min} (variant b). The variant a changes T_{mean} to T_0 if $T_{mean} < T_0$ and is expressed as follows.

Equation [2]

$$GDD = max\left(\frac{T_{max} + T_{min}}{2} - T_0,\ 0\right)$$

The variant b, is calculated using Equation 1, but adjusts T_{min} or T_{max} to T_0 if $T < T_0$, the equation is adjusted as follows.

Equation [3]

$$T < T_0 \ \rightarrow \ T = T_0$$

Where T may refer to T_{min} and/or T_{max} when the condition of being below T_0 applies.

For tropical areas, where the temperature may surpass a maximum threshold ($T_{0^{max}}$), resulting in limited development, the minimum temperature is adjusted using Equation 3 and the maximum temperature is adjusted to a maximum base temperature as follow.

Equation [4]

$$T_{max} > T_{0^{max}} \ \rightarrow \ T_{max} = T_{0^{max}}$$

Where $T_{0^{max}}$ is the maximum base temperature for growth, defined in `GDD()` using the argument `tbase_max`.

These modified equations are defined as 'a', 'b' and 'c', respectively, and can be selected using the argument `equation`.

By default, the function returns the degree-days that is accumulated over the time series using Equation 1. Additionally, the function may return the daily values of degree-days or the number of days that a given organism required to reach a certain number of accumulated degree-days. These values are defined by 'acc', 'daily' or 'ndays' and can be adjusted using the argument `return.as`. The required accumulated gdd is defined with argument `degree.days`. For example, the Korean pine (*Pinus koraiensis*) requires 105 $°C$ accumulated gdd to onset the photosynthesis (Wu et al. 2013). In that case, the `GDD()` will calculate the growing degree-days (gdd) and sum up the values until it reaches the defined gdd (105 $°C$) and return the number of days needed in the given season (GDD_{ndays}), as follows.

Equation [5]

$$\parallel GDD_{ndays} \parallel = \ ggd_1 \ + \ ... \ + \ gdd_n$$

Reference evapotranspiration

The reference evapotranspiration measures the influence of the climate on a given organism water needs, generally a crop species (Brouwer and Heibloem 1986). The function `ETo()` applies the Blaney-Criddle method, a general theoretical method used when only air-temperature is available locally. It should be noted that this method is not very accurate and aims to provide the order of magnitude of evapotranspitation. The reference evapotranspiration is calculated using the following equation.

Equation [5]

$$ETo = p \times \left(0.46 \times \frac{T_{max} + T_{min}}{2} + 8\right) \times K_c$$

Where p is the mean daily percentage of annual daytime hours, T_{max} is the maximum temperature, T_{min} is the minimum temperature, and K_c is the factor for organism water need may change according to the growth stage.

The percentage of daytime hours (p) is calculated internally by most methods in `ETo()` (except the array method) using the given latitude (taken from the inputted `object`) and date (taken from the inputted `day.one`). It matches the latitude and date with a table of daylight percentage derived from Brouwer and Heibloem (1986). The table can be verified using `climatrends:::daylight`.

Examples

Common beans

Replicate part of the analysis in van Etten et al (2019) with the beans data to show how we can use this package to capture the influence of climate variability on crop performance. The idea is to show the same PlackettLuce Tree.

Time series

Pick some random points in Norway (or Scandinavia??) and check how the trends on temperature indices over the last 20 years.

Seed germination or some GDD related analysis

Use the data from seed germination or crop growth to compute GDD. How many GDD a seed need to become a seedling?

Further development

Integration with other datasets as they become available in `R` via API client packages. New indices related to the physiology of crops to be implemented while I work on the rice data.

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