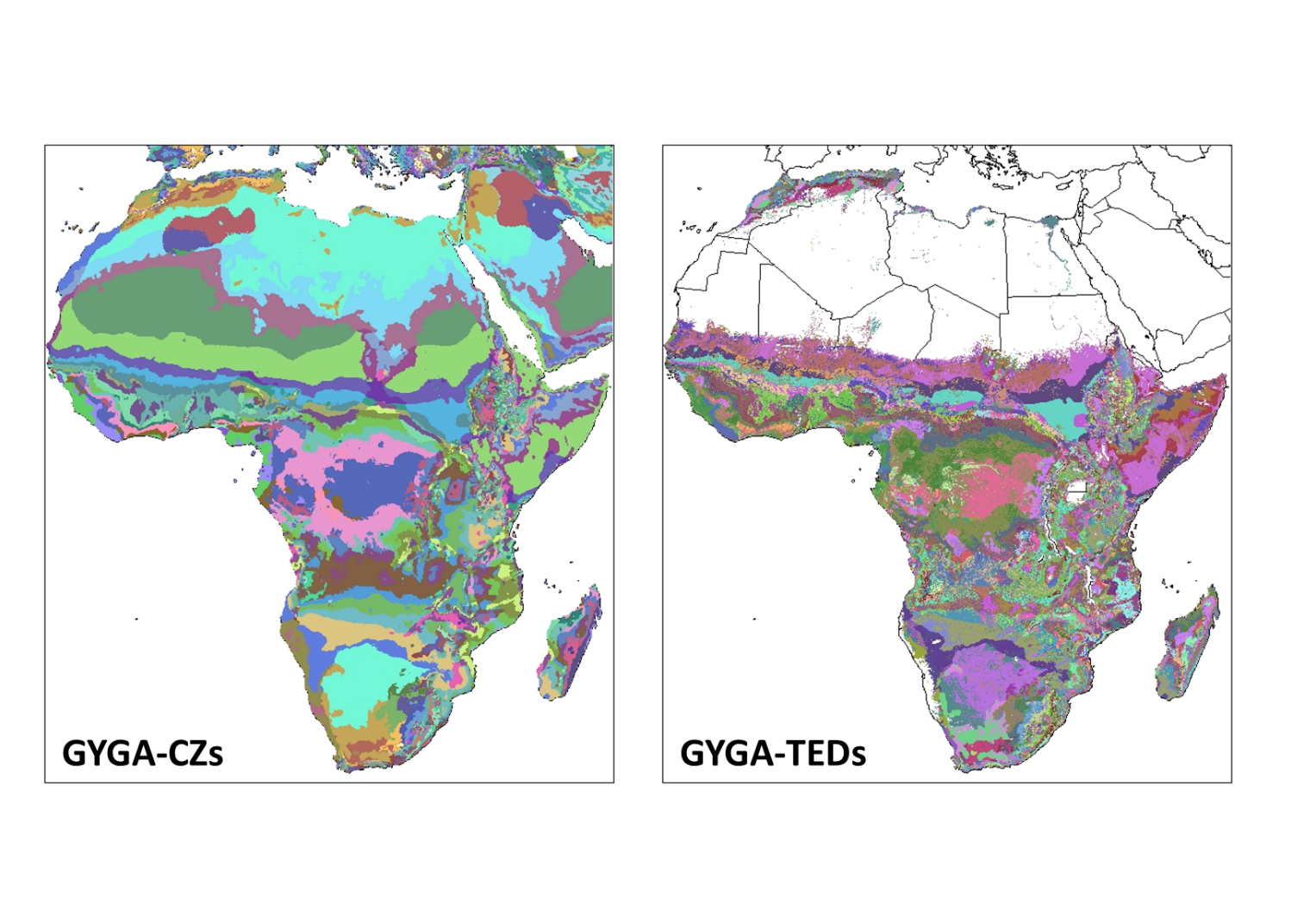
**The GYGA Technology Extrapolation Domains (GYGA-TEDs) for Sub-Saharan Africa**

**Introduction**

A robust spatial framework that delineates regions in which crop production technologies perform similarly can help address current limitations on extrapolation of results from agronomic ﬁeld experiments to larger regions. In principle, the impact of a particular agronomic technology should be predictable and of reasonably similar magnitude within a spatially deﬁned region with similar biophysical attributes. We developed a spatial framework called Technology Extrapolation Domains (TEDs) that delineates regions based on four biophysical attributes that govern rainfed crop yield and its inter-annual variability: (i) annual total growing degree-days (GDD), which, in large part, determines the length of crop growing season, (ii) aridity index (AI), which largely deﬁnes the degree of water limitation in rainfed cropping systems, (iii) annual temperature seasonality (TS), which diﬀerentiates between temperate and tropical climates, and (iv) plant-available water holding capacity in the rootable soil depth (PAWHC), which determines the ability of the soil to supply water to support crop growth during rain-free periods ***(Figure 1)***.

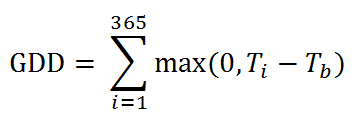


**Figure 1.** Sub-Saharan Africa GYGA-TEDs.

**Data sources and delineation of GYGA-TEDs**

1. Growing degree days (GDD)

The GDD were calculated as in Licker *et al.* ([2010](https://www.yieldgap.org/web/guest/cz-ted#_ENREF_2)) with:



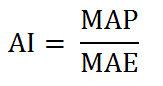
in which  is the temperature (°C) for each time step and is  the base temperature (0 °C for our calculations).  Licker *et al.* ([2010](https://www.yieldgap.org/web/guest/cz-ted#_ENREF_2)) used mean monthly temperatures for the period 1961-1990 from the CRU CL v. 2.0 dataset at 10' grid (<http://www.cru.uea.ac.uk/cru/data/hrg/tmc/>, ([New*et al.*, 2002](https://www.yieldgap.org/web/guest/cz-ted#_ENREF_5))) and downscaled it to a 5' grid.

1. Temperature seasonality

Temperature seasonality was taken from WorldClim (<http://www.worldclim.org/current> , data for current conditions (~1950-2000), Bioclim4 at 5' grid, ([Hijmans](https://www.yieldgap.org/web/guest/cz-ted" \l "_ENREF_1" \o "Hijmans, 2005 #740)*[et al.](https://www.yieldgap.org/web/guest/cz-ted" \l "_ENREF_1" \o "Hijmans, 2005 #740)*[, 2005](https://www.yieldgap.org/web/guest/cz-ted" \l "_ENREF_1" \o "Hijmans, 2005 #740))), calculated as the standard deviation of the 12 mean monthly temperatures × 100 (note that mean monthly temperatures are in °C × 10).

1. Aridity index (AI)

The annual aridity index values were taken from CGIAR-CSI (<http://www.cgiar-csi.org/data/global-aridity-and-pet-database>, at 30'' grid, ([Trabucco](https://www.yieldgap.org/web/guest/cz-ted" \l "_ENREF_6" \o "Trabucco, 2008 #807)*[et al.](https://www.yieldgap.org/web/guest/cz-ted" \l "_ENREF_6" \o "Trabucco, 2008 #807)*[, 2008](https://www.yieldgap.org/web/guest/cz-ted" \l "_ENREF_6" \o "Trabucco, 2008 #807); [Zomer](https://www.yieldgap.org/web/guest/cz-ted" \l "_ENREF_11" \o "Zomer, 2008 #806)*[et al.](https://www.yieldgap.org/web/guest/cz-ted" \l "_ENREF_11" \o "Zomer, 2008 #806)*[, 2008](https://www.yieldgap.org/web/guest/cz-ted" \l "_ENREF_11" \o "Zomer, 2008 #806))), calculated as:



in which MAP is the mean annual precipitation (mm × 100) and MAE the mean annual potential evapotranspiration (mm × 100). We aggregated these AI values to a 5' grid, taking the spatial average of the 100 cells at 30 arcsecond resolution within each 5 arcminute gridcell. Next, we multiplied the spatially averaged AI with 10000.

1. Root zone plant-available water holding capacity (RZPAWHC)

Plant-available soil water holding capacity in the root zone was taken from the Africa Soil Information Service (AfSIS; <http://www.isric.org/projects/afsis-gyga-functional-soil-information-sub-saharan-africa-rz-pawhc-ssa> version April 2015, af\_agg\_ERZD\_TAWCpF23mm\_\_M\_1km.tif, with a resolution of 1 × 1 km).

RZPAWHC is determined by evaluation and spatial interpretation of the AfSIS soil profile database:

1. the so-called "legacy" soil point data (Africa Soil Profiles database v1.2;18,500 points) and
2. all AfSIS sentinel site soil point data (approx. 9,600 points, including spectral data and 10% wet chemistry reference data), which were provided by AfSIS for this collaboration,
3. SoilGrids1km layers ([www.isric.org/explore/soilgrids](http://www.isric.org/explore/soilgrids)) produced at ISRIC using global models; updated and fine-tuned fitting a continental model, with finer resolution satellite data and above mentioned soil data, resulting in AfrSoilGrids250m ([www.isric.org/projects/africa-soilgrids-soil-nutrient-maps-sub-saharan-africa-250-m-resolution](http://www.isric.org/projects/africa-soilgrids-soil-nutrient-maps-sub-saharan-africa-250-m-resolution)).

**Aggregation of biophysical variables in classes**

Following Van Wart et al. (2013), aridity index and GDD values were aggregated into 10 classes and combined in a grid matrix with 3 classes of temperature seasonality to give a total of 300 classes (referred to as “climate zones”). Of these, only 265 occur in regions where major food crops are grown. RZPAWHC values were classified into 25 or 50 mm classes, with 0-50 mm as the lower class and >300 mm as the upper class. Climate zones were combined with the RZPAWHC map to create the TED maps, where each grid is assigned to a TED based upon the combination of the four biophysical variables (GDD, AI, TS, and RZPAWHC).

A coding system allows identifying the combination of biophysical attributes. Briefly, a unique code is assigned to each of the classes of biophysical variables. Then the code of the four biophysical variables within a given TED grid is added together to determine the code of the TED grid. Large GDD values correspond to warm locations while high TS values are associated to site with large differences in temperature among seasons. In the case of AI, low and high value are associated to dry and wet environments, respectively.

Coding for the biophysical variables is shown below:

|  |  |
| --- | --- |
| GDD (°Cd) | GDD code |
| 0 - 2670 | 1000 |
| 2671 - 3169 | 2000 |
| 3170 - 3791 | 3000 |
| 3792 - 4829 | 4000 |
| 4830 - 5949 | 5000 |
| 5950 - 7111 | 6000 |
| 7112 - 8564 | 7000 |
| 8565 - 9311 | 8000 |
| 9312 - 9850 | 9000 |
| > 9851 | 10000 |

|  |  |
| --- | --- |
| AI (-) | GYGA-CZ Value |
| 0 - 2695 | 000 |
| 2696 - 3893 | 100 |
| 3894 - 4791 | 200 |
| 4792 - 5689 | 300 |
| 5690 - 6588 | 400 |
| 6589 - 7785 | 500 |
| 7786 - 8685 | 600 |
| 8686 - 10181 | 700 |
| 10182 - 12876 | 800 |
| > 12877 | 900 |

|  |  |
| --- | --- |
| Temperature seasonality | GYGA-CZ Value |
| 0 - 3832 | 01 |
| 3833 - 8355 | 02 |
| > 8356 | 03 |

As a component of the GYGA-TED spatial framework, there are two classifications for RZPAWHC values. For the **fine TEDs** the RZPAWHC values are classified into ten 25 mm classes, with =< 50 mm and >250 mm as lower and upper classes, respectively. For the **coarse TEDs** the RZPAWHC values are classified into seven 50 mm classes, with 0-50 mm as the lower class and >300 mm as the upper class.

This classification of the variables resulted in the following ranges:

**Fine TEDs:**

|  |  |
| --- | --- |
| RZWHC (mm) | RZWHC Value |
| 0 - 50 | 100000 |
| 50 - 75 | 200000 |
| 75 - 100 | 300000 |
| 100 - 125 | 400000 |
| 125 - 150 | 500000 |
| 150 - 175 | 600000 |
| 175 - 200 | 700000 |
| 200 - 225 | 800000 |
| 225 - 250 | 900000 |
| > 250 | 1000000 |

**Coarse TEDs:**

|  |  |
| --- | --- |
| RZWHC (mm) | RZWHC Value |
| 0 – 50 | 100000 |
| 50 - 100 | 200000 |
| 100 - 150 | 300000 |
| 150 - 200 | 400000 |
| 200 - 250 | 500000 |
| 250 – 300 | 600000 |
| > 300 | 700000 |

**Examples for hypothetical TED codes are shown below:**

Value for each cell indicates the unique combination of soil type and climate for that cell. The value of the GYGA-TEDs is constructed by the sum of the three climate variables and the value of the RZPAWHC variable is added. A few examples:

|  |  |  |
| --- | --- | --- |
| * value 101001 = | RZPAWHC value | 100000 |
|  | GDD value | 1000 + |
|  | AI value | 0 + |
|  | Temperature seasonality value | 01 |
| * value 806801 = | RZPAWHC value | 800000 |
|  | GDD value | 6000 + |
|  | AI value | 800 + |
|  | Temperature seasonality value | 01 |
| * value 1010402 = | RZPAWHC value | 1000000 |
|  | GDD value | 10000 + |
|  | AI value | 400 + |
|  | Temperature seasonality value | 02 |

**TED evaluation**

Although the TED framework can be applied worldwide, evaluation of the TEDs required detailed and spatially explicit data of weather, soil, crop management and yields. The TED spatial framework was evaluated on its capacity to account for variation in crop performance and management practices across spatial and temporal dimensions using soybean and maize in the US Corn Belt as case studies ([Rattalino Edreira et al., 2018](file:///C:\Users\jandrade3\AppData\Local\Microsoft\Windows\INetCache\Content.Outlook\C5RS4761\technology_exrapolation_domains_teds_description_-_final_1_jire.docx#_ENREF_7)). In that study, the TED framework was able to distinguish regions with different yield level, yield stability, and management practices for the two crops (maize and soybean), across two spatial scales (county- and ﬁeld-level), and two dimensions (temporal and spatial) over a large geographic region with diversity in climate and soil that account for about one-third of global maize and soybean production. On a separate study, [Mourtzinis et al. (2020](file:///C:\Users\jandrade3\AppData\Local\Microsoft\Windows\INetCache\Content.Outlook\C5RS4761\technology_exrapolation_domains_teds_description_-_final_1_jire.docx#_ENREF_4)) compared the performance of different stratification methods, including the TEDs, to group farmer fields according to their biophysical background. Despite its simplicity, the TEDs exhibited similar performance to other more data-intensive approaches relying on a larger number of parameters.

**TED application**

The TED framework presented here can help (i) optimize the number of environments covered by a ﬁeld trial to maximize the crop area coverage or, alternatively, to reduce the number of sites without sacriﬁcing crop area coverage, (ii) select speciﬁc environments for testing a technology where it is most likely to have the greatest impact based on biophysical attributes of the selected TEDs, (iii) up-scale results from experiments or field trials to larger geographic areas, and (iv) identify geographic areas where a given technology is expected to have a similar impact. Examples showing applications of the TED framework can be found elsewhere ([Andrade et al., 2019](file:///C:\Users\jandrade3\AppData\Local\Microsoft\Windows\INetCache\Content.Outlook\C5RS4761\technology_exrapolation_domains_teds_description_-_final_1_jire.docx#_ENREF_1); [Mourtzinis et al., 2018](file:///C:\Users\jandrade3\AppData\Local\Microsoft\Windows\INetCache\Content.Outlook\C5RS4761\technology_exrapolation_domains_teds_description_-_final_1_jire.docx#_ENREF_5); [Rattalino Edreira et al., 2017](file:///C:\Users\jandrade3\AppData\Local\Microsoft\Windows\INetCache\Content.Outlook\C5RS4761\technology_exrapolation_domains_teds_description_-_final_1_jire.docx#_ENREF_8)).

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