

Web-based access, aggregation, and visualization of future climate projections with emphasis on agricultural assessments.

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Abstract

Access to climate and spatial datasets by non-specialists is restricted by technical barriers involving hardware, software and data formats. We discuss an open-source online tool that facilitates downloading the climate data from the global circulation models used by the ISI-MIP project. The tool also offers temporal and spatial aggregation capabilities for incorporating future climate scenarios in applications where spatial aggregation is important. We hope that streamlined access to these data facilitates analysis of climate related issues while considering the uncertainties derived from future climate projections and temporal aggregation choices.

Keywords: Climate data, CMIP5, Climate models, HUBzero, Growing season temperature, Growing season precipitation, Climate change and agriculture

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1. Motivation and significance

Studies of the effects of climate change on agriculture typically involve using observational data to determine the parameters connecting climate variables to agricultural productivity and then using future climate projections from global circulation models (GCM) to evaluate potential future impacts or the effects of alternative policies [e.g., 1]. Given the uncertainty surrounding future climate projections it is considered best practice to use the output of several GCM in order to obtain a range of potential outcomes [2]. Despite increases in the availability of climate data stemming from the coordination between climate modeling groups through the Coupled Model Intercomparison Project Phase 5 (CMIP5) and their collaboration with the Intergovernmental Panel on Climate Change, access by non-specialists is hindered by technical barriers including software, hardware and the need of specialized skills to handle non-standard formats [3]. In addition to access to data, spatial processing is not trivial requiring expertise in geographic information systems (GIS) methods to process both climate data as well as auxiliary datasets [4].

The tool discussed in this article seeks to reduce the technical barriers to access climate model outputs through a web-based facility that facilitates downloading and aggregating global grids (0.5 degree) of bias-corrected, monthly mean historical and future temperature and precipitation from the five General Circulation Models (GCMs) used by the Inter-Sectoral Impacts Model Intercomparison Project [ISI-MIP; 5, 6]. (See table 2 for included models). The scientific problem the tool contributes to solve is to facilitate the analysis of future climate scenarios in applications where spatial aggregation is important. This includes a wide range of economic analysis focused on either impact assessment [7, 8, 9] or policy analysis [10].

The tool targets mainly, but not exclusively, researchers interested on the effects of climate change on agriculture. At the most general level, the Climate Scenario Aggregator (CSA) tool can be used as a downloading platform of the raw GCM data in the ISI-MIP archive. The target user of this functionality is skilled with NetCDF formats, has a relatively powerful computer, reasonable bandwidth, and is comfortable with the scripting and/or programming languages needed for manipulating and processing spatially-explicit data. A second target user may need some assistance with basic pre-processing of the data, such as temporal and spatial aggregation. This user will benefit from the aggregation programs as well as preprocessed datasets for temporal aggregation (crop calendars) and spatial aggregation (e.g., from gridcells to countries.) Finally, a third target user may be interested in the download and aggregation capabilities of the tool, but wishes to employ al-

41 ternative spatial aggregation schemes (e.g., gridded population.)

42 The CSA tool is related to other tools that seek to facilitate access to
43 and spatial geoprocessing of climate data while leveraging shared resources
44 and expertise. Examples of these tools are given by [3], who developed
45 user-friendly software applications for downscaling climate data for ecological
46 modeling applications. Meanwhile, [11] have built an aggregation tool that
47 facilitates access to the gridded forecast of yield changes produced by the
48 The Agricultural Model Intercomparison and Improvement Project [AgMIP;
49 12].

50 2. Software description

51 The tool is available at the GEOSHARE HUBzero website (<https://mygeohub.org/tools/climatetool>) using any standard Internet browser.
52 The CSA tool allows users to calculate for each half-degree land pixel a crop-
53 specific growing season average value of temperature and precipitation using
54 the global crop calendars from [13] (See table 2 for crop coverage.) The
55 tool also permits aggregating the pixels to larger geographic units using crop
56 harvested area and production from [14]. All the programs—a java graphical
57 user interface (GUI) and a set of R functions— can be freely downloaded
58 and reused. Documentation and support for users include a User’s Manual¹
59 as well as a set of default regional maps and weighting schemes.
60

61 2.1. Software Architecture

62 HUBzero [15], is an open source software platform specializing in dissem-
63 inating simulation and data tools via the world wide web. Originated in the
64 nanotechnology community (<https://nanohub.org/tools/>), HUBzero has
65 evolved to constitute a flexible environment and recent efforts have focused
66 on developing capabilities for processing and delivering spatially explicit data
67 using shared remote resources which have given rise to a series of user com-
68 munities and shared tools². Users access the CSA tool at GEOSHARE using

¹Included as an Appendix for the reviewers convenience.

²Including the tools from the GeoSpatial Analysis and Building Blocks Project (GABBS, <https://mygeohub.org/groups/gabbs>): SWATShare (<https://mygeohub.org/groups/water-hub/swatshare>), MultiSpec (<https://mygeohub.org/tools/multispec>), Water Deficit Viewer (<https://mygeohub.org/tools/deficitviewer>), and the Active Learning Tool (<https://mygeohub.org/tools/act>); as well as of those from the GEOSHARE project: the AgMIP tool, which aggregates outputs from the AgMIP’s Global Gridded Crop Modeling Initiative at <https://mygeohub.org/tools/agmip>, and FLAT, a tool for downscaling national and sub-national level statistics on harvested area available at <https://mygeohub.org/tools/flat>.

69 an ordinary Web browser without having to download or compile any code
70 specific to the tools. The tool runs in an isolated light-weight virtual ma-
71 chine container and is displayed in the user’s web browser using a graphical
72 desktop sharing technology called Virtual Network Computing (VNC).

73 *2.2. Software Functionalities*

74 The CSA tool has four main functionalities: data download, data ag-
75 gregation, output and metadata, and visualization. Download, aggregation,
76 and visualization are implemented as tabs in the graphical user interface
77 shown in figures 1 and 2. The climate data is stored in NetCDF files. Each
78 file is identified by a file name with seven components that specifies a vari-
79 able: temperature (minimum, maximum, average) or precipitation; a climate
80 model: HadGEM2-ES [16], IPSL-CM5A-LR [17], MIROC-ESM-CHEM [18],
81 GFDL-ESM2M [19], and NorESM1-M [20]; a representative concentration
82 pathway [21]: historical, RCP2.6, RCP4.5, RCP6.0 and RCP8.5; and a time
83 period that ranges from 1960 to 20099. For instance:

```
84 tas_bced_1960_1999_noresm1-m_rcp2p6_2006-2010.mm.nc  
85 tas_bced_1960_1999_noresm1-m_rcp2p6_2011-2020.mm.nc  
86  
87  
88  
89 tas_bced_1960_1999_noresm1-m_rcp2p6_2091-2099.mm.nc
```

90 are global grids of monthly air surface temperature means (one grid for each
91 year in the period 2006-2099), projected by NorESM1-M [20], under repre-
92 sentative concentration pathway RCP2.6 [21].

93 In order to retrieve the data, the user selects a unique combination of
94 variable, climate model and scenario which are all presented in the tool’s
95 user front-end (figure 1). The user’s selections create a character string that
96 matches the file names stored in the the ISI-MIP archive. This character
97 string is used to retrieve all the available years— in most cases, each file
98 stores information on 10 years worth of data— for the selected scenario.
99 GEOSHARE’s Hub and the ISI-MIP archive are connected through Globus
100 Online [22], a service that facilitates transfer of large datasets.

101 Once in GEOSHARE’s Hub, the files are stored in a common server
102 workspace. Before each data request, the tool checks whether the data has
103 already been downloaded, and if so, indicates this to the user. This feature
104 avoids downloading the same data more than once. At this point, the user
105 can either download the raw NetCDF files for custom processing on her
106 desktop, or proceed to aggregate the data through the GUI implementation
107 in figure 2).

108 Aggregation is performed by three R functions. The first function reads
109 the data using the R NetCDF package by [23]. The second function estimates
110 pixel and crop specific growing-season averages of the chosen climate variable.
111 Planting and harvesting months for each pixel are from [13]. In many cases,
112 the harvesting month is in a different year than the planting month. For
113 example, planting of corn in most of Argentina occurs in October and the
114 crop is harvested in April of the following year. Meanwhile, corn planting in
115 the U.S. starts in May with crops harvested in September. In order to avoid
116 ambiguities we assign the average value of the variables (e.g. temperature)
117 over the growing season for the month in which the harvest occurs. So, the
118 value of the average growing season temperature for year 2000 corresponds
119 the the Argentinean harvest of April 2000 and the US harvest of September
120 2000 (see figure 3).

121 A third R function performs the aggregation from grid-cells to larger
122 geographic units. The user has the opportunity to select different aggregation
123 schemes or upload her own. For example, aggregation from the grid-cell to
124 country level requires a mapping that correlates each latitude and longitude
125 pair with a unique country name. The mapping schemes are simple comma
126 separated value files. By default, we have included regional mappings from
127 grid-cells to countries, country-AEZ regions, and global. Simple guidelines
128 for preparing these data files are in the User’s Manual, which can be retrieved
129 from either the description page of the tool. In addition the tool allows for
130 weighted and unweighted aggregations. Files are provided from weighted
131 aggregations using harvested areas and production based on the gridded crop
132 harvested area and yield statistics from [14] .

133 The CSA tool also keeps a record of the user’s choice producing a text file
134 that indicates the chosen combination of GCM, RCP and variables which can
135 be obtained by clicking on “Data description” in the Download tab (figure 1).
136 For users performing an aggregation in the Aggregation tab, the documen-
137 tation includes aggregation choices as well as the source of the aggregation
138 weights (see figure 2.)

139 **3. Illustrative Examples**

140 Figure 4 displays four plots that illustrate the versatility of the tool in
141 terms of spatial and temporal aggregation of the the GCM outputs. Fig-
142 ure 4.A compares growing-season temperatures for wheat in a single gridcell
143 near Manhattan, Kansas in the US. Figure 4.B displays historical and av-
144 erage temperatures during the growing season of maize for the US using
145 projections for RCP 2.6 for the five GCMs included in the ISI-MIP archive.
146 In this case, the individual gridcells have been weighted by their contribu-

147 tion to total US maize production using production weights. An interesting
148 feature of Figure 4.B is that allows to understand the uncertainty embedded
149 in the model and eventually include this uncertainty in modeling exercises
150 or impact analyzes. The two following figures, C and D, display temperature
151 and precipitation aggregated from individual gridcells to the global level us-
152 ing three different aggregation modalities: weighted averages using harvested
153 area weights, weighted averages using production weights, and unweighted
154 averages. These two figures exemplify the usefulness of the tool for evaluating
155 different empirical choices of aggregation at different spatial scales.

156 **4. Impact**

157 Our software makes three contributions. First it provides straightforward
158 access to an important number of models in the CMIP5 archive. Second, it
159 provides important GIS functionality for data aggregation. Finally, all the
160 downloading and processing is in remote servers. It is likely that these con-
161 tributions have varying degrees of appeal for different users, nevertheless,
162 by expanding access and lowering entry barriers to use, we expect that this
163 tool advances the study of the impacts of climate change in world agricul-
164 ture across several geographic scales. The potential research questions that
165 benefit for streamlined access to climate data include statistical analysis of
166 future climate patterns; modeling the human and ecological impacts of cli-
167 mate change; an the evaluation of adaptation and mitigation policies. The
168 tool also facilitates streamlined descriptions of climate patterns at different
169 spatial scales as well as exploring the effects of different aggregation mecha-
170 nisms.

171 **5. Limitations**

172 An important consideration to keep in mind is that these models are a
173 subset of the around thirty-six models that contributed to the CMIP5 data
174 archive. These five models were selected because they were the first to sup-
175 ply data that met the minimum data requirements of the ISI-MIP project [5,
176 p. 221]. It is also important to keep in mind that for many regions these
177 models are likely to underestimate the uncertainty in future climate projec-
178 tions [24]. In particular, these authors find that “the fraction of the of the
179 full range of future projections captured across different regions and seasons
180 by the ISI-MIP subset varies from 0.5 to 0.9 for temperature (median 0.75)
181 and 0.3 to 0.8 for precipitation (median 0.55).” This is a general problem
182 in climate scenario selection. Even if dry, wet, cool or hot climate projec-
183 tions can be specifically selected for particular regions, including the global

184 aggregation, these characteristics do not necessarily hold for other regions.
185 As such, a climate projection that is specifically dry and hot compared to
186 other projections in one region may be cool and wet in other regions. [24]
187 find that at least 13 climate model projections are needed to cover a sub-
188 stantial range of the uncertainty in all regions. This tool cannot be easily
189 extended to all climate projections from the CMIP5 archive, as these are not
190 available in bias-corrected form as done by [5], but we encourage users to
191 note the limited representation of scenario selection in the interpretation of
192 their applications.

193 **6. Conclusions**

194 Access to climate and spatial datasets by non specialists is hindered by
195 technical difficulties involving software and data formats as well as the need
196 for strong Internet bandwidth and storage capacity. This article discusses
197 a GEOSHARE HUBzero tool that expands access to the climate data that
198 underlies the AgMIP Global Gridded Crop Model Intercomparison (GGCMI)
199 Project to the broader scientific community who can benefit from these data,
200 but who may lack the resources to gain access to them. We hope that this
201 software tool enables researchers facing technical limitations to overcome
202 these barriers.

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331 [S2405880715300170](http://www.sciencedirect.com/science/article/pii/S2405880715300170)

| Nr. | Code metadata description | Value |
|------------|---|---|
| C1 | Current code version | Version 1.0.0 |
| C2 | Permanent link to code/repository used for this code version | https://mygeohub.org/tools/climatetool |
| C3 | Legal Code License | GNU General Public License |
| C4 | Code versioning system used | LZ |
| C5 | Software code languages, tools, and services used | Java, R |
| C6 | Compilation requirements, operating environments & dependencies | None |
| C7 | If available Link to developer documentation/manual | https://mygeohub.org/tools/climatetool |
| C8 | Support email for questions | Built-in HUBzero ticket support system |

Table 1: Code metadata

| Climate Models | Scenarios | Crops |
|--|---|---|
| HadGEM2-ES [16], IPSL-CMSA-LR [17], MIROC-EXM-CHEM [18], GFDL-ESM2M [19], NorESM1-M [20] | Historic, RCP8.5, RCP 6.0, RCP4.5, RCP2.6 | Barley (winter, spring), cassava, cotton, groundnuts, maize, millet, oats (winter, spring), potatoes, pulses, rapeseed-winter, rice, rye-winter, sorghum, soybeans, sugarbeets, sunflower, sweet potatoes, wheat (winter, spring), and yams |

Table 2: Coverage of the Climate Scenario Aggregator tool

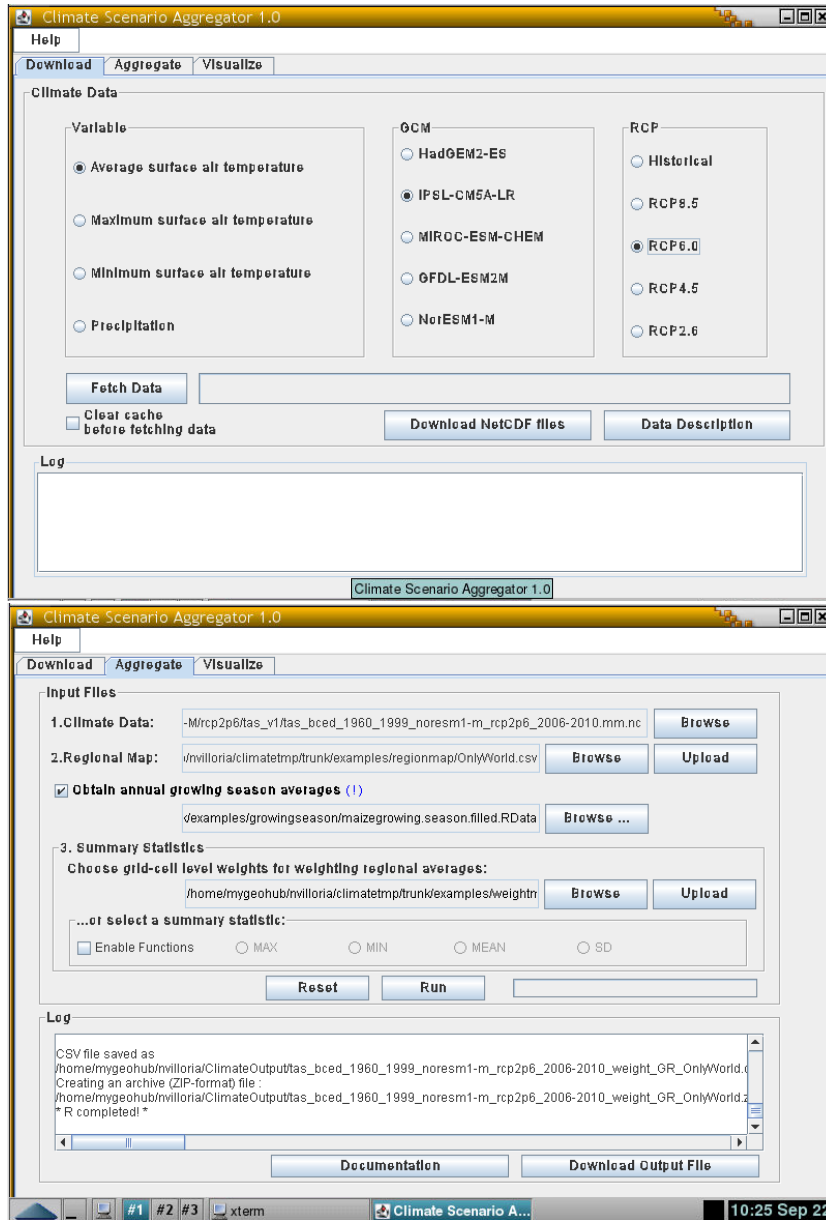


Figure 1: Climate Scenario Aggregator tool download tab. Interface for data selection and retrieval including climate model, variable, and RCP.

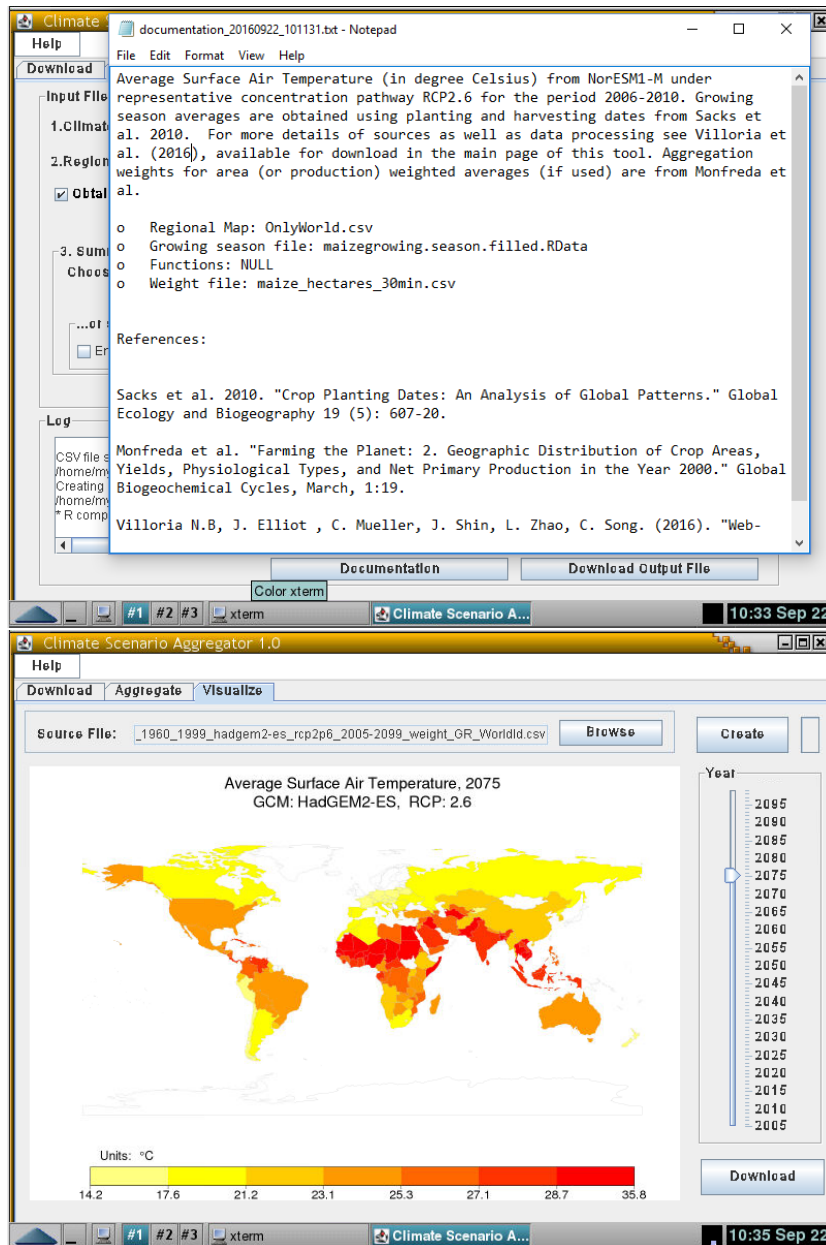


Figure 2: Climate Scenario Aggregator tool visualization, self-documentation and meta-data.

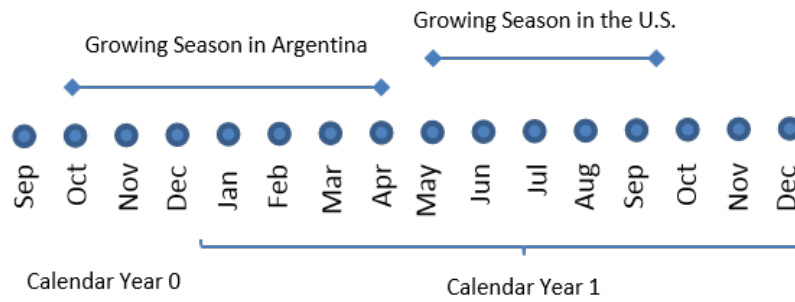


Figure 3: The average temperature/precipitation over the growing season is assigned to the calendar year in which the harvest season occurs. In the example, for Argentina, the average temperature/precipitation in Calendar Year 1 is taken over October 0-April 1 while in the U.S. (Midwest region) is taken over May 1-September 1. The planting and harvesting dates for each country are from [13].

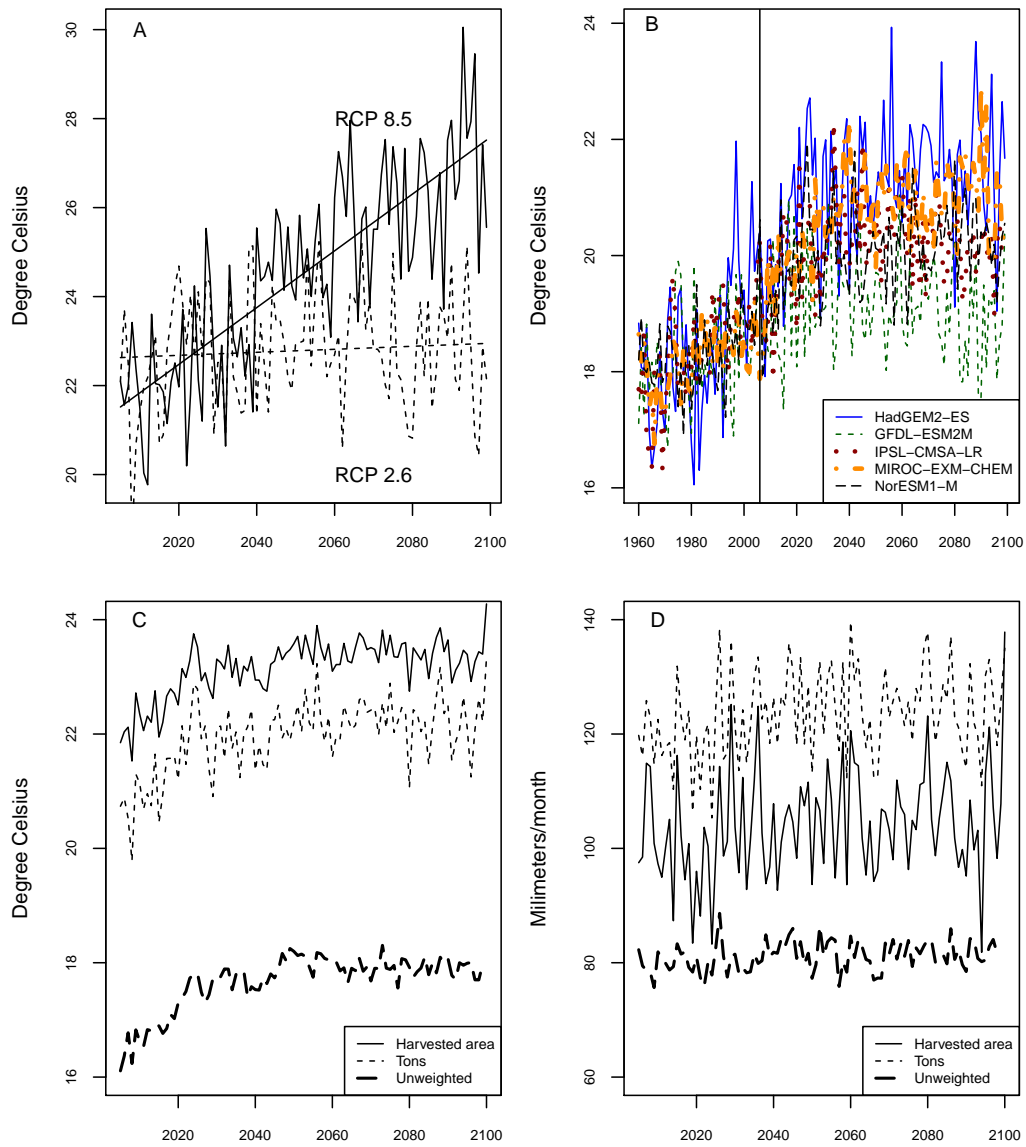


Figure 4: A: Average temperature during the wheat growing season at 96.25W-39.75N (near Manhattan, Kansas, USA) under RCP 2.6 and 8.5 from HadGEM2-ES ; B: Area-weighted average temperature during the maize growing season in the US, RCP 2.6 for the five available climate models; C: Global weighted (using harvested area and production weights) and unweighted average temperature over the maize growing season; D: Global weighted (using harvested area and production weights) and unweighted average precipitations over the maize growing season.