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Disaggregation of Global Circulation Model Outputs
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Summary

In light of agricultural researchers' and geographers' need for high resolution surfaces to assess climate change impacts on agriculture and biodiversity-related matters, downscaling of GCM (General Circulation Model) outputs has taken on particular importance, and several downscaling methods have been developed to date. These methods have a range of mathematical and/or physical formulations. Some researchers, however, state that downscaling of GCM forecasts is not possible and that the process might substantially and systematically increase uncertainties while reducing the accuracy of the forecasts. Higher resolution surfaces do not necessarily mean a higher accuracy. They rather suggest disaggregation of GCM forecasts. Disaggregation differs from downscaling in that it is unlikely that the former affects the original spatial or temporal GCM variability. Consequently, disaggregation is less vulnerable to criticisms that it alters original GCM patterns.

Here we present a set of disaggregated GCM predictions, as well as a global database on climate change data that can be used for crop modeling, niche modeling, and more generally, for assessments of climate change impacts on agriculture at fine scales. The dataset is applicable for any approach that might require monthly maximum, minimum, mean temperatures and monthly total precipitation (from which a set of bioclimatic indices were be also derived). This database (with a total of 441 different scenarios –sum of 24, 20 and 19 GCMs, times 7 time-slices) complements other existing databases that use downscaling, by providing a complementary method through which future climate scenarios can be developed at higher spatial resolutions than the original GCM spatial resolution.. The datasets are available online at http://gisweb.ciat.cgiar.org/GCMPage.

Introduction

In light of agricultural researchers' and geographers' need for high resolution surfaces to assess climate change impacts on agriculture and biodiversity-related matters, , downscaling of GCM (General Circulation Model) outputs has taken on particular importance, and several downscaling methods have been developed to date. Methods have a range of mathematical and/or physical formulations, from smoothing and interpolation of future climates or changes in climates, to neural networks, and Regional Climate Modeling. Some researchers, however, state that downscaling of GCM forecasts is not possible and that the process might substantially increase uncertainties while reducing the accuracy of the forecasts. Higher resolution downscaled surfaces do not necessarily mean more accurate forecasts derived products (i.e. products from impact assessment models).

The choice of using GCM data "as is" or attempting to increase GCM resolution turns into a paradox since (1) GCM outputs are not useful for impact assessment in most landscapes, and (2) downscaling methods might create a false sense of greater accuracy while in actuality they may be increasing uncertainties and reducing the accuracy of impact assessment models. In view of all this, spatial disaggregation of GCM outputs has been used by some researchers in order to maintain the gross representativeness of a GCM pattern in both space and time (Buytaert et al., 2009). Spatial disaggregation consists of adding coarse GCM cells to either local measurements of climate (from weather stations) or high resolution interpolated surfaces. The process uses anomalies or deltas, such as the so-called delta-method for downscaling climate surfaces, but does not use interpolation (either between weather stations or GCM cell centroids). It is therefore less likely to alter original GCM patterns.

Disaggregation provides an easy-to-apply and much more rapid method for developing high resolution climate change surfaces for high resolution regional climate change impact assessment studies, with a lower likelihood of altering original GCM patterns. Since disaggregation does not involve any downscaling, but rather the aggregation of 'big' GCM cells into either points (weather stations) or fine resolution cells, it constitutes a highly conservative method unlikely to draw criticism from climate researchers.

Using WorldClim (Hijmans et al., 2005) as the baseline climate ('current climate'), we applied spatial disaggregation to 24 different GCMs from the IPCC Fourth Assessment Report (2007), directly downloaded from the Earth System Grid (ESG) data portal, for the emission scenarios SRES-A1B (24 GCMs), SRES-A2 (19 GCMs), and SRES-B1 (20 GCMs), and for 7 different 30 year running mean periods. A total of 441 future climate scenarios were produced at four different spatial resolutions (30 arc-seconds, 2.5 arc-minutes, 5 arc-minutes, and 10 arc-minutes). Each climate scenario or dataset (SRES scenario – GCM – timeslice) comprises 4 variables at a monthly time-step (mean, maximum, minimum temperature, and total precipitation) and a set of bioclimatic indices (Nix, 1986; Busby, 1991). The data is freely available on http://gisweb.ciat.cgiar.org/dapablogs/dapa-climate/

The disaggregation method

Here we applied the simple disaggregation method based aggregation of anomalies (deltas) of original GCM outputs to a high resolution baseline climate. Anomalies were calculated as the difference between future 30-year averages to the 1961-1990 average of GCM outputs in three variables (maximum and minimum temperatures, and total precipitation). These anomalies were then applied to a baseline climate given by a high resolution surface (WorldClim; Hijmans et al., 2005). The method does not make any particular assumption, but simply 'updates' current climates to future climates by adding the corresponding changes to each variable.

The process consists of the following steps:

1. Gathering of baseline data (current climates corresponding to WorldClim)
2. Gathering of full GCM timeseries
3. Calculation of 30 year running averages for present day simulations (1961-1990) and 7 future periods (2010-2039, 2020-2049, 2030-2059, 2040-2069, 2050-2079, 2060-2089, 2070-2099)
4. Calculation of anomalies as the absolute difference between future values in each of the 3 variables to be disaggregated
5. Addition of anomalies surfaces to the current climates from WorldClim, using absolute sum for temperatures, and addition of relative changes for precipitation
6. Calculation of mean temperature as the average of maximum and minimum temperatures

WorldClim and full GCM timeseries are freely available in the internet, and all other calculations were carried out by means of Geographic Information Systems (GIS) software. Used formats are NetCDF (for GCM outputs), ESRI-GRID (for WorldClim and final disaggregated data), and ESRI-ASCII grids for providing standard and easy-to-use outputs to potential users of the data.

Baseline data

With an eye to providing *credible* future high resolution surfaces, we used WorldClim (Hijmans et al., 2005, available at http://www.worldclim.org/), a global database of climate surfaces at 30 arc-second spatial resolution (~1km at the Equator). This database was developed from compiled monthly averages of climate as measured at weather stations from a large number of global, regional, national and local sources, mostly from the 1950-2000 period, using the Thin Plate Smoothing Spline (TPS) algorithm (Hutchinson, 1995) that yielded climate surfaces for monthly maximum, minimum, mean temperatures and total monthly precipitation.

WorldClim contains data from the Global Historical Climate Network Dataset (GHCN; the WMO Climatological Normals (CLINO); the FAOCLIM global climate database; a database assembled by the International Center for Tropical Agriculture (CIAT); and additional databases from Latin America and the Caribbean (R-Hydronet), the Altiplano in Peru and Bolivia (INTECSA), the 'Nordic Countries' in Europe (Nordklim), Australia (BOM), New Zealand, and Madagascar.

WorldClim climate surfaces were developed from 47,554 locations with precipitation records, 24,542 locations with mean temperature records, and 14,835 locations with minimum and maximum temperature records. Other global datasets have been produced using fewer locations for both temperatures and precipitations (New et al., 2002), but WorldClim has the advantage of having higher spatial resolution, whilst maintaining accuracy (Figure 1).

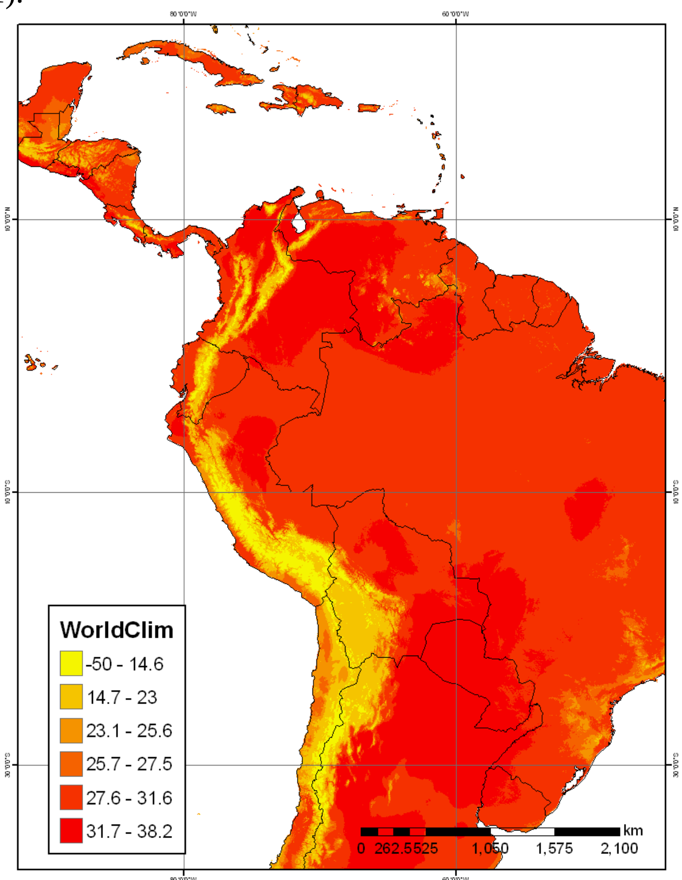

Figure 1 WorldClim surface corresponding to maximum temperature in January, at 30 arc-seconds spatial resolution

While we recognize that the dataset might not be perfect and/or accurate in all parts of the world, it does represent to a considerable degree current climates, as reported by instrumental records, at a scale that allows for the application of any modeling technique at a site-specific level. Critical areas where very low number of locations were used for interpolations are: the Amazon, the Sahara, Russia, Greenland, and some places in the mid-east, among others (see Hijmans et al., 2005 for further detail)

In addition, WorldClim has been employed considerably by modelers, conservationists and agricultural researchers because of its high resolution. The dataset has been cited more than 500 times in peer reviewed publications. For all the above reasons, we chose to use WorldClim for our baseline data, representing the 1961-1990 period (current climates hereafter).

Future GCM predictions

GCMs are representations of earth processes and are performed on powerful computers by climatic research centers over the world. To date, a variety of GCMs (with their respective versions) have been developed, tested, and their results have been made available to the public (IPCC, 2001, 2007). 24 Different GCMs were used in the Fourth Assessment Report (IPCC, 2007), each with different parameterization (Table 1, see atmosphere and ocean columns indicating resolutions). These GCMs were run under different, but not all, SRES emission scenarios (IPCC, 2000).. Outputs were produced for the SRES A1B, A2 and B1 emission scenarios.

Table 1 Available GCMs and principal characteristics (resolutions, references)

Model	Country	Atmosphere	Ocean	Reference
BCCR-BCM2.0	Norway	T63, L31	1.5x0.5, L35	N/A
CCCMA-CGCM3.1 (T47)	Canada	T47 (3.75x3.75), L31	1.85x1.85, L29	Scinocca et al. (2008)
CCCMA-CGCM3.1 (T63)	Canada	T63 (2.8x2.8), L31	1.4x0.94, L29	Scinocca et al. (2008)
CNRM-CM3	France	T63 (2.8x2.8), L45	1.875x(0.5-2), L31	Salas-Mélia et al. (2005)
CSIRO-Mk3.0	Australia	T63, L18	1.875x0.84, L31	Gordon et al. (2002)
CSIRO-Mk3.5	Australia	T63, L18	1.875x0.84, L31	Gordon et al. (2002)
GFDL-CM2.0	USA	2.5x2.0, L24	1.0x(1/3-1), L50	Delworth et al. (2004)
GFDL-CM2.1	USA	2.5x2.0, L24	1.0x(1/3-1), L50	Delworth et al. (2004)
GISS-AOM	USA	4x3, L12	4x3, L16	Russell et al. (1995)
GISS-MODEL-EH	USA	5x4, L20	5x4, L13	Schmidt et al. (2005)
GISS-MODEL-ER	USA	5x4, L20	5x4, L13	Schmidt et al. (2005)
IAP-FGOALS1.0-G	China	2.8x2.8, L26	1x1, L16	Yu et al. (2004)
INGV-ECHAM4	Italy	T42, L19	2x(0.5-2), L31	Gualdi et al. (2006)
INM-CM3.0	Russia	5x4, L21	2.5x2, L33	Diansky et al. (2002)
IPSL-CM4	France	2.5x3.75, L19	2x(1-2), L30	Marti et al. (2005)
MIROC3.2-HIRES	Japan	T106, L56	0.28x0.19, L47	Hasumi and Emori (2004)
MIROC3.2-MEDRES	Japan	T42, L20	1.4x(0.5-1.4), L43	Hasumi and Emori (2004)
MIUB-ECHO-G	Germany/Korea	T30, L19	T42, L20	Grötzner et al. (1996)
MPI-ECHAM5	Germany	T63, L32	1x1, L41	Jungclaus et al. (2005)
MRI-CGCM2.3.2A	Japan	T42, L30	2.5x(0.5-2.0)	Yukimoto et al. (2001)
NCAR-CCSM3.0	USA	T85L26, 1.4x1.4	1x(0.27-1), L40	Collins et al. (2005)
NCAR-PCM1	USA	T42 (2.8x2.8), L18	1x(0.27-1), L40	Washington et al. (2000)
UKMO-HADCM3	UK	3.75x2.5, L19	1.25x1.25, L20	Gordon et al. (2002)
UKMO-HADGEM1	UK	1.875x1.25, L38	1.25x1.25, L20	Johns et al. (2006)

Different Coupled Models Intercomparison Projects (CMIPs) have been created in order to support and enhance the knowledge on GCM-related science. The last existing CMIP is the CMIP-3 (PCMDI, 2007; IPCC, 2007), comprising the evaluation of some 22 to 24 different GCMs on a global scale. CMIP-3 also set up a platform for providing GCM outputs to the public, under the Earth System Grid (ESG) online platform (https://esg.llnl.gov:8443/index.jsp).

The IPCC-data portal (http://www.ipcc-data.org) provides some GCM outputs as well, but the most comprehensive dataset is provided by the ESG, including complete timeseries of: future simulations (2000-2100) at monthly time-steps, daily data for specific periods (e.g. 2020s, 2050s), yearly data, and 30 year running averages. The IPCC-data portal only provides the last one.

We downloaded data from ESG corresponding to full timeseries (1850-2100) of all available GCMs (24), at monthly time-steps, for the same 4 variables of interest to us (minimum, maximum, mean temperature, and total precipitation), for the 20CM3 (20th century simulation), and the SRES-A1B, A2 and B1 emission scenarios. Not all GCMs were run under all emission scenarios (Table 2).

Table 2 Available (o) and not available (x) GCM runs under baseline and three SRES scenarios

Model	20C3M	SRES-A1B	SRES-A2	SRES-B1
BCCR-BCM2.0	o	o	o	o
CCCMA-CGCM3.1-T63	o	o	x	o
CCCMA-CGCM3.1-T47	o	o	o	o
CNRM-CM3	o	o	o	o
CSIRO-MK3.0	o	o	o	o
CSIRO-MK3.5	o	o	o	o
GFDL-CM2.0	o	o	o	o
GFDL-CM2.1	o	o	o	o
GISS-AOM	o	o	x	o
GISS-MODEL-EH	o	o	x	x
GISS-MODEL-ER	o	o	o	o
IAP-FGOALS1.0-G	o	o	x	o
INGV-ECHAM4	o	o	o	x
INM-CM3.0	o	o	o	o
IPSL-CM4	o	o	o	o
MIROC3.2.3-HIRES	o	o	x	o
MIROC3.2.3-MEDRES	o	o	o	o
MIUB-ECHO-G	o	o	o	o
MPI-ECHAM5	o	o	o	o
MRI-CGCM2.3.2A	o	o	o	o
NCAR-CCSM3.0	o	o	o	o
NCAR-PCM1	o	o	o	x
UKMO-HADCM3	o	o	o	o
UKMO-HADGEM1	o	o	o	x
Total	24	24	19	20

An additional issue regards the availability of GCM outputs. Due to a lack of a clear agreement, not all research centers provided outputs on all variables; rather, each selectively decided which variables to provide, creating unfortunate date gaps for non-climatic research centers hoping to use these data. As such, minimum and maximum temperatures were not available for all GCMs--only for 11 (20C3M, A1B, B1) and 9 (A2). For those GCMs for which no maximum and minimum temperature data were available, we used the Multi Model Mean (MMM) of all the other GCMs. While we acknowledge that this process might have reduced variance among the different GCMs, we preferred to provide MMM-based outputs over not providing data for those models at all.

Anomalies: how and why?

Using the full present day (20C3M) monthly timeseries, we calculated 30 year running means around 1985 (1961-1990) as a baseline, for each of the GCMs and the 4 variables of interest. We then calculated 30 year running means for each of the emission scenarios andseven periods, so that the complete timeseries were reduced to 8 different 30 year averaged periods, as follows:

1. 1961-1990: The baseline climate, also referred to as 20C3M, or ‘current climates’
2. 2010-2039, referred to as 2020s
3. 2020-2049, referred to as 2030s
4. 2030-2059, referred to as 2040s
5. 2040-2069, referred to as 2050s
6. 2050-2079, referred to as 2060s
7. 2060-2089, referred to as 2070s
8. 2070-2099, referred to as 2080s

For each of the 7 future periods, the anomaly or delta with respect to the baseline climate was calculated for each of the variables and months.

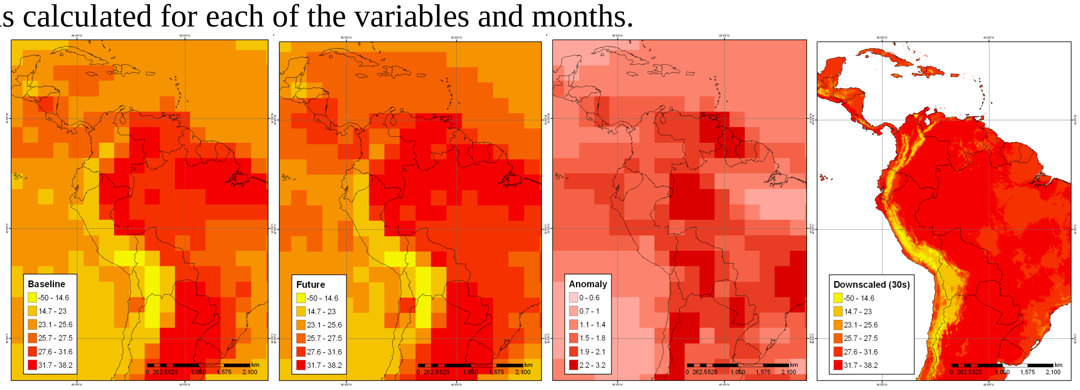

Figure 2 Illustration of the disaggregation process with January maximum temperature using the BCCR-BCM2.0 GCM pattern: (a) Baseline data (20C3M), (b) future data for 2050s (2040-2069 average), (c) delta or anomaly by 2050s, (d) future disaggregated surface at 30 arc-second spatial resolution

These surfaces were then applied to the baseline climates from WorldClim. In the case of temperatures (minimum and maximum temperatures), for each pixel, the anomalies in degrees Celsius were simply "added" to the actual value in degrees Celsius reported in WorldClim. Differences in baselines were neglected for temperatures (Eqn. 1), but taken into account for precipitation [Eqn. 2].

$$X_{F.i} = X_{C.i} + \Delta X_{I.i} \qquad \text{[Eqn. 1]}$$

$$X_{F.i} = X_{C.i} * \left| 1 + \frac{\Delta X_{I.i}}{X_{C.i} + 1} \right| \qquad \text{[Eqn. 2]}$$

Where,

$X_{F.i}$ is the future value of the pixel for the variable *X* (i.e. precipitation, temperature), in the month *i*,
$X_{C.i}$ is the current value (i.e. from WorldClim) of the pixel for the variable *X*, in the month *i*,
$\Delta X_{I.i}$ is the interpolated value of the delta or anomaly corresponding to the pixel, for the variable *X*, in the month *i*,

We added 1 millimeter to the denominator in Eqn. 2 in order to avoid indetermination in areas where current precipitation equals 0. In Eqn. 6, we used the absolute value of the change relative to the baseline period (i.e. WorldClim) to avoid monthly precipitation values going below 0 and to maintain homogeneities with WorldClim.

After calculating the corresponding future values for each of the 36 coarse resolution anomaly surfaces, we calculated mean temperatures, assuming a normal distribution of temperatures during the day (Eqn. 3).

$$T_{M.i} = \frac{T_{X.i} + T_{N.i}}{2} \qquad \text{[Eqn. 3]}$$

Where,

$T_{M.i}$ is the mean temperature in month *i*,
$T_{X.i}$ is the maximum temperature in month *i*,
$T_{N.i}$ is the minimum temperature in month *i*,

All these calculations were performed in Arc/Info (ESRI, 2008); however, they can be performed under any other automatable GIS software or any other package with the proper libraries (e.g. R, GRASS, Python, Java).

Future disaggregated climate surfaces

Our datasets therefore comprise the most up-to-date (with climate science) and comprehensive disaggregated set of climate change scenarios, with a total of 441 different scenarios (sum of 24, 20 and 19 GCMs, times 7 time-slices) at 30 arc-seconds spatial resolution. As a whole, original GCM uncertainties were maintained in future surfaces, so any uncertainty analysis done with original GCM data provides insights into the disaggregated surfaces. The method is highly conservative, keeping variability among GCM forecasts and providing 'updated' surfaces by assuming only that interactions between variables do not change in the future.

We acknowledge the risk of providing 30 arc-seconds future climate data, but we applied the disaggregation method to the original WorldClim dataset in order to maintain its original condition. However, since 30 arc-s future climate scenarios might cause a false sense of accuracy,, after all these calculations, we aggregated the 30 arc-s future data to 2.5, 5, and 10 arc-minute resolutions using nearest neighbor interpolation (Figure 3).

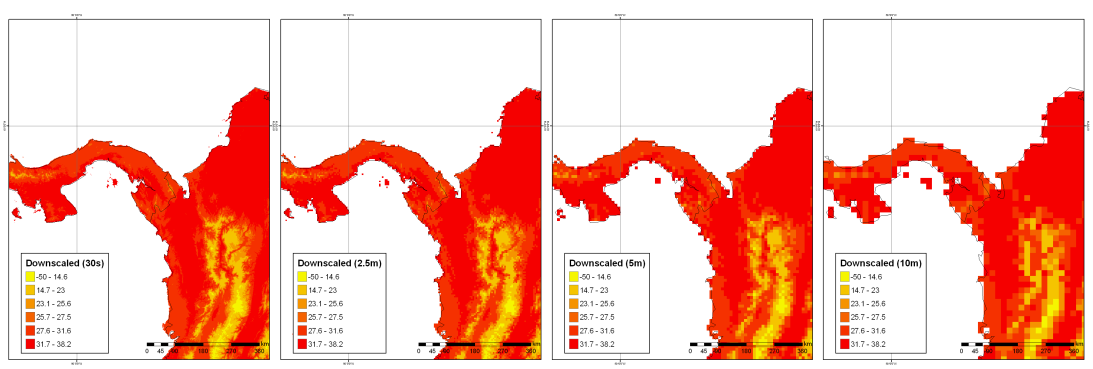

Figure 3 Comparison between downscaled surfaces at different spatial resolutions for an area in north-western Colombia including the Andes: (a) 30 arc-seconds, (b) 2.5 arc-minutes, (c) 5 arc-minutes and (d) 10 arc-minutes. Other resolutions than 30 arc-s are derived from 30 arc-s surfaces by nearest neighbor interpolation.

We still provide 30 arc-s data, but users of these data should be aware of the risks of using these data, given the assumptions we made in producing them. We suggest that the uncertainties in GCM forecasts always be taken into account, and that all users of these data dutifullyreport the assumptions involved in disaggregation.

Processing and storage capacity in research centers making use of these datasets might also be a limiting factor when using these data. We therefore suggest that research centers download the resolution datasets appropriate to their studies. This avoids over-processing.

Globally and freely available

A webpage has been created for any global user to download the datasets we produced. This webpage is hosted in Cali, Colombia, on CIAT's web server (http://gisweb.ciat.cgiar.org/GCMPage/) and includes a brief description of the data. It also contains links to information about all GCM patterns that were disaggregated (provided by the IPCC-CMIP3 data portal), as well asto the datasets in the following formats:

- ESRI Arc/Info binary grids for data at 2.5 arc-m, 5 arc-m, and 10 arc-m spatial resolution
- ESRI ASCII grids for data at 30 arc-s, 2.5 arc-m, 5 arc-m, and 10 arc-m spatial resolution

Beyond the monthly data, we also calculated 19 bioclimatic indices (see Nix, 1986; Busby, 1991), which are often used for niche and crop modeling and are related with biology and geography of species. These indices provide descriptions of annual trends (i.e. annual mean temperature, total annual rainfall), seasonality (temperature range, temperature and precipitation standard deviations), and stressful conditions (precipitation during dry or wet periods, temperatures during hot and cold periods). These data are also presented on our webpage.

Conclusions

Disaggregation appears to be a useful alternative, and more conservative, method to downscaling. Disaggregated future climate surfaces avoid misrepresentation of original GCM uncertainties. Of course, as with all methods(and even with theoriginal GCMs), disaggregation still does make several assumptions that must be taken into account when using the data as inputs for impact assessment models.

We used spatial disaggregation with WorldClim as our baseline and created a set of 441 different future climate scenarios at four spatial resolutions (including 30 arc-second [~1km]). The datasets are up-to-date and freely available, but should be used carefully (particularly those at 30 arc-s spatial resolution), given the assumptions we made in creating them. Coarse GCM cells were maintained, so uncertainties were maintained in their original forms.One key caveat to keep in mind is that changes in climates may occur at regional and local scales (particularly in highly heterogeneous landscapes) that at coarse scales (~100-200 km side cells) may not reflect.

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