Facility for Weather and Climate Assessments (FACTS)

A Community Resource for Assessing Weather and Climate Variability

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ABSTRACT: The Facility for Weather and Climate Assessments (FACTS) developed at the NOAA Physical Sciences Laboratory is a freely available resource that provides the science community with analysis tools; multimodel, multiforcing climate model ensembles; and observational/reanalysis datasets for addressing a wide class of problems on weather and climate variability and its causes. In this paper, an overview of the datasets, the visualization capabilities, and data dissemination techniques of FACTS is presented. In addition, two examples are given that show the use of the interactive analysis and visualization feature of FACTS to explore questions related to climate variability and trends. Furthermore, we provide examples from published studies that have used data downloaded from FACTS to illustrate the types of research that can be pursued with its unique collection of datasets.

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A facility for assessing weather and climate conditions

Droughts, heat waves, floods, and other extreme weather and climate events can have costly and devastating effects. The basis for anticipating such events more than a few weeks in advance lies in understanding their causal relationship with extreme subseasonal to interannual climate states, decadal variability, and long-term trends. While observations are essential to characterize these events and to place them in historical context, observations alone are not sufficient to fully establish these causal relationships. Climate model experiments can provide the framework necessary to disentangle the various factors that are responsible for weather and climate variability on these time scales, including extremes.

The Facility for Weather and Climate Assessments (FACTS) (www.psl.noaa.gov/repository/facts) developed at the NOAA Physical Sciences Laboratory (PSL) is a freely available resource that provides the science community with analysis tools; multimodel, multiforcing climate model ensembles; and observational/reanalysis datasets for addressing a wide class of problems on weather and climate variability and its causes. Researchers can use the FACTS website to quickly probe science questions through interactive analysis and visualizations and, if desired, download model and observational data for additional analysis. Educators can use the site for illustration of basic concepts of weather and climate variability. While other facilities provide data and tools for analyzing climate model simulations such as "KNMI Climate Explorer" (KNMI 2020) and "Climate Reanalyzer" (University of Maine 2020), FACTS offers unique datasets and analysis tools for the understanding of weather and climate variability and for extreme event attribution.

The FACTS data archive and website

The FACTS archive contains data from the Atmospheric Model Intercomparison Project (AMIP; Gates et al. 1999) and Coupled Model Intercomparison Project (CMIP; Hibbard et al. 2007) styles of climate model experiments (Table 1). For each experiment, many ensemble members (typically 20–50 realizations depending on the model) are available in the archive. These large ensembles are particularly useful for estimating the predictable signal and comparing that to the climate system's internal variability. The signal is obtained through the average across all ensemble members, and the so-called noise of internal variability can be estimated from the standard deviation across those same realizations. In more advanced applications, the probability density functions (PDFs) can be compared in their entirety.

FACTS also contains parallel suites of AMIP-style model experiments that can be intercompared to assess how, and by how much, events or conditions were influenced by climate change. One set of experiments consists of a set of factual runs, where historical forcings of sea surface temperature and atmospheric composition are used. A second set consists of

counterfactual runs, where the ocean boundary forcings and atmospheric composition are modified in the experiment by removing the estimated effects of long-term change, thereby retaining only an estimate of the natural variability (Stone et al. 2019). Comparison of factual and counterfactual experiments is an emerging approach (e.g., Sun et al. 2018) that has been increasingly used to inform extreme event attribution [e.g., see papers appearing in the *BAMS* special supplement "Explaining Extreme Events of 2017 from a Climate Perspective" (Herring et al. 2019)].

FACTS also includes a variety of atmospheric reanalysis and observational datasets that can be compared with the model simulations (see Table 1 for a representative list). Several of these datasets span the last century, including station-based analyses from the University of Delaware (UDEL 5.01; Willmott and Matsuura 2001) and the Global Historical Climate Network (GHCN CAMS; Fan and van den Dool 2008) as well as the Twentieth Century Reanalysis version 3 (20CR; Slivinski et al. 2019).

All data are stored in netCDF format at their native resolution and are regridded only when necessary during analysis (e.g., comparing data having different resolutions). To investigate and better understand high-impact events like droughts, heat waves and extreme precipitation, the archive of model experiments includes a selection of many relevant surface parameters (e.g., precipitation, 2-m temperature, soil moisture, and runoff) and pressure level data (wind components, geopotential heights). Monthly data are available for all models, reanalyses, and observations. The capabilities to analyze and visualize daily data for some datasets is in development.

The FACTS website is built on RAMADDA (Repository for Archiving, Managing and Accessing Diverse Data; https:// ramadda.org), a freely

Table 1. Summary of the principal types of datasets in the FACTS archive. Time period is inclusive of all datasets per type, some dataset periods are shorter than others. A more detailed listing of the available datasets, time periods and number of ensembles is available on the FACTS website (www.psl.noaa.gov/repository/factsdocs).

| Data type	Purpose	Examples	Time period
AMIP	Diagnose the response to observed boundary conditions like SST, sea ice, and atmospheric composition in the presence of chaotic atmospheric variability.	CAM5 (Neale et al. 2010)	1901–present
		ECHAM5 (Roeckner et al. 2003)	
Counterfactual AMIP	Diagnose the response to boundary conditions with an estimate of their long-term changes removed. Comparing this experiment to the AMIP experiments allows one to estimate the effect of long-term changes on the behavior of weather and climate.	CAM5 (Neale et al. 2010)	1979–present
		ECHAM5 (Roeckner et al. 2003)	
Ensembles of coupled climate models	Historical simulations and future projections to diagnose internal coupled variability and sensitivity to external radiative forcing.	CESM1 (Kay et al. 2015)	1920–2100
		CanESM2 (Arora et al. 2011)	
		CM3 (Donner et al. 2011)	
Reanalyses	Estimate observed conditions in the Earth system.	20CR (Slivinski et al. 2019)	1836–present
		ECMWF reanalyses (ERA5, CERA-20C; Hersbach et al. 2018; Laloyaux et al. 2018)	
		Japanese 55-year Reanalysis (JRA-55; Kobayashi et al. 2015)	
Observations	Estimate observed precipitation and temperature.	UDEL temperature and precipitation (Willmott and Matsuura 2001)	1880–present
		GHCN CAMS temperature (Fan and van den Dool 2008)	
		GISS Surface Temperature Analysis (GISTEMP; Lenssen et al. 2019)	
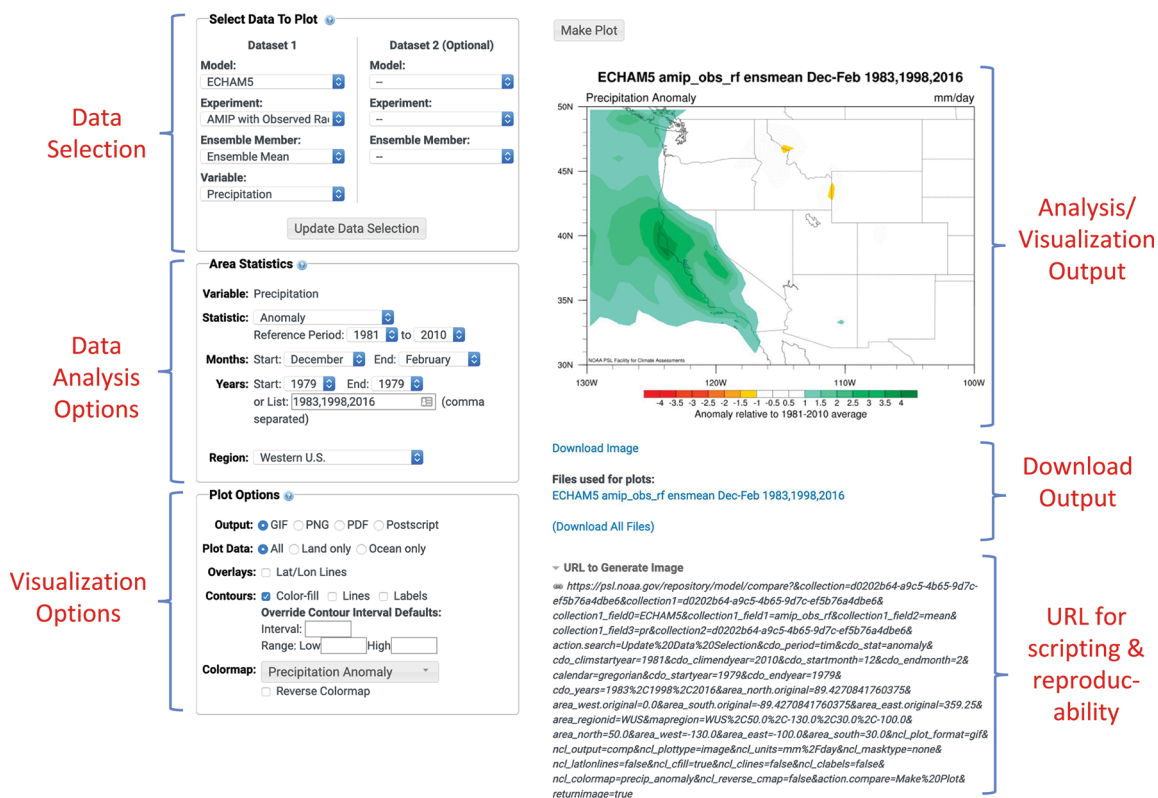
Fig. 1. FACTS tool web page showing the common features among the analysis and visualization components. See text for details.

available, FAIR (Findable, Accessible, Interoperable, and Reusable) data (Wilkinson et al. 2016) compatible content management system for geospatial (and other) data. The software was designed to be portable so that FACTS servers can be set up at other intuitions for their datasets. The modular design of the software enables reuse of analysis components in different contexts. The goal is to provide a similar user experience for each of the analysis tools. Analysis and plotting capabilities are provided through freely available and widely used software packages [Climate Data Operators (CDO), NCAR Command Language (NCL), R, Python].

Illustrations of FACTS capabilities

The FACTS website has two main features that enable research with the available model, reanalysis, and observed datasets. First, it has a built-in analysis and visualization component that allows users to quickly make figures, such as of composite and correlation analyses (Fig. 1). Second, the climate model data can be subset and then downloaded from FACTS, enabling users to perform their own diagnostics.

Interactive analysis and visualization. The interactive analysis and visualization capabilities allow users to explore the various models, experiments, and reanalysis/observation datasets. These capabilities are presented to the user as separate tools on the main FACTS web page. With these tools, users can assess the impact of forcing parameters on the same model between different experiments (e.g., effects of sea ice forcing alone), assess how different models respond to the same forcings, compare the same model/experiment over different time periods (e.g., early twenty-first century with late twentieth century), compare teleconnections
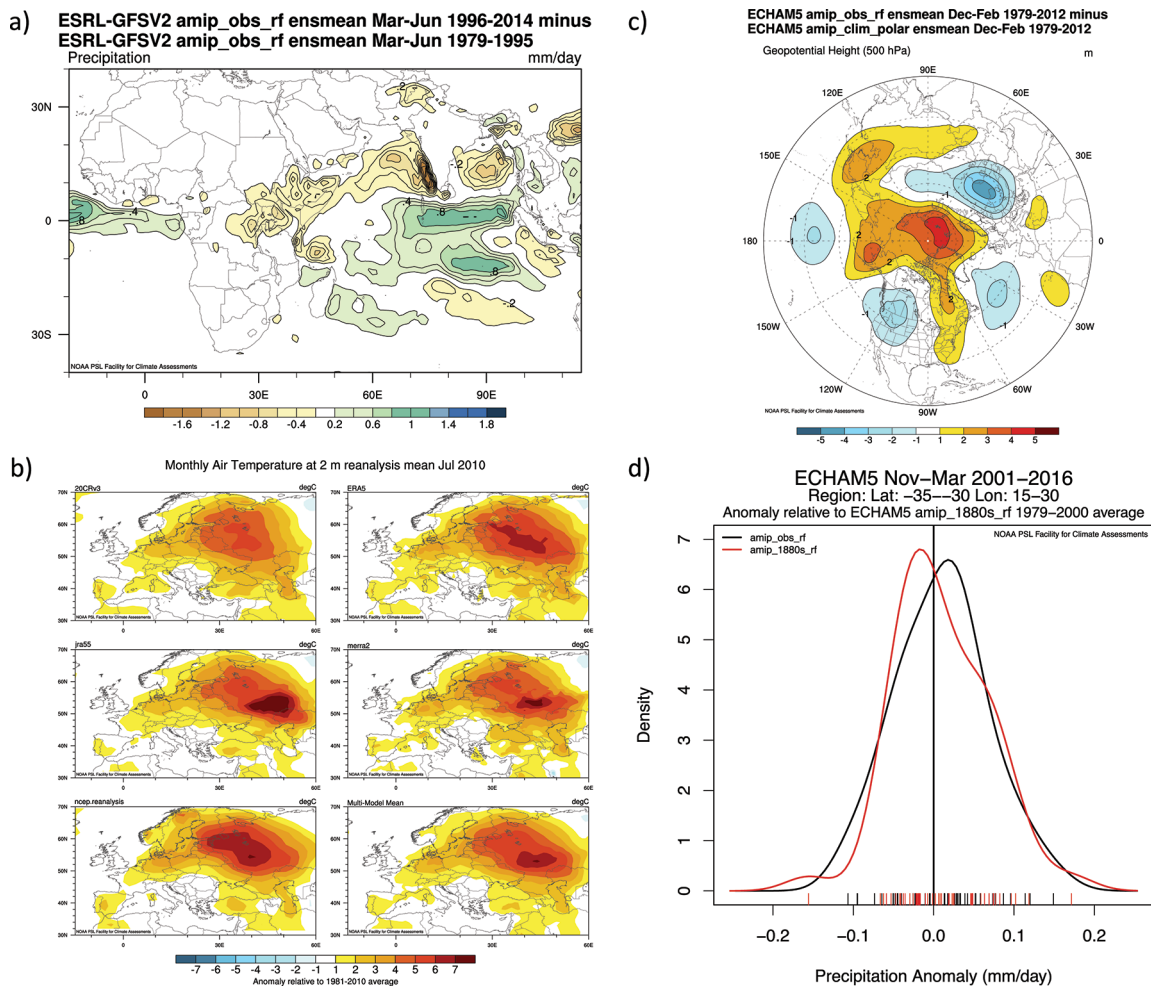
Fig. 2. Sample output produced on the FACTS website. (a) Comparison of changes in precipitation through time showing drying over the Horn of Africa in the ESRL-GFSv2 model. (b) Comparison of reanalysis datasets showing the temperature anomaly during the 2010 Russian heat wave. (c) Comparison of changes in 500-hPa heights due to sea ice forcing in the ECHAM5 model. (d) Histogram of precipitation anomalies in the early 2000s over South Africa for the factual and counterfactual runs of the ECHAM5 model.

of ENSO phases (e.g., strong/weak El Niño/La Niña), and correlate model and reanalysis data with climate indices (e.g., Niño-3.4).

For each of the analysis and visualizations tools, a user first selects the datasets, model experiments, ensemble member(s), and variable (Fig. 1). Once that selection is completed, the data analysis panel is populated based on the data selection. The user can then select the statistic they wish to analyze, the time period, and regional subset if desired. Visualization options such as contour intervals and color tables can be selected for the resulting plot. Once the plots are generated, they are displayed on the same page and are available for download. The web page output also includes links to download the files used to create the plots in netCDF and/or text formats as well as a URL to completely regenerate the visualization. This latter function is useful for creating scripts with replaceable parameters to easily generate the same plot for other models or time ranges. A tutorial on how to use the FACTS website is available online (www.psl.noaa.gov/repository /facts/userguide/index.html).

Examples of the FACTS visualization capabilities include examining temporal differences in conditions by subtracting the climatological average for one time period from another within the same climate model experiment (Fig. 2a), evaluating different model and reanalysis
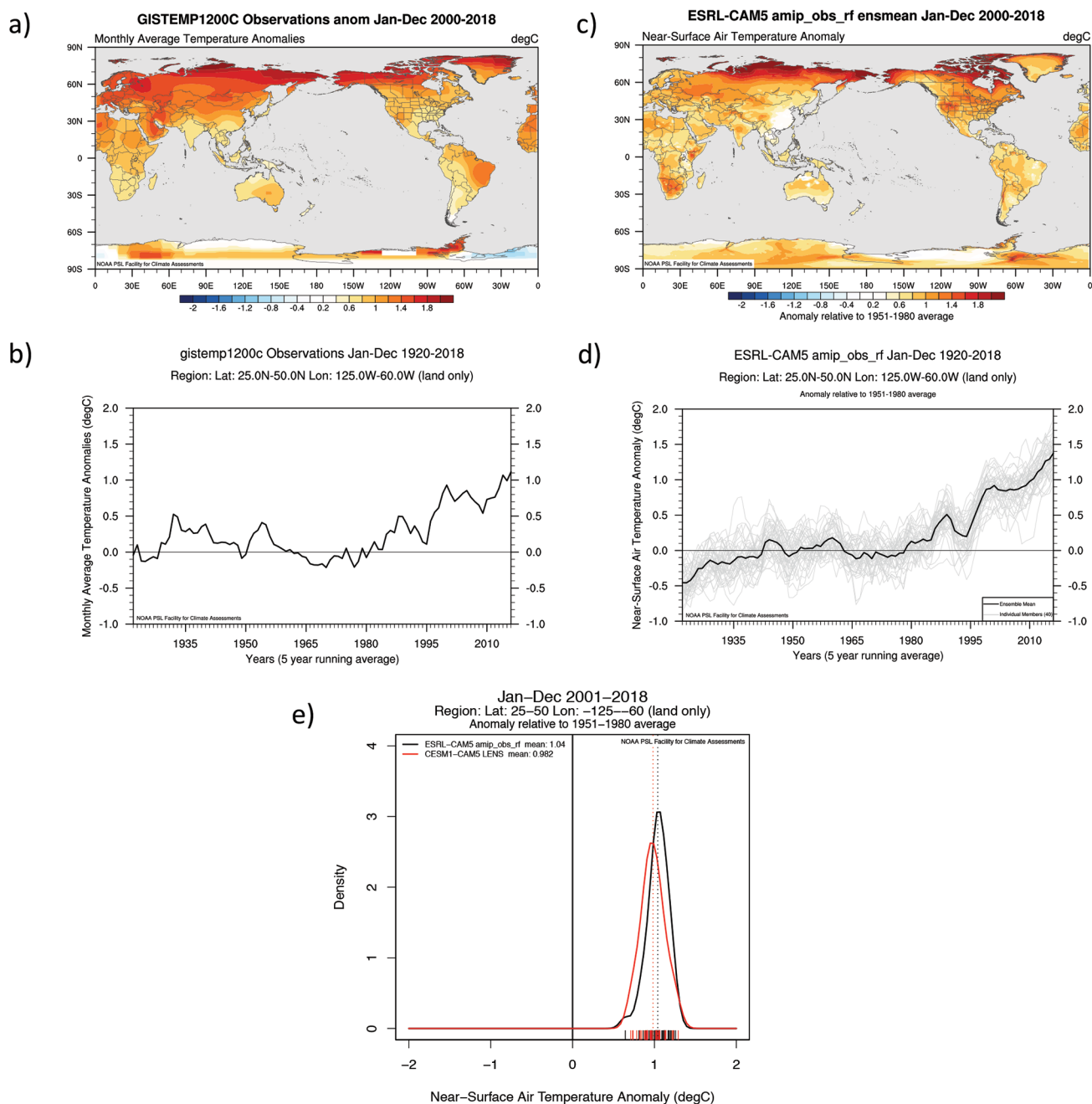
Fig. 3. Comparison of the observed temperature anomalies from GISTEMP with model-simulated temperature anomalies from CAM5. Composite annual global temperature anomaly maps for (a) GISTEMP observations and (c) CAM5 ensemble mean for the years 2000–18. Time series of (b) GISTEMP observed and (d) CAM5 simulated (ensemble mean, black line; ensemble members, light gray lines) temperature anomalies over the United States for the period 1920–2018. Temperature anomalies are relative to the 1951–80 climatology in all plots. (e) Comparison of AMIP-style simulation with a fully coupled (CMIP-style) simulation using the same atmospheric model (CAM5).

representation of conditions for an event or condition of interest (Fig. 2b), and assessing differences in the conditions for the same time period between two different climate model experiments (Fig. 2c). The distribution of possible outcomes for each of the ensemble members can be plotted as a histogram (Fig. 2d) and comparisons can be made between models, experiments, and time periods. FACTS users can also create time series of observational and model datasets (Fig. 3).

In the next two sections, we provide simple examples that show the use of the interactive analysis and visualization feature of FACTS to explore questions related to climate variability and trends.

Using FACTS to diagnose causes of long-term change. The FACTS observational and model simulation data can be used for exploratory analysis of trends and the causes for long-term change. For instance, near-surface temperature data spanning the last century can be used to explore basic questions regarding trends in the data. Figure 3a shows the FACTS-generated global map of observed land temperature anomalies for 2000–18 based on the NASA GISS station-based analyses. The data can also be probed temporally and regionally, with Fig. 3b showing the FACTS-generated time series of land temperature departures from 1920 to 2018 for the United States. The well-known features of the observed global rise in surface temperature are clear in these displays. Users have the flexibility to create time series over any portion of the globe, in addition to the global average itself.

A key capability of FACTS is that it enables comparison of long-term change in observations, as in Figs. 3a and 3b, with parallel analyses using climate simulations. Figure 3c repeats the analysis conducted on observations but uses a 40-member ensemble of the CAM5 model in which the known history of SSTs, sea ice, greenhouse gases, natural and anthropogenic aerosols, and solar variability are specified (i.e., AMIP factual). In this example, the model ensemble mean temperature anomaly for 2000–18 also reveals warming across all continents indicating that the observed warming was most likely due to time-evolving drivers, and was not a mere consequence of random atmospheric variability.

A frequent question that arises is whether the observed temperature rise was a deterministic response to the external forcing or only one of many possible outcomes, and an unlikely one as well? Fig. 3d includes the time series for each of the 40 ensemble members (light gray contours) in addition to the ensemble average (thick black contour). The model members suggest that the observed U.S. warming over the last century may have been on the low end of what could have occurred, suggesting that perhaps a stronger forced warming was obscured by atmospheric noise inherent in the climate system. The observed ~1.1°C warming by 2018 is more than a half degree less than the ensemble mean of ~1.8°C and a degree less than the maximum ensemble member. Of course, it is also possible the U.S. land temperature in the model is overly sensitive to the time evolving forcings, and/or that some forcings have not been completely represented (e.g., land use changes including irrigation and patterns of agricultural change). Clarification of those matters would require analysis of other models, or additional experiments using other forcings.

In FACTS, the user can also compare climate models driven by specific observed SSTs (i.e., AMIP experiments) with simulations generated using the same atmospheric component but coupled to a fully responding dynamical ocean and sea ice model (i.e., CMIP experiments). Figure 3e compares histograms of 2000–18 surface temperature anomalies averaged for the contiguous United States based on NCAR CAM5 (AMIP) model with the NCAR CESM1 (CMIP) model. The model statistics are similar, though not identical. In this analysis of U.S. temperature trends, the atmospheric model yields a slightly stronger warming than the coupled model, though diagnosing the reasons are beyond the scope of FACTS. Nonetheless, the FACTS exploratory analysis reveals—within the framework of model systems available on this portal—that the observed rise in U.S. temperatures was likely an unavoidable consequence of the forcing history during the last century. Cooling, or no change, rather than warming were not plausible outcomes.

El Niño and subseasonal to seasonal precipitation predictability. Model simulations hosted by FACTS can be used to diagnose sources of precipitation predictability on subseasonal to
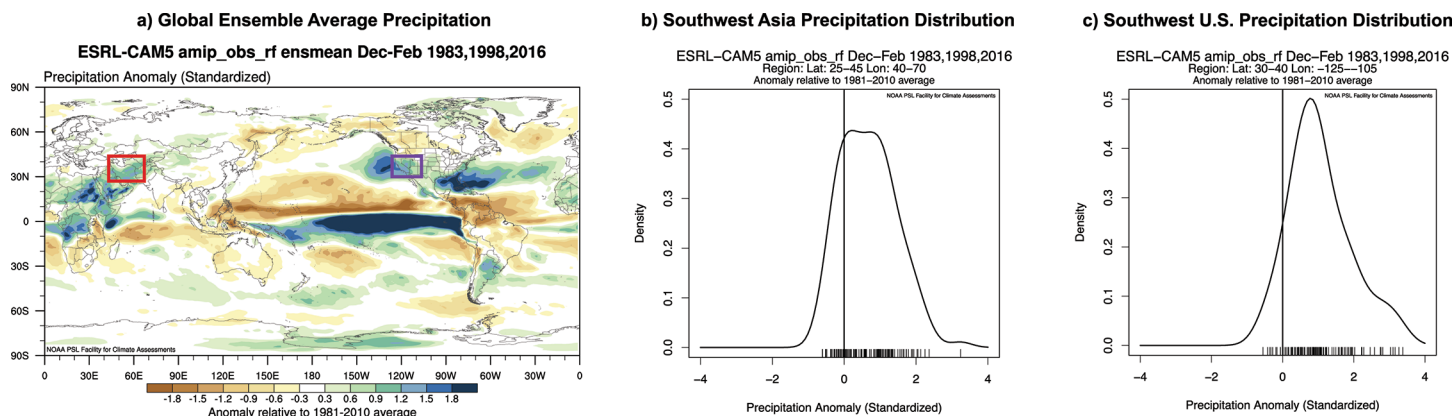
Fig. 4. Illustration of FACTS visualizations for probing precipitation predictability related to strong El Niño events. Based on CAM5 AMIP simulations during December–February of 1982/83, 1997/98, and 2015/16, (a) ensemble average standardized precipitation anomaly, (b) Southwest Asia [25°–40°N, 40°–70°E, red box in (a)] standardized precipitation anomaly probability distribution function, and (c) southwestern U.S. [30°–50°N, 130°–105°W, purple box in (a)] standardized precipitation anomaly probability distribution function.

seasonal time scales. For example, atmospheric model simulations forced by estimates of past ocean surface conditions (AMIP experiments), like CAM5 and ECHAM5, in which only the atmosphere and land surface freely evolve, allow one to diagnose the effect of observed El Niño events on precipitation.

Figure 4 illustrates how the FACTS analysis and visualization capabilities may be used to probe December–February precipitation predictability related to the recent strong El Niño events of 1982/83, 1997/98, and 2015/16. Based on the 40-member CAM5 AMIP ensemble, strong El Niño is related to above-average precipitation over central Africa, western Asia, and the southern tier of North America (Fig. 4a). Those same simulations also indicate that strong El Niño is related to below-average precipitation over Central America, northern South America, parts of southern Africa, and Indonesia.

Precipitation probability distributions for two regions over which the effect of strong El Niño is most evident, Southwest Asia and the southwestern United States, are shown in Figs. 4b and 4c, respectively. The probability distributions of possible outcomes based on each of the CAM5 ensemble members allows one to quantify the likelihood of below-, near-, and above-average precipitation. Findings from the inspection of the probability distributions include the following: 1) strong El Niño is related to a higher likelihood of increased wintertime wetness relative to average conditions; 2) the modal values of the regional precipitation distributions fall at one standardized departure from the climatological average, suggesting that a strong El Niño is associated with high precipitation predictability, given a signal-to-noise ratio exceeding one; and 3) while wet conditions become more likely over these regions during El Niño, there is still some chance for below-average precipitation.

Offline analysis. The interactive analysis/visualization capability of FACTS is designed to provide a "quick look" at the data, not to be a comprehensive data analysis platform. If further analysis is desired by the user, all the climate model data can be downloaded through a search interface (observations and reanalyses can be downloaded through the PSL dataset pages www.psl.noaa.gov/data/gridded/index.html). The data can be subset by model, experiment, ensemble member, or variable. Daily data can also be subset by time range.

Here we provide a limited number of examples from published studies that have used data downloaded from FACTS to illustrate the types of research that can be pursued with the unique datasets hosted on FACTS.

DIAGNOSING THE FORCED RESPONSE TO OBSERVED SSTs. Analysis of signal-to-noise ratios in ensembles of AMIP simulations, in which each realization is forced by the same time-varying sea surface temperatures and sea ice, allows one to estimate the predictability of regional weather and climate related to SST. For example, Hartmann (2015) regressed large ensemble AMIP mean circulation and temperature fields for three models (ECHAM5, GFSv2, and CAM4) onto an observational derived SST index time series. Using these data from FACTS, Hartmann (2015) determined that SST anomalies contributed to the anomalously cold winter of 2013/14 in the central and eastern United States and Canada. In another study, Johnson and Kosaka (2016) compared convective versus nonconvective eastern Pacific El Niño event differences in atmospheric circulation patterns among six FACTS AMIP models and two reanalyses. By analyzing data from FACTS, they found that all six models capture the reanalysis pattern of this difference although with some disagreement among the models in the strength of several centers of action of the teleconnection.

DIAGNOSING THE CLIMATE CHANGE CONTRIBUTION TO EXTREME WEATHER-RELATED CLIMATE EVENTS. The simulations hosted by FACTS can be used to determine whether anthropogenic climate change affects the frequency of occurrence and/or magnitude of extreme weather-related climate events. Large ensembles are prerequisite for meaningful diagnostics of changes in such extreme events. In one approach, statistics of extreme events of interest between the factual and counterfactual AMIP ensemble simulations can be compared. For example, Wolter et al. (2018) used the respective ECHAM5 simulations from FACTS to determine whether heavy winter precipitation events overall, and heavy snowstorms, have changed in the mid-Atlantic region due to long-term climate change.

In a second approach, CESM-LE and/or CAM5 AMIP historical simulations that start in 1920 can be diagnosed for different time slices (e.g., 1920–49 versus 1987–2016) to determine the anthropogenic climate change contribution for an extreme climate event. For example, Hoell et al. (2019) used data from FACTS to investigate the anthropogenic climate change contributions to the intensity of the U.S. northern Great Plains drought during May–July 2017. Their findings revealed that anthropogenic forcing made the occurrence of observed 2017 northern Great Plains drought intensity up to 1.5 times more likely and that this finding was robust in the coupled and AMIP simulations.

DIAGNOSING THE IMPACT OF OBSERVED ARCTIC SEA ICE LOSS. The FACTS data archive also includes a suite of experiments that allows the investigation of the role of Arctic sea ice loss on climate change in both the Arctic (e.g., Sun et al. 2018) and lower latitudes (Xue et al. 2017; Mori et al. 2019). For example, Sun et al. (2018) investigated the drivers of the 2016 record Arctic warmth using the AMIP factual, counterfactual, and fixed polar run simulations of the ECHAM5 model, as well as the CESM1 large ensemble of coupled climate simulations. With the set of AMIP experiments from FACTS, Sun et al. (2018) determined that three-quarters of the magnitude of 2016 annual mean Arctic warmth was forced, with about 60%–70% due to Arctic sea ice loss change and about 30%–40% due to drivers outside of the Arctic. A diagnosis of the CESM-LE indicates 60% of the 2016 Arctic warmth was due to human-induced climate change.

Future plans and summary

We will continue to develop and expand the FACTS data archive and enhance its visualization capabilities in support of research to improve the understanding of weather and climate variability. New model experiments, observed datasets, and additional Earth system reanalysis datasets will be added as they become available. Improved capabilities for analyzing daily observational, reanalysis, and model data and new visualizations including animations are currently in development. New capabilities to diagnose initialized forecast

ensembles such as the North American Multi-Model Ensemble (Kirtman et al. 2014) and the Global Ensemble Forecast System (Hamill et al. 2013) are being evaluated for inclusion on FACTS.

The FACTS data archive and interactive visualization components allow users to quickly investigate factors in extreme climate and weather events and then perform more detailed analyses with the data. The usefulness of this facility is highlighted in the case study analyses presented as well as the examples from peer-reviewed publications across the weather and climate community which used data from the FACTS archive. This capability is a resource for the entire weather and climate community to investigate the cause and effect linkages to occurrences of extreme subseasonal to interannual states and to better understand regimes shifts and long-term trends. More details on the models, experiments and variables available can be found on the FACTS website (www.psl.noaa.gov/repository/factsdocs). Ongoing feedback for additional improvements to the system can be made through the FACTS website.

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