Advancing a Coordinated Strategy for Decision-Relevant Climate Data Products for the United States

Paul A. Ullrich, Lawrence Livermore National Laboratory and University of California Davis

Daniel R. Feldman, Lawrence Berkeley National Laboratory

Jay Alder, United States Geological Survey

Jen Bewley, Institute for Defense Analyses

Melissa Bukovsky, University of Wyoming

Keith Dixon, National Oceanic and Atmospheric Administration

Ethan Gutmann, NSF National Center for Atmospheric Research

Kripa Jagannathan, Lawrence Berkeley National Laboratory

Andrew Jones, Lawrence Berkeley National Laboratory, University of California Berkeley

Rao Kotamarthi, Argonne National Laboratory

Hugo Lee, NASA Jet Propulsion Laboratory

Fred Lipschultz, Universities Space Research Association

Jeremy Littell, United States Geological Survey

Elias Massoud, Oak Ridge National Laboratory

Rachel McCrary, NSF National Center for Atmospheric Research

Richard Moss, Andlinger Center for Energy and the Environment, Princeton University

Stefan Rahimi-Esfarjani, University of Wyoming

Andrew Schwarz, California Department of Water Resources

Tanya L. Spero, Office of Research and Development, US Environmental Protection Agency

Scott Steinschneider, Cornell University

Liqiang Sun, National Oceanic and Atmospheric Administration

Adrienne M. Wootten, South Central Climate Adaptation Science Center, University of Oklahoma

Corresponding Author: Paul A. Ullrich, ullrich4@llnl.gov

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Abstract

Climate adaptation practitioners, planners, and policymakers rely on historical reconstructions and future projections of regional to local climate for adaptation, resilience, and risk management. To serve the many needs of these users, climate data must be relevant for informing the decision-making process ("salient"), consistent with our physical understanding of the global Earth system ("credible"), backed by expert judgment ("authoritative"), and publicly available and ready for use ("accessible"). As more decision-relevant climate data products are being developed to address outstanding needs, important challenges have emerged around the selection, evaluation, use, and standardization of these data products. This article examines opportunities and challenges associated with regional climate data for the United States and describes nascent efforts to build a coordinated strategy among communities of producers and users to maximize the utility of decision-relevant datasets. A community of practice (CoP) is now emerging to benefit both end-users and data producers. The CoP will enable enhanced evaluation protocols, improved uncertainty quantification, and eased data distribution and usage, informed by ongoing input on data needs and feedback on quality and usability of data from a wide range of user communities. Broad coordination among interested parties and periodic reviews of the state of the field are vital to the success of this community of practice.

Significance Statement

The need for actionable information on climate risks continues to grow across the United States, as communities work to address the localized risks faced by people, infrastructure, and ecosystems. While the climate science community advances the scientific understanding of global and regional Earth System change along with the processes relevant to those specific climate risks, two persistent gaps remain: developing usable data products and sharing of knowledge about them. This paper describes the state of decision-relevant climate data products and suggests near-term directions to cultivate a community of practice to support improved decision-making given a wide range of potential climate futures.

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Capsule

This paper presents the state of the practice and near-term directions to advance the development, dissemination, and utilization of decision-relevant climate data products through a community of practice.

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Introduction

Earth system models (ESMs) are among our best tools to advance our understanding of the Earth system and its response to forcing through comprehensive, physics-based simulation of the Earth's atmosphere, oceans, surface, and sub-surface. Although ESM data are highly relevant to our understanding of present and future climate, raw ESM output is often insufficient for meeting localized and actionable information needs for adaptation planning, vulnerability assessment, and mitigation because of the mismatch in the temporal and spatial scales needed to characterize decision-relevant features (i.e., daily or monthly at ~1 degree latitude/longitude vs. sub-daily at ~12-km or finer grid spacing), the scarcity of decision-relevant variables beyond temperature and precipitation, and the limited representativeness of the variables that are provided. Collectively, the volume of data from ESMs (Petrie et al. 2021) and large uncertainties ascribed to models, downscaling or regional-scale process understanding (Lafferty and Sriver 2023) can make data intractable for decision-making. To resolve these issues, observational and ESM data are typically downscaled, debiased, validated, and provisioned, leading to "decision-relevant climate data products" (DRCDPs).

DRCDPs encompass both observation-based and model-generated datasets, incorporate ESM information, and span various geographies and variables relevant to the Earth system at the scales relevant for decision-making. Although our primary focus here is on long-period large ensembles over regional-to-national spatial domains, DRCDPs also include hindcasts, storyline simulations, or more localized products. Acknowledging that different DRCDPs are produced to address different needs, these data products should nonetheless have the following characteristics:

- **Salient [S]:** Products should align closely with practitioners' decision context and provide the necessary variables at the spatial and temporal scales and cover the spatial and temporal domains needed to inform decision-making.
- **Credible [C]:** Data should be consistent with observations and shown to capture key physical processes (i.e., they should be right for the right reasons, and both their correctness and the reasons for their correctness understood and explainable). They

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should also accurately represent the frequency and character of recurring regional atmospheric phenomena, within acceptable levels of uncertainty for users.

- **Authoritative [Au]:** Data products and the methods used to generate those products should be backed by independent experts and user feedback.
- **Accessible [Ac]:** Data should be publicly available, compatible with existing workflows, and tractable by users with varied technical expertise.

These characteristics are drawn from seminal literature on characteristics of actionable knowledge more broadly (such as the credibility, legitimacy and salience framework by Cash et al. 2003 and the fit, interplay and interaction framework by Lemos et al. 2012), which were then adjusted for the specific context of decision-relevant data products. For instance, legitimacy was interpreted as authoritative for this context, and fit and interplay are encompassed within the accessible category. Particularly it is noted that here authoritativeness is assessed through a process where producers, evaluators, and users are all brought in to vouch for the value of a product; it does not simply refer to experts putting their stamp of approval on a product, but that actual users of that data have to provide reviews of its value.

The path from end-user need to generating and vetting effective data products can take years and includes many steps, with user feedback needing to be incorporated at key stages (Figure 1). Each of these steps intends to ensure data are best aligned with the four definitive criteria (S, C, Au, Ac) of DRCDPs above:

- **Generation of observations and observation-based products [C]:** Observations include a variety of *in situ* and remotely sensed datasets that contribute to gridded observation-based products. These datasets constrain the statistics of key Earth-system variables and serve as training or validation data for DRCDPs.
- **Data production and standardization [S,Au]:** Motivated by end-user need and engagement with the end-user community, climate data producers develop datasets supported by observation-based data and model simulations. There are several methods for data production (Figure 2). A priori standardization can be performed to unify spatial coverage of data. A posteriori standardization can conform dataset

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structure, variable names, and metadata to common standards to enhance their interoperability.

- **Bias adjustment [C]:** Raw model output contains biases that can make the data inappropriate for some users. Bias adjustment (BA), often referred to as bias correction, can overcome or mitigate some of these issues, though care must be taken to ensure the process is defensible.
- **Benchmarking, evaluation, and quality control [C,Au]:** Independent evaluation of data can ascertain if statistics, processes and features are consistent with observations and physical principles. This information can be provided to data producers to improve their data products.
- **Derived products [S]:** DRCDP-derived data may be created to better meet user needs, including climate indices, subsequent model simulations and their output (e.g., hydrologic model runs), weather generators, and/or data consolidated into stakeholder-aligned regions.
- **Data synthesis [S]:** By considering multiple DRCDPs together, uncertainties in climate statistics can be better quantified and instances of consensus among products can be identified.
- **Visualization, analysis, and data provisioning [S,Ac]:** Use of DRCDPs can be enhanced by static and interactive visualizations, targeted analyses of those data (i.e., data reductions), and distribution of those datasets and associated derived products through public data portals.
- **Guidance for end-users [S]:** Data producers, evaluators, scientists, and end-users collaborate to interpret the outcomes revealed by the suite of DRCDPs. These interactions also influence the next generation of DRCDPs.

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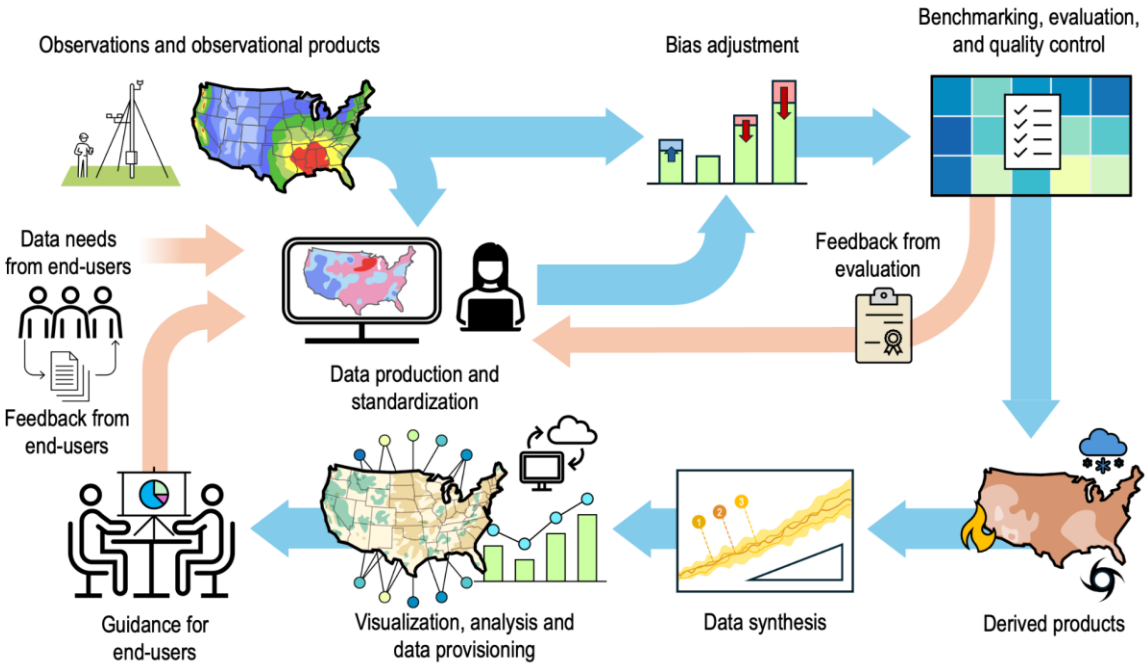

Figure 1: An integrated workflow for the production, evaluation, and use of decision-relevant climate data products. Blue arrows denote data transfer pathways. Brown arrows denote pathways for communication between groups, envisioned to be facilitated by the community of practice.

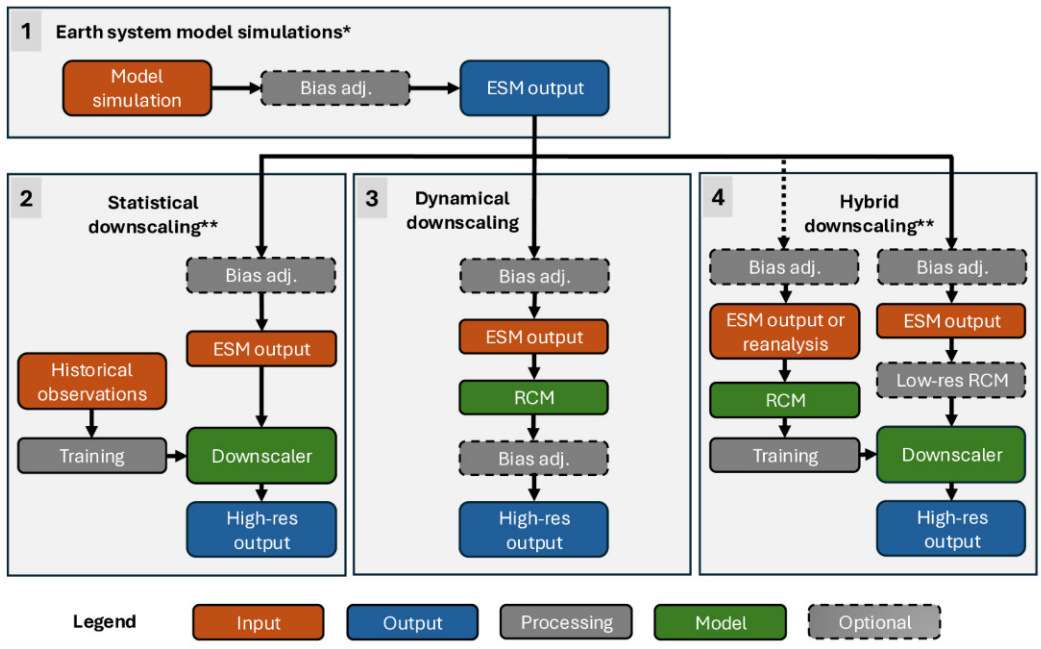

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Figure 2: Decision-relevant data production methods. *Includes low-resolution, high-resolution, ultra-high-resolution, and regionally refined simulations. **AI/ML can also be used for these downscaling methods.

At present there are no standards or organizations in the US that govern climate data production, data provisioning, or the development of user guidance. This has meant that climate services organizations, along with independent efforts at understanding climate impacts, have largely operated in isolation and have had to develop their own in-house best practices around DRCDPs. The recent development of the *Fifth National Climate Assessment* (NCA5; USGCRP 2023) revealed that the interconnected nature of the DRCDP development process would benefit from increased communication among data producers, data evaluators, end-users, and others working with these datasets. Most end-users lack the resources to create a new DRCDP and instead must choose from existing products to address their use cases. The reasons for selecting data products vary (Table 1), and sometimes pragmatism outweighs fitness-for-purpose for practitioner needs.

The need for increased connectivity among data producers, translators, and stakeholders motivated a multi-agency workshop, held in Berkeley, California in November 2023, to characterize the state of the practice and develop practical activities to initiate a community of practice (CoP) (U.S. DOE 2024). Additional workshops, including one hosted by the NASA Jet Propulsion Laboratory in October 2024 and a Town Hall at the 2024 Fall Meeting of the American Geophysical Union (Joseph et al. 2024), further highlighted the interagency and interdisciplinary needs for DRCDPs. These interactions cultivated a deeper understanding of how DRCDPs are produced, evaluated, synthesized, and prepared for informing end-users. This process revealed opportunities, challenges, and gaps that could be addressed to improve efficiency and enhance the utility of these datasets.

The proposed CoP would coalesce around a unified strategy within the US to address this need, avoid redundancy among participating agencies and groups, and ensure sustained momentum. Working groups that could be part of a CoP have already been initiated to build a unified vocabulary around decision-relevant data, fill data gaps, catalog available products, develop a common and practitioner-friendly data format, establish a common evaluation protocol,

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coordinate cyberinfrastructure for distribution and analysis of these products and collect expert guidance on these products. Notably, this is not the first CoP in the climate data space. For example, the Coordinated Regional climate Downscaling Experiment (CORDEX), which is part of the World Climate Research Program's Regional Information for Society Core Project, advances and coordinates downscaling through an international CoP (Giorgi et al. 2009). Data developed for CORDEX spans all global land areas and requires standardization of simulations for compatibility across downscaling methods and regions. However, despite international success and a vibrant international community, the community still has issues with effectively coordinating statistical downscaling, and in the US, CORDEX has yet to gain widespread community support. Here, we propose a CoP encompassing a broader group of data producers, developers of downscaling methods, evaluators, and end-users to fulfill US data needs.

Table 1: Common reasons by practitioners to use a particular data source, derived from the authors' experiences and discussions among the practitioner community.

Reason to Use a Data Source	**Explanation**
Word-of-mouth	Suggested by a colleague or collaborator.
Existing collaboration and/or investment (inertia)	Previous work continues with a data producer or a DRCDP.
Agency affiliation	Use of a data product produced by that agency.
Regulatory mandate	Statutes prescribe the use of a particular product.
Used in prominent studies and/or reports	Using a DRCDP in some prominent studies and reports (e.g., in the NCA) promotes confidence in the validity of the DRCDP.
Includes unique/required variable or phenomena	Some variables or meteorological phenomena are only available in a subset of DRCDPs.
Geographic coverage	Some geographic regions are only available in a subset of DRCDPs. Enhanced geographical coverage may be required to capture the development of upstream atmospheric phenomena.
At the spatial scales	Higher spatial resolution is only available in a subset of DRCDPs.

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needed	
At the temporal scales needed	Higher temporal resolution is only available in a subset of DRCDPs.
Based on evaluation for the region	An evaluation using some combination of metrics, diagnostics, and/or published research identifies a particular product.

This paper synthesizes and organizes past discussions to identify ongoing directions for action by our proposed CoP that could improve the quality and coverage of existing DRCDPs. The suggested directions of action identified in this paper echo others who have recognized these needs. However, we aim to provide a fairly comprehensive list of these examples so we can coordinate as a community, form a unified strategy, and avoid redundancy. These examples are organized in accordance with Figure 1. An initial goal of the nascent CoP is to clarify the actions' urgency, prioritization, and where there are opportunities to make progress in each area. This roadmap for parallel efforts is designed to ascertain future successes and regularly revisit progress in each area.

Ongoing Directions for Action

Observations and observation-based products

Observations and observation-based products are foundational to every DRCDP. They capture the ranges and multivariate statistical distributions over the historical record and reflect the many processes that produce such observations. For the contiguous United States (CONUS), there is a rich and dense suite of data for at least the past 50 years, including high-frequency ground-based observations, twice-daily upper-air measurements, satellite retrievals, radar reflectivities, locally dense ground-based networks (i.e., mesonets), and data from special studies of atmospheric phenomena. These data capture atmospheric conditions at the ground and aloft, including measurements of weather and air quality parameters. Such information is used to build a climatology that can then be used to train and evaluate DRCDPs. Longer observational records better represent natural and forced variability in local, regional and

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global processes. Areas with observational records that are shorter or sparser (e.g., US regions outside the CONUS, known as the OCONUS) would benefit from new observational sources (Global Observing System 2021) or innovative observational proxies. Globally, long-term records of surface air temperature and surface precipitation are often used for developing DRCDPs, but records are much less robust for commonly used variables including hub-height wind speeds, solar radiation, and humidity. While collecting data is laborious and expensive, the interruption or cessation of data collection hampers climate data record development (Weatherhead et al. 2016).

Observation-based products present apparent additional opportunities. Widely used observation-based products over the CONUS include the Parameter-elevation Regressions on Independent Slopes Model (PRISM; Daly et al. 2008), nClimGrid (Durre et al. 2022), DayMet (Thornton et al. 2021), and the Livneh dataset (Livneh et al. 2015; Pierce et al. 2021), but while all intend to be representative of historical conditions, spatial and temporal differences arise from the choice of input datasets and processing methods.

To highlight an example of why choices in datasets and processing methods are so consequential, Pierce et al. (2021) found issues with a seemingly innocuous and reasonable decision by Livneh et al. (2015) to construct a daily precipitation dataset (which was subsequently widely-used for downscaling training). Specifically, Livneh et al. (2015) gridded precipitation data in regular 24-hour intervals, but the raw precipitation measurements were collected at different times-of-day, leading to an artificial splitting and muting of extreme precipitation events. The result, prior to a correction by simply not gridding the data into 24-hour intervals, was a training dataset that had up to 21% too few precipitation days and too low evapotranspiration and runoff.

Ongoing progress in collecting observations and reinterpreting previous observations, as well as ongoing improvements in gridding methodology (Mankin et al. 2025), presents opportunities to regularly revisit and update historical observation-based products. These differences can have significant impact on gridded data, especially statistically-downscaled products (Mizukami et al. 2016).

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Data production and standardization

ESM data are projected to regional and local scales using "downscaling" to better align with the needs of practitioners. Downscaling is typically conducted using either statistical (Giorgi and Mearns 1991) or dynamical (physics-based) (Dickinson et al. 1989) models, each of which contains tradeoffs for ensemble size, suite of variables, and spatial and temporal resolution (e.g., Mearns et al. 2018). Numerous downscaled datasets are currently available over the U.S. (Tables 2 and 3), generally produced from simulations conducted under the Coupled Model Intercomparison Project (CMIP; Eyring et al. 2016). However, coverage for the OCONUS is sporadic, and some regions may only have one set of dynamically downscaled simulations (Basile et al. 2024); in part, this is because of the aforementioned sparsity of observations in these regions, suggesting a possible opportunity for novel data production approaches.

Increased regional climate data generation for the U.S. presents an opportunity to characterize, quantify uncertainties in, and intercompare those data. Propelled by recent progress (Lafferty et al. 2023; Risser et al. 2024; Rahimi et al. 2024; Hall et al. 2024; Hartke et al. 2025), the development of rigorous and inclusive frameworks for basic quantification and characterization of downscaling technique uncertainties could be beneficial, given the plethora of new downscaled ESM datasets. The need for such frameworks is imminent, as large ensembles of artificial intelligence and machine learning (AI/ML) downscaled datasets are becoming increasingly common (e.g., Chegwidden et al. 2022; Rastogi et al. 2025; Ignacio-Lopez et al. 2024).

DRCDPs can be easier to use, evaluate, and compare when they have common attributes. Where feasible, interoperability of these DRCDPs would be enhanced with common variable names and file metadata, such as Climate and Forecast (CF; Eaton et al. 2003) and Climate Model Output Rewriter (CMOR; Mauzey et al. 2024), as well as guidance on file chunking for easier processing. Data standardization, even with tools like CMOR, can require a significant time investment by a user or evaluator, suggesting an opportunity to make this process more accessible. Developers could be further incentivized to standardize their data to be hosted on services such as the Earth System Grid Federation (ESGF).

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There is nevertheless tension between standardization and the operational needs of end-users, who may require data in particular formats (e.g., to be compatible with Geographic Information System software). This suggests an opportunity for the community to lower bars to adoption of new datasets, for instance through the development of conversion tools to enhance data translatability.

Bias adjustment

Bias adjustment (BA, i.e., the re-alignment of model data with observations) is commonly used in regional ESM downscaling (Ehret et al. 2012; Maraun 2016; Lafferty et al. 2023; Risser et al. 2024). For statistically downscaled datasets, BA is applied a posteriori to the variables desired for downstream use (e.g., precipitation, near-surface air temperature), typically using methods based on quantile mapping (Giorgi 2019; Maraun 2016). With dynamical downscaling, the ESM boundary conditions may be bias adjusted before downscaling (e.g., Kim et al. 2023) and/or downscaled variables may be bias adjusted after downscaling. However, intervariable correlations can be compromised if those variables undergo BA independently (François et al. 2020). To date, best practices for BA have not been developed to address if or how BA should be applied, although some recommendations have been given (Maraun et al. 2017). As such, there is an opportunity for a BA working group to develop guidance on appropriate and beneficial uses of BA.

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Table 2: Several modern high-resolution statistically or AI/ML downscaled ESM datasets including both the historical period and future projections.

Statistically or AI/ML Downscaled Dataset	Spatial Coverage & Resolution	Temporal Frequency & Period	Driving Models No. Future Scenarios	Variables
Localized Analogs (LOCA2) (Pierce et al. 2023)*	CONUS 6km	daily 1950-2100	27 CMIP6 ESMs 3 scenarios	temperature precipitation
Multivariate Adaptive Constructed Analogs version 2 (MACA) (Abatzoglou and Brown 2011)	CONUS 6km/4km	daily 1950-2100	20 CMIP5 ESMs 2 scenarios	major surface variables**
NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) (Thrasher et al. 2012)	Global 25km	daily 1950-2100	21 CMIP5 + 34 CMIP6 ESMs 2 scenarios	major surface variables**
NASA Earth Exchange Downscaled Climate Projections (NEX-DCP30) (Thrasher et al. 2024)	CONUS 1km	daily 1950-2100	30 CMIP6 ESMs 4 scenarios	temperature precipitation
Ensemble Generalized Analog Regression Downscaling (En-GARD) (Gutmann et al. 2022; Hartke et al. 2024)	CONUS + AK + HI 12-1km	daily 1950-2100	20 CMIP6 ESMs 3 scenarios	temperature precipitation
SWA9505V3: SECURE Water Act Section 9505 CONUS Climate, Hydrology and Hydropower Projections (Kao et al. 2022)	CONUS 4km	daily 1980-2099	6 CMIP6 ESMs 2 scenarios	major surface variables**
Seasonal Trends and Analysis of Residuals Empirical Statistical Downscaling Model (STAR-ESDM) (Hayhoe et al. 2024)*	CONUS 4km	daily 1950-2100	23 CMIP6 ESMs 2+ scenarios	temperature precipitation

* this dataset was included in the NCA5 Atlas
** see reference for more information

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Table 3: Several modern high-resolution dynamically downscaled ESM datasets with data from both the historical period and future projections.

Dynamically Downscaled Dataset	Spatial Coverage & Resolution	Temporal Frequency & Period	Driving Models No. Future Scenarios	Regional Model
Climate Risk & Resilience (ClimRR) (ANL 2023; Wang and Kotamarthi 2015)	N. America 12km	3-hourly 1995-2004 2045-2054 2085-2094	3 CMIP5 ESMs 2 scenarios	WRFv3.2
CONUS404 (Rasmussen et al. 2023)	CONUS 4km	hourly 1980-2020	ERA5 Reanalysis + pseudo global warming 1 scenario	WRFv3.9.1
EPA Dynamically Downscaled Ensemble (EDDE) version 1 (Nolte et al. 2021)	N. America 36km	hourly 1975-2005 2025-2100	2 CMIP5 ESMs 2 scenarios	WRFv3.4.1 WRFv3.6
EDDE version 2 (Spero et al. 2025)	N. America 12km	5-minute hourly 1985-2014 2025-2100	1 CMIP6 ESM (more planned) 2 scenarios	WRFv4.5.1
HyperFACETS / IM3 Thermodynamic Global Warming (TGW) Experiments (Jones et al. 2023)	CONUS 12km	hourly 3-hourly 1980-2019 2020-2059 2060-2099	ERA5 Reanalysis + thermodynamic global warming 4 scenarios	WRFv4.2.1
North American CORDEX (Diaz-Sierra et al. 2022; Mearns et al. 2017; Bukovsky and Mearns 2020)	N. America 25km and/or 50km	hourly daily monthly 1950-2100	Various CMIP5/6, 3 scenarios (32 unique simulations)	7 regional climate models
Pacific Northwest National Laboratory (PNNL) Western US Ensemble (Chen et al. 2023)	WUS 6km	hourly 6-hourly 1981-2020 2041-2070	NARR + pseudo global warming 1 scenario	WRFv3.8
SWA9505V3 Dynamically Downscaled Ensemble (Kao et al. 2022)	CONUS 4km	daily 1980-2059	5 CMIP6 ESMs 1 scenario	RegCM
Western US Dynamically Downscaled Dataset (WUS-D3) (Rahimi et al. 2024)	WUS 9km*	6-hourly	15 CMIP6 ESMs 1 scenario	WRFv4.1.3

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* available at 3km over California and the Rocky Mountains

Benchmarking, evaluation and quality control

Benchmarking refers to the process of comparing a product against similar products, while evaluation refers to assessment of that product against standard criteria. Together these efforts promote confidence in DRCDPs' representation of historical and future weather events and their associated statistics.

Although data producers evaluate their own products, widely accepted standards, associated software, and independent testing could facilitate more comprehensive evaluation and enable more comprehensive benchmarking. Emerging literature, particularly from the UK Climate Projections (UKCP18), has started to identify specific dimensions for assessing the quality of regional climate information (Pacchetti et al. 2021a; Pacchetti et al. 2021b). For instance, Pacchetti et al. (2021a) identify diversity, completeness, theory, adequacy for purpose, and transparency as key quality dimensions under which regional climate information may be evaluated. A standard evaluation protocol would further enable the tracking of product performance over time, support documentation of systematic errors across models, and identify anomalous behavior in particular models that can be reported to producers (Meehl et al. 1997).

Of course, differences in DRCDP production methods need to be considered in any intercomparison; for example, statistical downscaling leads to large ensembles of a few variables, while dynamical downscaling produces a small ensemble of many variables. Additionally, different use cases emphasize different performance metrics and impose requirements on the spatial and temporal resolution of the data (e.g., long-term regional droughts vs. localized flooding from a thunderstorm), reflecting the potential to develop a taxonomy of user inquiries and a set of relevant evaluation criteria for each associated inquiry (potentially informed by AI, as discussed in Dee et al. 2024). For variables such as winds, humidity, radiation, and snow, additional work is needed to develop or identify appropriate reference (i.e., observation-based) products and define meaningful use-inspired metrics.

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DRCDPs are also now used to examine more complex phenomena (e.g., extreme heat that includes humidity, fire weather, drought, energy production, and freezing rain), so benchmarking frameworks are needed to address these phenomena and to evaluate multivariate temporal and spatial relationships and covariances.

Practitioners are increasingly considering the potential consequences of climate change, so new strategies are needed to ensure DRCDPs are physically consistent and trustworthy for projecting the future (e.g., Bukovsky et al. 2017; Mindlin et al. 2023; Doblas-Reyes et al. 2021). For example, Massoud et al. (2023) evaluated the equilibrium climate sensitivity (ECS) of Earth system models to ameliorate the "hot model problem" in CMIP6; similar constraints on ECS at regional scales could be used to identify physically inconsistent behavior in downscaled products. Emergent constraints, applied at regional scales, provide another avenue to potentially assess future projections (Hall et al. 2021).

Standardized evaluation and benchmarking does introduce a host of additional questions: should a minimum performance threshold be applied to our DRCDPs before use? To what degree should that threshold depend on the application and the consequences of an incorrect result being used? Are there products that experts should discourage end-users from even using in general or for specific use-cases? With rapid growth in the number of available products and limited bandwidth, end-users typically have to choose only one or a small subset of products for their needs; consequently, one could wonder to what degree robustness is lost when only a subset of products are employed? These questions do not yet have clear answers, but a rich literature is now emerging that suggest possible heuristics when a decision is needed (e.g., Goldenson et al. 2021; Dee et al. 2024). This literature also suggests that such standards for evaluation need to be developed collaboratively with a group that includes a diverse set of data producers, data users and evaluators (Freitas et al. 2025; Jagannathan et al. 2024).

AI/ML methods, including historically trained models, model emulators, and foundation models, are an emerging approach for DRCDP production that raise new evaluation challenges. A common concern is the ability of these models to capture weather outside the bounds of their training data, despite this also being an issue for statistical methods and the dynamical

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model parameterizations (Ullrich et al. 2025). However, unlike traditional approaches, the "black box" nature of AI/ML models means it is difficult to understand model behavior under these circumstances. These AI/ML models have the ability to better capture the behavior of complex systems with higher complexity, and such expressivity is sometimes required (Camps-Valls et al. 2025). Simultaneously, there is also a need to better understand how AI/ML fits into the ecosystem of data production methods and what limitations and opportunities they provide, possibly necessitating a working group on AI/ML downscaling. AI/ML may also bolster data evaluation by identifying anomalous behavior in DRCDPs, analogous to how existing large language models can identify erroneous code, or by providing a friendly user interface for addressing targeted queries.

Derived products

Derived products are computed from raw DRCDP time series and include climate indices, model simulations driven by DRCDPs, and similarly distilled datasets. Large ensembles of simulated meteorological records produced by weather generators are emerging forms of derived products and can allow for systematic stress testing and risk analysis in water, agricultural, and other environmental systems (Najibi et al. 2024a,b). In general, derived products can be more useful to decision-makers than raw downscaled ESM datasets (Karl et al. 1999; Kenney et al. 2020; Anderson et al. 2021; McGinnis and Mearns 2021). Centralizing the creation of derived products and provisioning them to end-users would avoid large data transfers and redundant computations. Alternatively, standard open-source pipelines or workflows for computing these quantities from DRCDPs with corresponding metadata would ensure consistency in computation and avoid the need to develop new ad hoc codes (either from data producers or user agencies) (e.g., Bourgault et al. 2023). The ability to customize such workflows presents certain advantages. For example, users' abilities to apply different thresholds to universally important variables for different regions could provide more regionally tailored output. Notably, the generation of these products would be streamlined if data products adopted common data standards, including consistent data provenance, and clear documentation of methods and assumptions.

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Data synthesis

As demonstrated by CMIP, CORDEX, and in recent work constraining ECS (Sherwood et al. 2020), robust insights can emerge when multiple models and approaches for generating and analyzing DRCDPs are considered together (Wootten et al., 2020, 2023). However, combining data products to better constrain projections requires careful consideration of ensemble size, differences in statistical distributions (including the impact of BA), the model training process, and available driving ESMs and scenarios. DRCDPs are almost never perfectly aligned, but this should not preclude combining them to reinforce the conclusions of a study or prevent efforts to contrast them in the same framework. Quantifying confidence based on agreement between products is critical for assessing uncertainty, as highlighted in Lafferty and Sriver (2023) on uncertainty in downscaling. When providing future projections, presenting either a single best estimate or a range of outcomes to users impacts how uncertainty is communicated (Massoud et al. 2019, 2023). Scientifically grounded guidance for data synthesis could be developed by drawing strength from the variety of data production methods.

Visualization, analysis, and data provisioning

Compared to global climate analysis, which requires spatial and temporal granularity throughout the atmosphere, enhancing decision-relevance from DRCDPs often requires only summaries of a few relevant and regionalized variables, simplifying the analytics, visualization, and data provisioning. This greatly reduces the storage, computation, and visualization requirements, even when summarized to commonly used spatial units, such as geopolitical boundaries, watersheds, ecosystems, management units, or tribal lands. Online tools and data access portals use different approaches tailored for disparate users (see Vano and Lukas 2022). These tools offer scientific rigor to examine available data (i.e., threshold analytics, time-series analyses, intensity-duration-frequency curves), are well documented or provide open code bases, and provide common data formatting options. Such tools include assumptions about user needs, scientific background, selection of appropriate datasets for the topic area, and provision of visualization or analytical tools. Consequently, there has been an increase in available tools, which sometimes hinders the ability to identify the most appropriate data.

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Current tools are often built on a single pre-selected DRCDP rather than offering a spectrum of products that could reveal important insights. Catalogs (e.g., the National Center for Atmospheric Research's climate data guide; UCAR 2025; Schneider et al. 2013) and efforts at joint evaluation that quantify the strengths and weaknesses of each product (Ullrich 2023) are two valuable approaches for improving awareness of the data ecosystem. A notable challenge arises from a lack of standards between products, leading to the need for customized visualizations and analytical tools. Two key initiatives are underway to mitigate these challenges by improving community standards for file structures and for metadata to improve interoperability and by taking advantage of that standardization to improve access to products and analytical tools. The Program for Climate Model Diagnosis and Intercomparison (PCMDI), in collaboration with the Earth System Grid Federation (ESGF), has set standards for downscaled products that are compatible with existing tools for GCMs (Massoud et al. 2025). These efforts have already provided early success at meeting the data provisioning needs of users. Additionally, USGCRP's Climate Resilience Information System (CRIS) aims to provide more comprehensive support by integrating access to data, analytics, and expert guidance, helping users better understand and act upon climate resilience needs through partnerships with extension groups and boundary organizations. This holistic approach to providing data and decision-support tools advances the potential relevance of climate projections for end-users.

Guidance for end-users

Numerous DRCDPs have been successfully created and delivered to meet growing needs for regional and sectoral applications. However, improved data have not necessarily fostered better decision-making (Findlater et al. 2021; Hewitt et al. 2017), owing to the lack of appropriate guidance on using the available data to inform decisions (Barsugli et al. 2013; Tang and Dessai 2012). General guidance on how to use climate data and information (e.g., Snover et al. 2013; Terando et al. 2020; Kotamarthi et al. 2021) requires considerable tailoring and contextualization to be of practical use to decision-makers (Moss et al. 2019; Freitas et al. 2025). Therefore, literature on climate information and services has increasingly advocated for a demand-driven and use-centric approach to developing and provisioning climate data and guidance (Daly 2021; Weichselgartner 2019; Bruno Soares and Buontempo 2019).

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A use-centric approach to guidance would need to reflect the spectrum of climate data applications, users' technical capabilities, and the complexity of information required for adaptation. Many successful examples and case studies of climate data use offer valuable lessons for guidance development. For example, a small set of "champion" users from the Water Utility Climate Alliance and the U.S. Bureau of Reclamation and the Electric Power Research Institute's Climate READi team, have made innovative advances in climate data use for decisions and discussed their lessons learned (Vogel et al. 2016; Smith et al. 2022; Lai et al. 2022). Social sciences studies also examined the types of climate data users and their unique needs and capabilities (Wilby and Lu 2022), how users have used or intended to use climate data (Jagannathan et al. 2023; Reveco-Umaña 2023), the types of metrics users find useful (Vincent et al. 2020), and the challenges faced in using current data and tools (Bessembinder et al. 2019). Additional social sciences and collaborative research, as well as communication could help to better understand users' data needs (particularly for cases where users are not able to immediately articulate their specific data needs), as well as examine how well current data products are serving/can serve users' needs (Findlater et al. 2021; Hewitt et al. 2017).

In addition to being informed by practice, guidance may be collaboratively and iteratively developed through engagements between data producers, evaluators, and users (Jagannathan et al. 2024; Freitas et al. 2025). User perspectives, priorities, and challenges could be integrated into guidance to meet the practical needs of decision making (Bessembinder et al. 2019). Existing efforts (e.g., Boyles et al. 2024) have begun this transition, but could benefit from more direct collaboration with decision makers. Particularly, such guidance should include collaboratively developed recommendations on how users can choose (e.g., data products, models, scenarios) for various types of applications, pros and cons of different choices, how data credibility can be examined, and how uncertainties can be characterized. Suggested best practices while working with limited computational capacities (i.e., needing to work with limited amounts of data) and in time-sensitive applications are also necessary. Guidance should also be accompanied by simultaneous capacity building for data producers, evaluators, and users (Bruno Soares and Buontempo 2019; Bessembinder et al. 2019). For instance, data producers and evaluators may benefit from training on how to listen, understand, and respond

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to user needs (Porter and Dessai 2017) and on principles of translational science (e.g., Enquist et al. 2017). Similarly, users may benefit from training on best practices in climate data use and on how to enhance their technical and computational capabilities. This training and the available guidance for users will require routine updates as new and improved data products emerge, particularly with the increasing production of AI/ML datasets.

Improving communication pathways via an emerging community of practice

Addressing the opportunities identified in the previous sections and advancing the production and appropriate use of climate projections requires engaging many areas of expertise and types of knowledge (Mach et al. 2024; Mariotti et al. 2024), such as climate modeling, model evaluation, data science, statistics, applied mathematics, and sector-specific modeling (e.g., hydrology, public health, engineering, ecology, energy). In addition, end-users of climate science, including private and public sector decision-makers, leaders of non-government organizations, landowners, and other practitioners need to be engaged to clarify information needs, and understand innovations in the use of climate data and products. On a project level, dialogue and collaboration across these areas of expertise has been occurring, particularly through processes of "co-production," collaborations between scientists and users that frame questions and information needs, including required variables, spatial and temporal scales, analytical tools, credibility assessments, information formats, visualizations, and technical guidance (Meadow et al. 2014; Vincent et al. 2018a; Jagannathan et al. 2021; Cullen et al. 2023). However, broader collaborations across multiple projects could highlight areas of improvement across contexts. Encouraging collaboration among participants across a breadth of expertise is challenging because these knowledge domains are highly specialized. A CoP could promote needed collaboration among different branches of climate science and evaluation.

In general, a CoP is a group of people who share a common interest or challenge and who interact regularly to improve their knowledge and skills and advance understanding of complex issues (Wenger et al. 2002). CoPs are subsequently well-positioned to disseminate knowledge across wider groups (Gill et al. 2024). To be successful, CoPs must be defined around shared

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challenges, interests and opportunities that incentivize members to participate actively and over a sufficiently long and sustained period to make progress (Cundill et al. 2015). The approach to establishing, building, and sustaining this CoP leverages the substantial body of work that recognizes the cultural and institutional assumptions underlying the use of a CoP for both providing as well as scaling up climate services (Lemos et al. 2025; Gill et al. 2024). The theory of CoPs established in Wegner (1998) has been foundational for CoP development and grown to include strategies to grow CoPs (Li et al. 2009; Cundill et al. 2015; Vincent et al. 2018b), especially as they relate to specific requirements for climate services (Srinivasan et al. 2011; Iyalomhe et al. 2013; Vaughan and Dessai, 2014). Ultimately, CoPs are uniquely capable in being able to address climate service needs that require an informal transdisciplinary network of people from different organizations (Gill et al. 2024), who are committed to working together to address a complex challenge. However, the varied interests of members can constrain the ability of the CoP to focus on concrete, tangible results, and further there could also be challenges in long term sustainability and facilitation of the CoP (Vincent et al. 2018b). We start by focusing on the low-hanging fruit on which there is broad consensus as to the needs for DRCDP advancement.

Here, the tasks for a CoP are highly technical and include improving evaluation of climate information for use, developing standards for different types of climate information, and providing technical guidance to different sectors of end users. Transparency and institutional neutrality are two important principles for a successful CoP (Page and Dilling 2019). Participants need to work toward sharing their methods, approaches, and data, while adhering to their organizational clearance processes. Further, in instances when individual participants may have competing methods and interests, the CoP process must be institutionally neutral. Some CoPs have been anchored within existing networks with a neutral stance, such as professional societies who have a long-term standing in the community. Connecting this emerging CoP with other complementary CoPs (such as CORDEX and other relevant World Climate Research Programme activities, American Society of Adaptation Professionals, American Geophysical Union's Science to Action network) could minimize duplicative roles. Some of the initial groundwork to assemble a CoP was undertaken as part of the 2023 Berkeley workshop (U.S.

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DOE, 2024) and subsequent collaborative engagements (including assembling this group of authors), under the anticipation of expanding these nascent efforts.

As the CoP takes form, we envision that a recruitment strategy for expanding the community could take many forms. Initial recruitment could be through a townhall or session at a professional society (e.g., the American Geophysical Union – AGU – or American Meteorological Society – AMS) meeting or at relevant CORDEX or CMIP meetings, (which is attended by many climate data users and producers). Outreach could also be to key private sector data providers through a landscape web-review, and also reaching out to a broader suite of users through connections with boundary agencies and other communities of practice such as ASAP (American Society for Adaptation Practitioner) or WUCA (Water Utilities Climate Alliance) or Mountain West Climate Services Partnership. Finally, partners could be found in regions/agencies that are under-represented in our group through a gap-analysis on representativeness of the CoP. The overall goal will be to build a well-balanced and representative CoP that is broader beyond our individual projects. However, since the DRCDP CoP will be sustained through volunteer time initially, some of these expectations might be limited based on who is able to volunteer their time.

Initially, we envision that this CoP will be sustained by volunteering and small contributions from individual participants who might be able to bring in resources to support coordination and engagements of the community. Many current participants have described this work as closely related to their primary scientific work enabling their voluntary participation initially. Given the many different sources of support for primary scientific work, the co-benefits of the CoP for current participants serves as an important source of diversification to enable continuity. We are also taking into account recognized approaches and challenges for transdisciplinary CoPs (Vincent et al. 2018b). The platforms of professional societies such as the AGU and AMS are potential venues for convening the community, increasing the visibility of the CoP's work, and a means to recruit new partners. As the CoP grows, funding would be required for maintenance, co-ordination and growth of this CoP. Support could come from foundations or private sector or non-profits interested in climate data, or leverage partnerships with other

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similar CoPs such as CMIP or CORDEX or other such communities to further explore mutually beneficial options.

One of the key contributions of the CoP would be to develop collectively agreed upon standards of evaluation for DRCDP datasets. These standards would be collaboratively developed by the community and include perspectives of a diverse set of producers, evaluators and users (and other stakeholders). We also envision the CoP to engage an external advisory group and update these standards at regular intervals further providing credibility to the framework. By establishing a commonly agreed upon and regularly updated evaluation framework for all datasets, the CoP can help to maintain institutional neutrality of standards of evaluation for DRCDPs and provide effective assessments of when, where and for what purposes various datasets should or should not be used.

Future directions

There is clearly room to advance the development, evaluation, and effective use of DRCDPs. Virtually all of that advancement requires collaboration that a community can accomplish but is often challenging for individual, isolated contributors.

To that end, a plan to track and evaluate community progress would promote transparency and encourage momentum (Boon et al. 2024; Vaughan and Dessai 2014; Bamzai-Dodson and McPherson 2022). Metrics can serve to advance the co-production of climate science information (Reed et al. 2022), but careful consideration is needed to ensure that metrics are formulated to achieve their goals (Van Noorden 2010). Given the previous stasis in the DRCDP community, it is critical that any metric should reflect bona fide progress to advance the state of the practice for DRCDPs.

One straightforward way to measure success is whether the findings here eventually become less meaningful, resonant, and impactful to the authors and readership. A steady or increasing rate of meaningful endpoints is likely to arise from the DRCDP community, including papers, reports, proceedings, meetings, tools, infrastructure, standards, and practices. If the CoP is

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successful and as it matures, within five years, readers who are familiar with at least one of the DRCDP topics may feel that the material presented here has aged and that the issues raised herein have been meaningfully and at least partially addressed. Conversely, if all of the material presented here still is fully relevant to the state of the practice, then the progress of the CoP will have been limited. Such a self-reflective assessment metric, while qualitative, can be converted into a quantitative metric based on those endpoints, to the extent that such a quantification promotes progress.

More concretely, there are very practical considerations that need to be made for maintaining and expanding this CoP. Outreach to interested communities that currently are not aware of and/or do not have the means to participate is critical for both the impact of the CoP, its ability to be a useful example for other climate service CoPs, and the stakeholders' perceptions of the impact of the CoP. It is therefore especially important to engage with vulnerable populations through their representatives and advocates while also monitoring economic, social, and health impacts to identify vulnerable populations that may have little to no representation or advocacy. Nevertheless, the long-term success of a CoP must recognize that the time-scales of developing and maintaining datasets do not necessarily align with the time-scales of interest by supporting agencies. Therefore, volunteer efforts and in-kind contributions are critical, and those that produce co-benefits for participants are foundational for sustaining and growing this CoP.

In closing, we emphasize that success of the CoP requires active engagement from the participants of the community and acknowledgement that there is benefit in working together on opportunities around decision-relevant data. We expect that a successful CoP effort in the US could be a model for elsewhere in the world, particularly those regions where resources are limited and future climate uncertainties remain high.

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Data Availability Statement

No datasets were generated or analyzed during the current study.

Disclaimer

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