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A Survey of Precipitation Data for Environmental Modeling

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Abstract: There is always a challenge of obtaining the "best" data to inform environmental models. Here we present different types of available precipitation datasets while detailing temporal and spatial resolution, potential errors in the dataset, and optimal performance scenarios. Our goal is to inform modelers of the various types, resolutions, and sources of precipitation data available for environmental modeling. Precipitation is the main driver in the hydrological cycle and modelers use this information to understand water quality and water availability. Environmental models use observed precipitation information for modeling past or current conditions, while simulated data are used to predict future conditions as well as recreate historic conditions. Several precipitation datasets and data generation methods such as National Climatic Data Center (NCDC) rain gauges, National and Global Land Data Assimilation (NLDAS, GLDAS), Next Generation Weather Radar, and Stochastic Weather Generators are described, giving their strengths and weaknesses. USEPA's Hydrologic Micro Services (HMS) project has developed a collection of interoperable water quantity and quality modeling components that leverage existing internet-based data sources and sensors via a web service. The precipitation component of USEPA's Hydrologic Micro Service (HMS) will provide the information and data from multiple sources through the web service for modeling purposes.

Keywords: Environmental Modeling; Precipitation; Hydrological Cycle

1. INTRODUCTION

Precipitation has great importance because it influences drinking water availability, supports agriculture, and maintains freshwater resources. Precipitation data are integral inputs for many watershed, air, erosion and agricultural models as well as climate-predicting projects. It determines flood/drought conditions, hydrologic transportation of contaminants, best management practices, and regulations. Precipitation data are generated through direct observation and model simulation. Observed data are captured directly from rain gauge stations, or technologically observed from radar and satellites. Simulated precipitation data are mathematically generated through mechanistic models that use parameterizations, statistical probabilities, or historical trends. There are many types of precipitation datasets with different spatial and temporal resolutions available for different project needs (Table 1). Each data type has strengths and weaknesses depending on its intended use. Here, we discuss different types of available precipitation datasets with details including temporal and spatial resolution, potential errors in the dataset, and optimal performance scenarios. We also discuss the benefits and deficiencies of certain precipitation datasets. Readers may use the information presented here to guide them on choosing precipitation data for their modeling or managing requirements. Focusing on a project's purpose and understanding its questions, goals, and needs are vital for selecting input data since exploratory, planning, and regulatory purposes have different input criteria and uncertainty thresholds (Harmel et al., 2014).

Some precipitation datasets are not readily available to the public in a readable format, may have missing information which decreases their usefulness, and can be time consuming or cumbersome to access. To overcome this problem in accessing water resource data, web services allow researchers, managers, and the public to become more familiar with the data and better informed to make improved decisions. Improving data access can result in reduced duplication of efforts and save time and money. Accessing web services from data providers, simulating model data, downloading precipitation data, shifting time-series to local time zones as needed, computing statistics, and flagging missing values are improvements needed in datasets for the modeling community. The USEPA's Hydrologic Micro Services (HMS) precipitation component allows the user to view and compare multiple data sources to make an educated decision on which data to use. Having multiple modeling components and various datasets in one place aids a water resource manager acquiring data. HMS currently implements several precipitation datasets, shown as the asterisks in Table 1.

2. HISTORY OF PRECIPITATION DATA

Rain gauge records have been available for hundreds of years. The first scientific report on differences in measured precipitation using height from rain gauges was by William Heberden in 1770 (Tapiador et al., 2012). As technology has advanced, rain gauge data has become more accurate in determining the amount of rainfall at a particular location. During World War II, radar operators searching for enemy ships and aircraft found that precipitation caused 'false' echoes on their screens (NOAA, 2017); thus began the development of precipitation detection radar. Radar-based precipitation information overcame the lack of spatial resolution in rain gauge data (Hu et al., 2014). As research in meteorology continued, there was a need to study macro-scale rainfall which then led to the use of satellites to monitor cloud cover and precipitation events around the world. Scientific advancements in spacecraft satellites and high-resolution sensors provide information to calculate precipitation amounts. Observed data gives a realistic view of precipitation in the past or in real time, but cannot predict future conditions. Using mathematical equations, simulated precipitation was therefore created to fill data gaps and predict future scenarios.

3. DIFFERENCES IN OBSERVED AND SIMULATED PRECIPITATION DATA

Observed datasets give information about past or current rainfall events, but often have gaps in the time series due to lack of measurement. Observed data are also more localized spatially due to providing information at specific sites or over an area. Rain gauge data are observed at a single location in space, and interpolation methods must be used to estimate precipitation across a broader spatial extent or assumed to represent constant precipitation over a region. Precipitation simulations can provide past or future precipitation quantities in a seamless time series over a global extent, at different spatial discretizations. Generally, simulated data are best used for non-extreme weather patterns, mountainous regions, and colder weather; observed data performs best in warm weather and documents extreme events very well (Harmel et al., 2002). Studies have shown that input precipitation data from observed and simulated datasets impact watershed model outputs (Golden et al., 2010; Tuo et al., 2016). Modeling projects that use more than one type of dataset may be more accurate in reproducing precipitation patterns than a single dataset, but the spatial and temporal resolutions of different datasets must be considered in calibration (Tuo et al., 2016).

The spatial resolution in purely observed datasets are not uniform due to random station locations or radar blocking. Since rainfall is not distributed evenly, rainfall estimates are often misleading; interpolation of observed data is a significant limitation in accurately modeling responses to rainfall because data cannot be validated at every position, and values may differ within a grid cell for gridded

Table 1. Description of Precipitation Datasets

	Type/Name	Precip Output	Temporal Resolution	Resolution (Degree Grid)	Time Period	Coverage	Time lag	Method	Source
Satellite	TRMM	mm/hr	3 hourly	0.25x0.25	1998-2015	35N 35S to 50NS	n/a	Microwave, Infrared	TRMM
	GPM	mm/hr	30 minute	0.1x0.1	2014-	60N 60S	4-6 hours	Microwave, Infrared, Satellite Precip Radar	GPM
	CMORPH	mm/hr	30 minute, 3 hourly	0.07277x0.07277, 0.25x0.25	2002-	60N 60S	18 hours	Morphing of Microwave and Infrared	CMORPH
	PERSIANN CCS	mm/hr	Hourly	0.04x0.04	2003-	60N 60S	1-2 days	Infrared, Cloud segmentation algorithm	PERSIANN-CCS
	PERSIANN CDR	mm/day	Daily	0.25x0.25	1983-2015	60N 60S	n/a	Infrared, Artificial Neural Network	PERSIANN CDS
Radar	NEXRAD	mm/hr	1, 3 hourly	1x1 N. America	1994-	160 sites in the US	2-4 days	Radar, Precipitation Processing System	NEXRAD
	TDWR	mm/hr	Hourly	1x1 N. America	2001-	45 sites in US	4days	Radar, Precipitation Processing System	RADAR
Rain Gauge	GPCC Full Data	mm/mo	Monthly	0.5x0.5	1901-2013	7000 US, 65000 Worldwide	n/a	Weighted Method for grid	GPCC
	*NCDC	inch	Hourly	By Station	1951-	72N -15S, -60E 130W	6 months	Gathering of multiple stations GHCN, COOP, QCLCD	NCDC
	*Daymet	mm/day	Daily	0.0089x0.0089	1980-2015	N. America	1 year	Spatial truncation of Gaussian weighting filters of ground station locations	Daymet
Combined	*NLDAS	kg/m2/hr	hourly	0.125x0.125	1979-	N. America	4 days	Integration of CMORPH and RADAR	LDAS
	*GLDAS	kg/m2/hr	3 hourly	0.25x0.25	2000-Dec 2016	90N 60S	2 months	Incorporation of satellites and ground-based observations	LDAS
	*PRISM	mm/mo	Monthly, Yearly	0.04x0.04	1981-	CONUS	1 month	Climatologically Aided Interpolation (CAI) of gauge stations with RADAR	PRISM
	CMAP Pentad RT	mm/day	Daily	2.5x2.5	1979-Dec 2016	88N 88S	1 month	Filling in gaps from gauge data with satellite (CMORPH)	CMAP
Simulated	WRF	mm/hr	Daily	0.03x0.03	User Specified	Global	n/a	NWP Microphysics/Cumulus Schemes	WRF
	ECHAM	mm/day	Daily	0.703125x0.703125	User Specified	Global	n/a	Numeric Weather Prediction and Parameterization	ECHAM
	CESM-CAM	mm/day	Daily	0.35x0.35	User Specified	Global	n/a	NWP and Non-parametric, CMIP5	CAM
	*WGEN	mm/day	Daily	HRU	1960-2100	Site Specific	n/a	Stochastic	WGEN

*Currently implemented in USEPA's HMS

datasets. With all precipitation datasets, coarser spatial resolutions lead to more approximations about rainfall distribution, and interpolation introduces known biases to the results (Tapiador et al., 2012). There is no way to determine the exact weather condition at every point in space, which means that all datasets have limitations. Observational data often have missing values due to station maintenance or equipment malfunction; error sources can be due to sampling errors, calibration uncertainty, or random errors. Instrument and calibration uncertainty also pose potential sources of bias. Due to the inability to accurately measure snow and frozen precipitation in all observational techniques, observed datasets are most accurate during warm weather conditions. Simulated outputs from mathematical equations do not depict precipitation events with as much detail as observed datasets. Correctly simulating patterns, seasonal variations, and characteristics of precipitation with mathematical models is an area of active research (Eyring et al., 2016).

4. OBSERVED DATA

Observational data provide a historical record of past precipitation events using direct rainwater catchment in rain gauges or with technical instruments from a distance (e.g., radar and satellite sensors). Observational systems give a more accurate depiction of the amount of rain produced by an extreme event like hurricanes or monsoons at a specific location. There are three main types of observational data, rain gauge, radar, and satellite which are described in Table 2, although, combining these types of data is often used for modeling purposes.

Rain gauge data can provide estimates of rain accumulation at exact locations; when using rain gauge data, an observed value represents uniform precipitation in the area around the gauge. Rain gauge data are universally considered the best source of reference data for precipitation observations (Tapiador et al., 2012). Gauge data are the most accurate representation of precipitation at a precise location (Kim, 2014; Price et al., 2014) but limitations stem from mechanical issues or operational errors. Research on climatology requires long-term datasets of precipitation, and only rain gauge data have enough historical information for this type of research. Some rain gauge resources are the National Climatic Data Center (NCDC; https://www.ncdc.noaa.gov/), the Global Precipitation Climatology Centre (GPCC; https://climatedataguide.ucar.edu/climate-data/gpcc-global-precipitation-climatology-centre), and Daymet (https://daymet.ornl.gov/) which is an interpolated gridded dataset.

Radio Detection and Ranging (RADAR), detects precipitation in the troposphere by sending radio waves into the atmosphere in pulses and radio waves are sent back when the wave makes contact with a raindrop. A reflectivity-to-rainfall equation – the Precipitation Processing Subsystem (PPS) -- estimates rainfall amounts (Nelson et al., 2010). Radar technology can locate precipitation within a range of 230 km from the station and reports data close to real time (NOAA, 2017). Bias in the radar dataset comes from signal blockage, bright band contaminations, range dependency, and radar calibration errors. Next Generation Weather Radar (NEXRAD; https://www.ncdc.noaa.gov/nexradinv/) is the largest collection of forecasting radars accessible for research in North America. It is composed of 160 WSR-88D ground radars across the United States.

Satellite-based precipitation data are derived from infrared and microwave measurements taken from satellites in space. Satellites are the only way to retrieve global homogeneous estimates of precipitation on relatively fine spatial scales (Tapiador et al., 2012). The Tropical Rainfall Measuring Mission (TRMM; https://pmm.nasa.gov/data-access/downloads/trmm) was a single satellite used to detect precipitation in the tropics from 1998 to 2015. The Global Precipitation Mission (GPM; https://pmm.nasa.gov/data-access/downloads/gpm) of 2014 is a continuation of TRMM's mission with a larger range of detection (Skofronick-Jackson, G. 2017). The Climate Prediction Center Morphing (CMORPH; http://www.cpc.ncep.noaa.gov/products/janowiak/cmorph_description.html) and the Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN; http://chrsdata.eng.uci.edu/) are two other satellite derived datasets that are often used in environmental modeling. Since rain gauge data are often sparse in some areas and may contain missing values, satellite and radar data have been combined with gauge data to fill the gaps, as in the Climate Prediction Center Merged Analysis of Precipitation (CMAP) and Climate Hazards Group Infrared Precipitation with Station data (CHIRPS). In addition to the previously stated datasets, there are many more datasets that combine multiple observational methods including the popular National and Global Land Data Assimilation System (NLDAS, GLDAS; https://disc.sci.gsfc.nasa.gov/hydrology/data-rods-time-series-data) and Parameter-elevation Relationship on Independent Slopes Model (PRISM; http://www.prism.oregonstate.edu/explorer/) datasets.

Many studies have compared observational datasets and their ability to estimate precipitation amounts and their effect on model output. Sun et al. (2018) provides an overview of 30 global precipitation products from gauge-based, satellite-related, and reanalysis products. They determined the magnitude of precipitation estimates deviated by as much as 300 mm/yr among the datasets with reanalysis data having the largest discrepancies. Gao et al. (2017) studied the impacts of three different precipitation sources (rain gauge, radar, and a combined reanalysis dataset) in Soil and Water Assessment Tool (SWAT) streamflow simulations. Price et al. (2014) investigated whether NEXRAD data, corrected with rain gauge data by the Multisensor Precipitation Estimation (MPE) algorithm, would improve simulations in watershed models; they found that adjusted radar precipitation estimates using gauge data consistently performed better than non-adjusted radar data. Blending and merging observed datasets can significantly improve precipitation estimates (Ebert, 2007; Huffman et al., 1995; NOAA, 2017)

Table 2. Summary of observed precipitation dataset characteristics.

Observed	Method	Spatial Extent	Spatial Resolution	Temporal Resolution	Years of data	Precipitation Output	Error
Rain Gauge	Physically collected on the ground	Specific location	Lat.-Lon. of station, 0.009x0.009 or 0.5x0.5-degree grid interpolation	Hourly, Daily, Monthly, Yearly	100 years	Underestimates heavy rainfall events	Random error, mechanical issues, location
Radar	Technologically collected on the ground	Radial area around station (radius 230km)	1x1 degree grid, lat. and lon. of station	Hourly, 3-hourly,	30-40 years	Overestimates heavy rainfall events, underestimates light rainfall, more accurate close to center of area	Signal blockage, hail misreading
Satellite	Technologically collected from space	Latitude range (60°N, 60°S)	0.04x0.04-degree grid 0.1x0.1-degree grid 0.25x0.25-degree grid	Half-Hourly, Hourly, Daily	20 years or less	Underestimates rain from warm top clouds	Frozen precipitation, multilayer clouds

5. SIMULATED DATA

Simulated data, based on mechanistic computer models, can fill data gaps to produce a continuous time series for model input. Weather prediction models are mathematically-driven models that simulate precipitation from the past as well as the future. Simulated precipitation measurements make computation easier for modelers because there are no missing values nor time spent on data retrieval. Three main types of models simulate precipitation data: Numerical Weather Predictors (NWP), stochastic models, and nonparametric models. A summary of the model characteristics is presented in Table 3.

Numerical weather prediction models integrate differential equations that describe fluid flows to predict rainfall and other atmospheric conditions. Two major types of equations used to estimate precipitation describe microphysics and cumulus clouds. Microphysics parameterization schemes resolve the process of rain production, and cumulus parameterization schemes describe effects of cumulus clouds in rain events. Combining them determines rainfall occurrences and amount (Yang et al., 2015). The Weather Research and Forecasting (WRF; http://www2.mmm.ucar.edu/wrf/users/download/get_source.html) model and the European Centre Hamburg Model (ECHAM; http://www.mpimet.mpg.de/en/science/models/echam/) are two examples of numerical weather prediction models.

Stochastic models, among the simplest prediction models, use statistics and probabilities associated with weather data to predict atmospheric parameters (Harmel et al., 2002). To generate precipitation, a Markov Chain Model determines the probability of having a wet day or a dry day, then finds the probability of a wet day following a dry or wet day (Wilks & Wilby, 1999). Historical precipitation measurements of 20 years or more is recommended to initiate the Markov chain; then, an equation using mean daily rainfall, standard deviation of daily rainfall, and a skew coefficient gives the amount of rainfall on a particular wet day. Stochastic models often fail to accurately describe the length of dry or wet periods and model output can be skewed based on historical input data, thus requiring statistical verification. An example of a stochastic model is Weather Generator (WGEN), which is used in the Water Erosion Precipitation Project (WEPP) and the Soil and Water Assessment Tool (SWAT).

Nonparametric models resample historic data to find trends and weather characteristics for future data simulations. Nonparametric simulations use large numbers of observational data to create a probability density function that best describes the data (Sharma, 2000). It is assumed (but cannot be guaranteed) that models which accurately predict historic weather patterns are more likely to accurately predict future weather patterns (Rupp et al., 2013). Global Circulation Models (GCM) use a combination of nonparametric tends and numeric predictions to generate precipitation data on a global scale.

Table 3. Summary of simulated precipitation dataset characteristics.

Simulated	Method	Inputs	Spatial Resolution	Spatial Extent	Error
Numerical Weather Prediction	Cumulus and microphysics schemes	Atmospheric conditions and thresholds	0.03x0.03-degree grid 0.703x0.703-degree grid	Global or limited area model (LAM)	Scheme selection
Stochastic	Probability	20-year history of precipitation	Site specific	Global or delineated area	Skewed distributions
Non-Parametric	Historical trends	Long historical records and emission scenarios	0.35x0.35-degree grid 1.4x1.4-degree grid	Global or regional downscaled	Model drift from observed data

6. DISCUSSION

Precipitation is a difficult variable to measure precisely and there is a challenge in capturing data from unexpected small storms. In calibrating the SWAT model for river basin modeling, Tuo et al. (2016) found that precipitation is the main source of uncertainty. Observed and simulated precipitation datasets have strengths and weaknesses in providing an accurate representation of rainfall amounts. Simulated datasets from numerical weather prediction, stochastic models, and nonparametric models provide a seamless time series and perform well in cold weather, mountainous regions, and non-extreme conditions. Simulated future data are applicable for managing and planning purposes since there is a need for information about changes in future precipitation. Observed datasets often include gaps in the time series due to lack of measurement, but they perform best in warm conditions and reflect extreme weather events well. Direct rainfall measurement from rain gauges is preferred by researchers since assumptions are not made and there are long measurement records. Many studies comparing differences in precipitation datasets for regional analysis have been performed, (e.g., Costa & Foley, 1998; Fekete et al., 2004; Tapiador et al., 2012).

Precipitation plays a large role in the availability of drinking water, erosion, and transportation of contaminants. Selection of precipitation data has crucial effects on hydrological model performance; thus, choosing precipitation datasets based on method, time step, and resolution needs to be carefully thought out (Tuo et al., 2016). Regulatory, planning, and exploratory purposes require different levels of uncertainty. Regulatory projects must have very little error and uncertainty while exploratory projects encourage uncertainty. A need for advancements in precipitation accuracy, length of record, and free availability is still a recurring problem in the modeling community. There is no “best” precipitation dataset, only the most appropriate for a given purpose. As Harmel et al. (2002) said, *"Historical data provide only one realization or ‘picture’ of a previous weather pattern that may not represent future climate scenarios”.*

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