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Evaluation of precipitation products over complex mountainous terrain: A water resources perspective

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ABSTRACT

The availability of in situ measurements of precipitation in remote locations is limited. As a result, the use of satellite measurements of precipitation is attractive for water resources management. Combined precipitation products that rely partially or entirely on satellite measurements are becoming increasingly available. However, these products have several weaknesses, for example their failure to capture certain types of precipitation, limited accuracy and limited spatial and temporal resolution. This paper evaluates the usefulness of several commonly used precipitation products over data scarce, complex mountainous terrain from a water resources perspective. Spatially averaged precipitation time series were generated or obtained for 16 sub-basins of the Paute river basin in the Ecuadorian Andes and 13 sub-basins of the Baker river basin in Chilean Patagonia. Precipitation time series were generated using the European Centre for Medium Weather Range Forecasting (ECMWF) 40 year reanalysis (ERA-40) and the subsequent ERA-interim products, and the National Centers for Environmental Prediction/National Center for Atmospheric Research reanalysis dataset 1 (NCEP R1) hindcast products, as well as precipitation estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN). The Tropical Rainfall Measurement Mission (TRMM) 3B42 is also used for the Ecuadorian Andes. These datasets were compared to both spatially averaged gauged precipitation and river discharge. In general, the time series of the remotely sensed and hindcast products show a low correlation with locally observed precipitation data. Large biases are also observed between the different products. Hydrological verification based on river flows reveals that water balance errors can be extremely high for all evaluated products, including interpolated local data, in basins smaller than 1000 km^2. The observations are consistent over the two study regions despite very different climatic settings and hydrological processes, which is encouraging for extrapolation to other mountainous regions.

1. Introduction

Precipitation is a key variable for water resources management so reliable estimates of precipitation are crucial. The estimation of precipitation in the Andes of Ecuador and Patagonia is assessed here. In mountainous regions, deriving time series of spatially averaged precipitation is often complicated by a significant spatial and temporal variability in precipitation. This problem is further aggravated by the very sparse rain gauge networks in mountainous regions such as the Andes [1]. This can make the estimation of precipitation difficult. In order to improve the estimation of precipitation, methods for estimating precipitation from satellite measurements have been developed in recent years. Errors arise in the satellite-derived precipitation from various sources. For example, precipitation for products such as TRMM 3B42 and PERSIANN are estimated using infrared images. This can cause significant underestimation of precipitation from low clouds as well as false alarms from high but relatively thin clouds that are at low temperatures [2]. For instance, warm frontal precipitation is associated with higher cloud-top temperatures than convective precipitation [3]. Light snow has a maximum frequency around −16 °C whereas all other precipitation types (including rain, freezing rain and heavy snow) are bi-modal, with maximum precipitation at −16 °C and −35 °C to −50 °C. Therefore precipitation estimation from cloud-top temperature is affected by precipitation type [4]. Finally, the infrequent coverage of low earth polar orbiting satellites means that short duration convective storms may be missed by the satellites [5].

The appropriate scale to use spatially averaged precipitation products should thus be large enough to reduce random errors but retain topographical gradients [6,7]. The appropriate temporal scale for precipitation products is region and basin specific.

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However, the assessment of precipitation products for a particular region is dependent upon the local rain gauge network [8]. The incorporation of uncertainty estimates in satellite precipitation products would enable users to more appropriately use these datasets [9].

2. Summary of precipitation products

2.1. Satellite and composite products

The Tropical Rainfall Measurement Mission (TRMM) was launched in November 1997 to orbit at a low altitude of about 320 km and to cover the entire tropics between 30°N and 30°S twice a day [10]. However, this orbit was changed to 403 km in 2001 to reduce fuel consumption and to extend the observation period [11].

Several algorithms [12–14] have been developed to make use of data from the TRMM mission. The TRMM 3B42 algorithm has a temporal resolution of 3 h and a spatial resolution of 0.25°. The algorithm uses data from geostationary satellites with infrared sensors that measure cloud-top temperatures and from low earth orbiting satellites, which use microwave satellites to provide a more direct estimate of precipitation [14].

TRMM 3B42 is produced by combining data from the TRMM 2A25 precipitation radar (PR) with infrared images to produce an optimised data series [14]. However, the TRMM satellite has a poor temporal resolution due to the low sampling frequency of the satellite. TRMM orbits the Earth 16 times a day and so flies over most tropical locations once or twice a day [15]. Therefore the monthly totals from TRMM are used to calibrate the infrared precipitation estimates from the Geostationary Operational Environmental System (GOES) series, which has a temporal resolution of 3 h [11]. The approach taken is thus to use the more frequent but indirect infrared estimates calibrated using the more accurate but infrequent microwave observations [16,17]. However, there are uncertainties associated with the estimation of precipitation from cloud-top temperature. Parameters such as radiance thresholds, required to determine whether precipitation occurs, vary markedly from one situation to another [11]. Precipitation estimation from cloud top temperature is generally worse over continents than the oceans, particularly for low precipitation amounts [18]. TRMM 3B42 has been found to provide a reasonable performance at monthly timescales.

The TRMM 3B42 research product (version 6) is created by scaling the real time TRMM 3B42 series to the monthly 1° grid Global Precipitation Climatology Centre (GPCC) data derived from rain gauges to produce an optimised data series [14]. TRMM 3B42 has been found to provide a reasonable performance at monthly timescales. However, it struggles to correctly identify and reproduce moderate and light precipitation events on short timescales. Furthermore, it is possible that on occasion this monthly bias removal may cause high precipitation rates to be underestimated and low precipitation to be overestimated [16].

PERSIANN uses an adaptive neural network algorithm to combine high frequency (48 readings a day) geosynchronous satellite based gridded infrared images (including GOES-8, GOES-9, GOES-10, GMS-5, MetSat-6, MetSat-7) and low frequency (1–2 readings a day) TRMM 2A12 instantaneous rain, which is derived from the TRMM TMI microwave imager [19,20]. Thus the final precipitation estimates are derived from the infrared data but are adjusted to be consistent with the TRMM and TMI derived precipitation [15,21]. PERSIANN has a temporal resolution of 3 h and is on a spatial grid of 0.25° between 50°N and 50°S. The neural network scans a 5×5 moving window of infrared pixels, surrounding each central pixel in turn. Five features are extracted from the pixels and are classified into groups associated with different cloud surface characteristics. For each group, a multivariate linear function relates the infrared values to rain rates [15]. The adaptive neural network means the product can adapt its calibration for different precipitation regimes [8].

2.2. Reanalysis hindcast products

We also use the reanalysis hindcast products ERA-40, ERA-interim and NCEP R1. NCEP R1 hindcast data are available from 1948 to present on a 6 hourly timestep and a 2.5° grid. ERA-40 data is available on a 6 hourly basis from 1957–2002 with a resolution of around 2.5°. This has now been superseded by ERA-interim, which is available on a 6 hourly basis from 1989 – date and has a resolution of around 1.5°.

Gridded hindcast products such as ERA-40 and NCEP R1 are the weather model assimilated outputs from weather observations around the globe for a given timestep. Weather models are usually run to produce forecasts for hours and days into the future using observations from satellites, radars and weather balloons for numerous weather variables including temperature, relative humidity and atmospheric vapour pressure. However for hindcast products, only historical observations are used, to produce a new forecast. The model is re-started at every timestep with new historical observations and is not allowed to run in forecast mode. Long time-series of gridded weather model outputs can then be constructed using the same weather model through time. As newer weather models are developed, they can be re-run using the historical observations to construct a data series that is not biased due to a change in model structure. However, although the model is frozen, the data that are available have changed significantly over time, with the inclusion for the first time in 1972 of satellite data, temperature profilers in 1973 and microwave channels for atmospheric water vapour over the oceans in 1987 [22].

2.3. Gridded observational products

Long term average precipitation gridded datasets such as the TRMM climatology [23], WorldClim [24] and Climate Research Unit (CRU) CL 2.0 [25] products are also considered. The CRU CL 2.0 data are obtained from rain gauge observations and are available on a 10' grid for all land areas excluding Antarctica. The data set consists of mean monthly climate variables for 1961–1990 including precipitation, wet-day frequency, temperature, relative humidity and sunshine duration. Data were interpolated using a thin-plate spline methodology and predictor variables of latitude, longitude and elevation. Local topographic variations in precipitation that are not dependent upon one of the three independent variables (latitude, longitude and elevation) are assumed to be noise and are not resolved in this dataset. This may cause errors in the dataset for data sparse areas. South America was highlighted as an area with high errors [25].

The WorldClim data is calculated from rain gauge data and is available on a 30 arc s grid. The dataset extends from 1950–2000 where possible. This time period was used because it enabled the inclusion of more rain gauges than the period 1961–1990, with the constraint that only rain gauges with at least 10 years of data were included. The differing time periods assume that there was no change in average precipitation during this time. The dataset consists of monthly average, min and max precipitation and max temperature. The interpolation of precipitation was undertaken using a thin-plate smoothing spline algorithm using latitude, longitude and elevation and independent variables. The WorldClim dataset uses 57% more rain gauges worldwide than the CRU CL 2.0 [25] dataset, especially in South America where data from the