2.2. Climate variability and trends

Francisco J. Tapiador

University of Castilla-La Mancha (UCLM), Spain

“Climate variability” is defined as the temporal variations of the atmosphere-ocean system around a mean state. The term “natural climate variability” is further used to identify climate variations that are not attributable to or influenced by any activity related to humans (American Meteorological Society, 2021). Regarding “climatic trends”, those are defined as a climate change characterized by a reasonably smooth, monotonic increase or decrease of the average value of one or more climatic elements during the period of record (American Meteorological Society, 2021).

The variability of precipitation has two dimensions in climate. The first one is how precipitation departs from the average over a number of years, say the 1990–2020 mean over the 1960–1990 mean, at each location on the globe. The second one is how to gauge climate variability as a whole looking at precipitation. The latest is the province of studies analyzing the dominant modes of variability and includes research on the Pacific Decadal Oscillation (PDO), the Atlantic Multidecadal Oscillation (AMO), the Indian Ocean Dipole (IOD) and the El Niño Southern Oscillation (ENSO). Good climate models correctly simulate the Madden-Julian Oscillation (MJO), ENSO and the mean Intertropical Convergence Zone (ITCZ). Those processes are also precisely identified as a fingerprint in the precipitation field. Thus, satellite precipitation estimates are fundamental to achieve a proper representation of such climate variability and to validate models (cf. Chapter 2.3 below).

Precision and accuracy of the precipitation estimates are both important, as is the global scope. It is known that the changes in global mean precipitation are determined by changes in radiative cooling of the atmosphere (Stephens and Ellis, 2008), so it is extremely important to be as precise as possible in determining such changes to understand changes in the radiative forcing, either by natural or anthropogenic causes. Regional estimates are also a must. In the tropics, mean precipitation and the extreme of the distribution is largely dominated by organized mesoscale convective systems (Roca et al., 2014; Rossow et al., 2013), and the trends in precipitation are related to the fate of organized convection (Tan et al., 2015). Latent heating algorithms that have been developed for satellite rain data diagnose the convective/stratiform partitioning from characteristics of the rain and reflectivity fields to produce realistic heating profiles and thus to improve the modeling of the climate variability. Indeed, model parameterization errors become obvious only when higher-order variability metrics such as PDO, AMO, IOD, MJO and ENSO are used. The continental diurnal cycle, which depends on the timing of the transition from bottom-heavy to top-heavy latent heating profiles, is also relevant for climate variability and trends analyses. In fact, precipitation was instrumental in documenting the existence and propagation of MJO anomalies (Madden and Julian, 1994; Del Genio et al., 2015; Wang et al., 2015). Here, the advantage of precipitation over the more commonly-used outgoing longwave radiation (OLR) is that OLR anomalies over the Maritime Continent can be affected by the fairly ubiquitous high cloud cover. Instead, the rain anomalies have proved to be very helpful in isolating the onset phase of the MJO, when shallow and congestus rain dominate as the biggest sources of error in GCM cumulus parameterizations and in preventing the development of a robust MJO. This particular case illustrates that it is precisely because of its complexity that precipitation can be superior to other variables: OLR-based indices of convection greatly overestimate surface rain over Africa, because they sense only the high cold clouds and cannot tell that rain is evaporating more strongly into the relatively dry lower troposphere there and not reaching the ground to the

DOI: 10.13021/gewex.precip.2.2

extent that it does in humid regions such as the Amazon (Liu and Zipser, 2005; Ling and Zhang, 2011).

Regarding the ENSO, a precipitation-based definition of an extreme El Niño event (those events for which the Niño-3 rainfall index is above 5 mm day^{-1}) has been proposed. It is based on the precipitation anomalies averaged over the Niño-3 (5°S–5°N, 150°–90°W) region (Cai et al., 2014, 2017). Based on this precipitation-based index, Cai et al. (2014) analyzed Coupled Model Intercomparison Project (CMIP) phase 3 (CMIP3) and CMIP5 models and found a doubling in the occurrence of extreme El Niño events in the future in response to greenhouse warming, while no significant change in statistics in extreme El Niño events is found based on the “classical” Niño-3.4 SST index. Power et al. (2013) also shows that ENSO-driven precipitation exhibits a clearer longer-term change than SST anomalies. Thus, precipitation may be seen as a better field to reveal, diagnose and quantify the nonlinear relationship between the variability in the climate system and changes in mean state. There is more evidence on the central role of precipitation: the precipitation response to SST during strong El Niño events encapsulates the process associated with the nonlinear amplification of the Bjerknes feedback (Takahashi and Dewitte, 2016) and therein can be considered a better metric of El Niño–Southern Oscillation (ENSO) extremes than SST anomalies alone. Thus, the relationship between precipitation in the eastern equatorial Pacific (Niño-3 region) and the SST gradient near the equatorial region during El Niño exhibits a marked nonlinear pattern that enhances or eases the detection of extreme events.

There are many available precipitation datasets suitable for climate validation (Tapiador et al., 2017). The existence of different approaches and merging methods is a plus in climate variability and trends studies. When satellite estimates differ, important information is revealed. Identifying trends and breakpoints in precipitation series is not trivial, but has proved useful in the context of validating climate models (Figure 2.2.1, Tapiador et al., 2018; Tan et al., 2015). For example, the considerable discrepancy between passive microwave and radar estimates of rain rate in the eastern Pacific ITCZ (Liu and Zipser, 2013) revealed that assumptions about the depth or microphysical properties of rain-producing clouds are valid. While the issue has been known for a long time, the specific details, and crucially the mechanistic description, are better

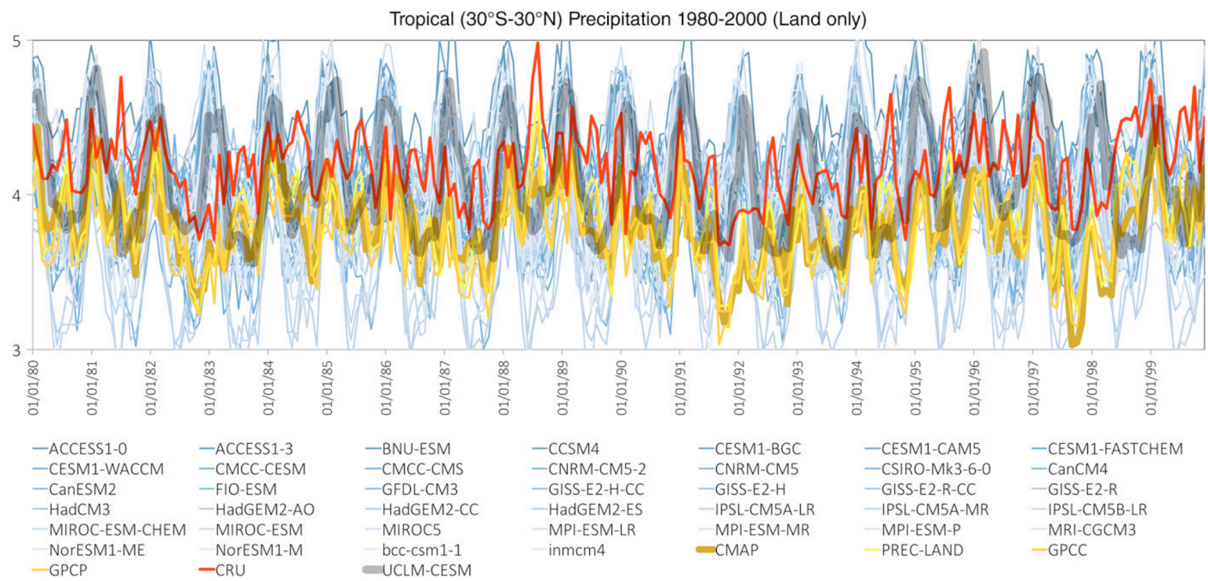

Figure 2.2.1. Time series of tropical (30S–30N) precipitation (mm/day) over land for 1980–2000. From Tapiador et al., 2018

expressed in terms of precipitation. Therein, it is important to keep and maintain a host of precipitation datasets from different sources and methodologies. Single, one-instrument and multisource datasets are both valuable for analyzing different aspects of the climate variability and the trends. Section 2.4 below delves more deeply into the nature of 11 comprehensive datasets and acknowledges that none of them can be considered as the “true” representation of global precipitation. A first-order metric such as the global (60N-60S) mean precipitation over land can vary from 1.81 mm/day (GSMap) to 2.33 mm/day [PERSIANN-Climate Data Record (PERSIANN-CDR)]. Differences in the polar areas are larger. Such discrepancies raise several challenges on the appropriate approach to follow in the validation of climate models for present climate simulations (cf. Chapter 2.3 below). Careful consideration of the algorithmic choices and the sampling errors (cf. Chapter 1.1 above) is also required when these datasets are used for analyzing climate variability and trends. Large uncertainties in extremes in both reanalysis and observations (Chapter 2.5 below) also raise issues on their fitness-for-purpose on this realm. Error modeling (Chapter 3.2 below) is fundamental for the use of satellite precipitation datasets for these applications.

There are more examples of the need for satellite precipitation data in climate variability research. Processes of SST-wind-precipitation interaction are also likely involved in long-term trends and variability in the surface circulation in the tropics (Tapiador et al., 2019). For instance, while in the subtropical eastern boundary upwelling regions, an increase of the equatorward winds is expected (and observed in some regions) owing to the poleward displacement and intensification of the anticyclone/Hadley cells. In the tropical Pacific region, the trends in upwelling-favorable winds are more ambiguous and are sensitive to concurrent changes in SST and rainfall, as observed off Peru from coupled model experiments (Belmadani et al., 2014). Therefore, processes associated with moist convection and subsidence in the far eastern Pacific are likely important to understand trends in upwelling systems, and their investigation will benefit from precipitation observations and will require model evaluations based on those.

Regarding climate variability in precipitation, the fingerprints have been observed following different methods and approaches (Hidalgo et al., 2017; Kenyon and Hegerl, 2010). The impact of anthropic activity in climate variability is a major driver (Vera et al., 2019). Multidimensional analyses involving other environmental sciences also require detailed precipitation data (Trauernicht, 2019; Suarez and Kitzberger, 2010). The use of precipitation data for analyzing extremes in the climate variability realm is also valuable (van Pelt et al., 2015; Shawul and Chakma, 2020; Liu and Allan, 2012; Ummenhofer and England, 2007; Teegavarapu, 2016). Precipitation estimates over the poles are also of interest: Antarctica is significantly colder and more prone to climate variability than the Arctic, although both regions are strongly responsive to large-scale variability including the northern and southern annular modes (Screen et al., 2018).

To conclude this section, it is worth noting that climate variability and trends are relevant for a number of applications. Climate services are mostly targeted at informing adaptation to them, widely recognized as an important challenge for sustainable development. The role of satellite precipitation datasets is central in this realm. Better identification of the modes of climate variability, the definition of new precipitation-based metrics and novel methods to gauge trends and changes, all depend on the continuous availability of long, continuous and global measurements of liquid and solid precipitation (cf. Chapter 3.1 below). The need to continually improve the precipitation estimates from satellite and new developments in the observation network should follow the path imposed by progresses in modeling.

2.2.1. References

American Meteorological Society, 2021: Natural Climate Variability. Glossary of Meteorology, https://glossary.ametsoc.org/wiki/Climate_variability.

American Meteorological Society, 2021: Climatic Trend. Glossary of Meteorology, https://glossary.ametsoc.org/wiki/Climatic_trend.

Belmadani, A., V. Echevin, F. Codron, K. Takahashi and C. Junquas, 2014: What dynamics drive future wind scenarios for coastal upwelling off Peru and Chile*? Climate Dynamics*, 43, 1893-1914, doi:10.1007/s00382-013-2015-2.

Cai, W., S. Borlace, M. Lengaigne, P. van Rensch, M. Collins, G. Vecchi, A. Timmermann, A. Santoso, M. McPhaden, L. Wu, M.H. England, G. Wang, E. Guilyardi and F.-F. Jin, 2014: Increasing Frequency of Extreme El Niño Events due to Greenhouse Warming. *Nature Climate Change*, 4, 111–116, DOI: 10.1038/nclimate2100.

Cai, W., G. Wang, A. Santoso, X. Lin and L. Wu, 2017: Definition of Extreme El Niño and Its Impact on Projected Increase in Extreme El Niño Frequency. *Geophysical Research Letters,* https://doi.org/10.1002/2017GL075635.

Del Genio, A.D., J. Wu, A.B. Wolf, Y. Chen, M. Yao and D. Kim, 2015: Constraints on Cumulus Parameterization from Simulations of Observed MJO Events. *Journal of Climate*, 28, 6419–6442, https://doi.org/10.1175/JCLI-D-14-00832.1.

Hidalgo, H.G., E.J. Alfaro and B. Quesada-Montano, 2017: Observed (1970–1999) climate variability in Central America using a high-resolution meteorological dataset with implication to climate change studies. *Climatic Change* 141, 13–28, https://doi:10.1007/s10584-016-1786-y.

Kenyon, J., and G.C. Hegerl, 2010: Influence of modes of climate variability on global precipitation extremes. *Journal of Climate*, **23**(23), 6248–6262, https://doi.org/10.1175/2010JCLI3617.1.

Ling, J., and C. Zhang, 2011: Structural evolution in heating profiles of the MJO in global reanalyses and TRMM retrievals. *Journal of Climate*, 24, 825–842, doi:10.1175/2010JCLI3826.1.

Liu, C., and R.P. Allan, 2012: Multisatellite observed responses of precipitation and its extremes to interannual climate variability. *Journal of Geophysical Research Atmospheres*, vol. 117, D3, https://doi.org/10.1029/2011JD016568.

Liu, C., and E.J. Zipser, 2005: Global distribution of convection penetrating the tropical tropopause, *Journal of Geophysical Research,* 110, D23104, doi:10.1029/2005JD006063.

Liu C., and E. Zipser, 2013: Regional variation of morphology of the organized convection in the tropics and subtropics, Part I: regional variation, *Journal of Geophysical Research,* 118, 453–466, doi:10.1029/2012JD018409.

Madden, R.E., and P.R. Julian, 1994: Observations of the 40-50 day tropical oscillation-A review. *Monthly Weather Review*, 122: 814–837.

Power, S., F. Delage, C. Chung, G. Kociuba and K. Keay, 2013: Robust twenty-first-century projections of El Niño and related precipitation variability. *Nature*, 502, 541–545.

Roca, R., J. Aublanc, P. Chambon, T. Fiolleau and N. Viltard, 2014: Robust observational quantification of the contribution of mesoscale convective systems to rainfall in the tropics. *Journal of Climate*, 27, 4952–4958, doi:10.1175/JCLI-D-13-00628.1.

Rossow, W.B., A. Mekonnen, C. Pearl and W. Goncalves, 2013: Tropical precipitation extremes. *Journal of Climate*, 26, 1457–1466, doi:10.1175/JCLI-D-11-00725.1.

Screen, J.A., C. Deser, D.M. Smith, X. Zhang, R. Blackport, P.J. Kushner, T. Oudar, K.E. McCusker and L. Sun, 2018: Consistency and discrepancy in the atmospheric response to Arctic sea-ice loss across climate models. *Nature Geoscience*, 11, 3, 155–163, DOI:10.1038/s41561-018-0059-y.

Shawul, A.A., and S. Chakma, 2020: Trend of extreme precipitation indices and analysis of long-term climate variability in the Upper Awash basin, Ethiopia. *Theoretical and Applied Climatology*, 140, 635–652, https://doi.org/10.1007/s00704-020-03112-8.

Suarez, M.L., and T. Kitzberger, 2010: Differential effects of climate variability on forest dynamics along a precipitation gradient in northern Patagonia. *Journal of Ecology*, https://doi.org/10.1111/j.1365-2745.2010.01698.x.

Takahashi, K., and B. Dewitte, 2016: Strong and Moderate nonlinear El Niño regimes. *Climate Dynamics*, doi: 10.1007/s00382-015-2665-3.

Tan, J., C. Jakob, W. B. Rossow and G. Tselioudis, 2015: Increases in tropical rainfall driven by changes in frequency of organized deep convection. *Nature*, 519, 451–454, doi:10.1038/nature14339, http://dx.doi.org/10.1038/nature14339.

Tapiador, F.J., A. Navarro, A. Jiménez, R. Moreno and E. García-Ortega, E. 2018: Discrepancies with satellite observations in the spatial structure of global precipitation as derived from global climate models. *Quarterly Journal of the Royal Meteorological Society*, 144, 419-435, https://doi.org/10.1002/qj.3289.

Tapiador, F.J., A. Navarro, V. Levizzani, E. García-Ortega, G.J. Huffman, C. Kidd, P.A. Kucera, C.D. Kummerow, H. Masunaga, W.A. Petersen, R. Roca, J.-L. Sánchez, W.-K. Tao and F.J. Turk, 2017: Global precipitation measurements for validating climate models. *Atmospheric Research*, 197, 1–20, https://doi.org/10.1016/j.atmosres.2017.06.021.

Tapiador, F.J., R. Roca, A. Del Genio, B. Dewitt, W. Petersen and F. Zhang, 2019: Is precipitation a good metric for model performance? *Bulletin of the American Meteorological Society*, 100(2), 223–233, https://doi.org/10.1175/BAMS-D-17-0218.1.

Teegavarapu, R.S.V., 2016: Climate variability and changes in precipitation extremes and characteristics. In: *Sustainable Water Resources Planning and Management Under Climate Change* (E. Kolokytha, S. Oishi, R. Teegavarapu, eds.). Springer, Singapore, https://doi.org/10.1007/978-981-10-2051-3_1.

Trauernicht, C., 2019: Vegetation—Rainfall interactions reveal how climate variability and climate change alter spatial patterns of wildland fire probability on Big Island, Hawaii. *Science of the Total Environment*, 650, 459–469, https://doi:10.1016/j.scitotenv.2018.08.347.

Ummenhofer, C.C., and M.H. England, 2007: Interannual extremes in New Zealand precipitation linked to modes of Southern Hemisphere climate variability. *Journal of Climate*, 20(21), 5418–5440, https://doi.org/10.1175/2007JCLI1430.1.

van Pelt, S.C., J.J. Beersma, T.A. Buishand, B.J.J. van den Hurk and J. Schellekens, 2015: Uncertainty in the future change of extreme precipitation over the Rhine basin: the role of internal climate variability. *Climate Dynamics*, 44, 1789–1800, https://doi.org/10.1007/s00382-014-2312-4.

Vera, C.S., L.B. Díaz and R.I. Saurral, 2019: Influence of anthropogenically-forced global warming and natural. Climate variability in the rainfall changes observed over the South American Altiplano. *Frontiers in Environmental Science*, https://doi:10.3389/fenvs.2019.00087.

Wang, S., A.H. Sobel, F. Zhang, Y. Qiang Sun, Y. Yue and L. Zhou, 2015: Regional Simulation of the October and November MJO Events Observed during the CINDY/DYNAMO Field Campaign at Gray Zone Resolution. *Journal of Climate*, 28, 2097–2119.