Characterizing Predictability of Precipitation Means and Extremes over the Conterminous United States, 1949–2010*

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ABSTRACT

The proper understanding of precipitation variability, seasonality, and predictability are important for effective environmental management. Precipitation and its associated extremes vary in magnitude and duration both spatially and temporally, making it one of the most challenging climate parameters to predict on the basis of global and regional climate models. Using information theory, an improved understanding of precipitation predictability in the conterminous United States over the period of 1949–2010 is sought based on a gridded monthly precipitation dataset. Predictability is defined as the recurrent likelihood of patterns described by the metrics of magnitude variability and seasonality. It is shown that monthly mean precipitation and duration-based dry and wet extremes are generally highly variable in the east compared to those in the west, while the reversed spatial pattern is observed for intensity-based wetness indices except along the Pacific Northwest coast. It is thus inferred that, over much of the U.S. landscape, variations of monthly mean precipitation are driven by the variations in precipitation occurrences rather than the intensity of infrequent heavy rainfall. It is further demonstrated that precipitation seasonality for means and extremes is homogeneously invariant within the United States, with the exceptions of the West Coast, Florida, and parts of the Midwest, where stronger seasonality is identified. A proportionally higher role of variability in regulating precipitation predictability is demonstrated. Seasonality surpasses variability only in parts of the West Coast. The quantified patterns of predictability for precipitation means and extremes have direct applications to those phenomena influenced by climate periodicity, such as biodiversity and ecosystem management.

1. Introduction

Identifying patterns of variability and seasonality for precipitation is crucial because these climatic fluctuations exert both immediate and long-term controls on hydrology, biogeochemical cycling, and ecosystem services. Evidence for climate change and its impacts has mounted over the past several decades (e.g., IPCC 2014; Melillo et al. 2014). Specifically, for precipitation, observational and simulation-based studies have provided key insights regarding the seasonal and regional variations of precipitation (e.g., Cayan 1996; Groisman et al. 2012; Donat et al. 2013a,b; Abatzoglou et al. 2014; Felzer and Sahagian 2014; Powell and Keim 2015; Berg and Hall 2015; Dai et al. 2015; Guilbert et al. 2015) and how such spatiotemporal patterns connect with large-scale climatic processes and local feedback mechanisms (e.g., Li et al. 2011; De Martino et al. 2013; Alter et al. 2015). Despite these advances, evidence has remained vague regarding precipitation extremes, and limited information is available for a systematic quantification of the concurrent fluctuation patterns of precipitation means and extremes. This paper represents an initial step toward rectifying this lack.

Precipitation patterns and extremes vary spatially and temporally in terms of intensity, duration, and frequency, making this one of the most challenging climate parameters to characterize and predict (Melillo et al. 2014). Current efforts in quantifying precipitation fluctuations are sporadic and limited to the investigations of

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the variability for a particular season or specific region. Taking the United States as an example, Cayan (1996) investigated interannual variability of snow water equivalent in the west; Groisman et al. (2012) quantified temporal changes in intense precipitation in the central United States; Abatzoglou et al. (2014) characterized seasonal precipitation variability in the Pacific Northwest; Powell and Keim (2015) summarized temporal trends in daily precipitation extremes over the Southeast; Berg and Hall (2015) provided evidence for an increased extreme precipitation interannual variability over California; Dai et al. (2015) analyzed growing season precipitation trends in the Midwest; and Guilbert et al. (2015) revealed patterns of increased persistency and intensity of precipitation in the Northeast. These studies provided a foundation for fundamental understanding of the region-specific spatiotemporal fluctuations of precipitation, but a cohesive scheme for the entire United States based on a consistent interpolation method has not been previously developed. In comparison, Fatichi et al. (2012) provided one of the first attempts that systematically characterize the global seasonal and interannual precipitation fluctuations and demonstrated a strong statistical dependency of interannual variability to intra-annual seasonality. Despite its global significance, little knowledge can be inferred regarding the variability of precipitation extremes. Finally, indices describing large-scale atmospheric patterns (e.g., El Niño–Southern Oscillation) are limited by their capacity in explaining the region-specific temporal variability; the broad spatial dynamics of precipitation variability are often not well represented (Fatichi et al. 2012).

This study therefore attempts to provide a United States–based investigation quantifying variability and seasonality of precipitation extremes based on a simple and interpretable method developed by Colwell (1974), hereinafter referred to as the Colwell index. Statistical analyses of precipitation variability have traditionally been done using techniques such as coefficient of variation (CV) (e.g., Fatichi et al. 2012), percent difference, change in probability distributions over two different time periods (e.g., Fischer et al. 2013; Shen et al. 2016), and frequency analysis (e.g., Kao and Ganguly 2011; Zheng et al. 2015). These techniques have revealed many spatiotemporal features of precipitation variability, but their utility for quantifying precipitation predictability is limited, because a variable precipitation (as defined by coefficient of variation for example) can range from completely predictable (variable but with recurrent magnitude fluctuation) to completely unpredictable (variable but without recurrent patterns) (Burgess and Marshall 2014). In comparison, the Colwell index provides statistical inferences relating changes in recurrent pattern with changes in magnitude fluctuation (see the supplemental material for details). Further, the index provides an overall score of predictability based on the quantifications of the magnitude fluctuation and seasonal recurrent likelihood so as to reveal predictability of the system under consideration and thus to facilitate decisions regarding environmental management (Colwell 1974; Burgess and Marshall 2014; Lawson et al. 2015). As such, the Colwell index represents an appealing way to characterize the spatial patterns of precipitation predictability that discerns the relative influences of seasonality and variability.

The utilization of the Colwell index for understanding recurrent patterns of a phenomenon has been well documented in previous studies. For example, Poff and Ward (1989) investigated the flooding and biodiversity implications of streamflow variability using long-term discharge data in the United States; Loe et al. (2005) attempted to correlate climate predictability with breeding phenology in the red deer population in Europe; and Mohammed et al. (2015) explored possible scenarios of runoff predictability under future warming projections based on modeling simulations. Additionally, there are numerous investigations exploring the effectiveness of the Colwell index in comparison with other techniques that aim at identifying periodicity. It has been suggested that the Colwell index is less sensitive than the Fourier transformation or spectral analysis in detecting significant periodicity in metric datasets (Stearns 1981; Gan et al. 1991; Beissinger and Gibbs 1993). However, more relevant to the current study, it has been shown that the Colwell index relates well statistically with estimates of seasonality and predictability based on spectral densities (Beissinger and Gibbs 1993) and Fourier analysis (Sabo and Post 2008), and it performs better than single estimates of variation, such as standard deviation or coefficient of variation (Beissinger and Gibbs 1993). More significantly, sophisticated techniques such as spectral analysis or the Fourier transformation, unlike the Colwell index, do not yield single values of parameters to characterize the temporal fluctuations in the time series (Gan et al. 1991). Therefore, with rigorous data control and standard data manipulation techniques, the Colwell index can provide a rather simple yet informative estimate of predictability; it is thus applicable to those phenomena that depend upon climate periodicity, such as biodiversity, and ultimately influences ecosystem management.

With this in mind, this study aims to utilize the Colwell index for three objectives: 1) to provide quantifiable representations of precipitation variability and seasonality based on precipitation means and extremes over

Table 1. Definition of precipitation extremes and their abbreviations, adopted and modified based on Karl et al. (1999). R99P and R95P have been modified from their original definition to be percentile-based extremes rather than the sum of precipitation over the percentiles. R05S and R01S are new indices developed for extreme dry conditions.

Extreme index	Definition	Unit	Category
RX1D	Monthly max 1-day precipitation within each month	mm	Intensity
RX5D	Monthly max 5-day precipitation within each month	mm	Intensity
R99P	99th percentile of daily precipitation for each month of each year	mm day^{-1}	Intensity
R95P	95th percentile of daily precipitation for each month of each year	mm day^{-1}	Intensity
R20L	Percent of days within each month with daily precipitation greater than 20 mm day^{-1}	%	Duration
R10L	Percent of days within each month with daily precipitation greater than 10 mm day^{-1}	%	Duration
R05S	Percent of days within each month with daily precipitation less than 5 mm day^{-1}	%	Duration
R01S	Percent of days within each month with daily precipitation less than 1 mm day^{-1}	%	Duration

the period of 1949–2010 in the conterminous United States; 2) to investigate the spatial similarities and differences between predictabilities generated based on precipitation means and those generated based on precipitation extremes; and 3) to compare information revealed by the Colwell index to that based on traditional coefficient of variation methods.

2. Materials and methods

a. Precipitation extreme indices and dataset

A subset of precipitation-related extreme indices defined by the Expert Team on Climate Change Detection and Indices (ETCCDI) was adopted and modified by this study, as shown in Table 1 (details in Karl et al. 1999; Alexander et al. 2006; Sillmann et al. 2013a,b). Specifically, there are four intensity-based wetness indices (R99P, R95P, RX1D, and RX5D), two duration-based wetness indices (R20L and R10L), and two duration-based dryness indices (R05S and R01S). Daily gridded meteorological data for the conterminous United States at ⅛° resolution for the period of 1949–2010 (Maurer et al. 2002; Livneh et al. 2013) were used to compute monthly means and extremes of daily precipitation, and the latter were subsequently used to compute the Colwell index (described in the next section). The Maurer (2013) dataset was originally created by spatially interpolating National Oceanic and Atmospheric Administration (NOAA) Cooperative Observer (COOP) stations based on the synergraphic mapping system algorithm of Shepard (1984) and then matching them to the long-term average of the Parameter-Elevation Regressions on Independent Slopes Model (PRISM) precipitation climatology (Daly et al. 1994, 1997). The average density of the COOP stations is 1 station per 700 km^2 in the United States, but a more sparse distribution is present in the Southwest. The reasons for using a gridded dataset rather than station-based observations are threefold: 1) gridded data provide a better representation of spatial patterns and transitions; 2) it provides a complete (i.e., no missing data) and consistent (i.e., in terms of identical temporal coverage and spatial resolution) dataset to generate precipitation extremes and the subsequent Colwell index; and 3) its gridded format allows comparison to future continental-scale gridded datasets. It is important to note that the Maurer gridded dataset is subject to various data quality [e.g., observer biases in the COOP Network (Daly et al. 2007)] and interpolation uncertainties [topographic adjustment and station location and density biases (Di Luzio et al. 2008)] that provide a level of uncertainty to our results [for effects of data coverage on estimates of precipitation mean and variability, see Wan et al. (2013)].

b. Colwell index and its derivations

The Colwell index is a simple metric system generated based on the mathematics of information theory and is analogous to autocorrelation analysis and to some aspects of harmonic analysis (Colwell 1974; Mohammed et al. 2015). It provides quantifiable estimates of the probability of precipitation to persist at a certain level, interannually and intra-annually, thus making inferences regarding its predictability. Three coefficients are estimated, with V as precipitation magnitude variability, S as seasonality, and P as the score of predictability that is described by scores of V and S ($P = V + S$). The coefficient S varies inversely with intra-annual persistence, meaning that S reaches its minimum when the probability occurrence of precipitation in each month is independent of the month (i.e., no seasonality); V varies inversely with the magnitude of precipitation fluctuations (which are binned into different levels), meaning that it reaches its minimum when the levels of precipitation fluctuate to the maximum degree possible, regardless of the intra-annual pattern. Simply put, high V indicates low variability, and high S indicates high seasonality. Coefficients of P, V, and S vary on a scale between 0 and 1. Scores of V and S are thus inversely covarying over a large part of the United States. Details of the mathematical derivation of the Colwell index and a walk-through example based on single-grid monthly mean precipitation data to compute the Colwell index are provided in the supplemental material text 1 (Tables S1 and S2, and Fig. S1).

Regionally aggregated Colwell index coefficients were compared through box plots, following the region classification scheme identified in Fig. S2. To test the bin-size effect on the computed Colwell index, a sensitivity test that classifies precipitation into 6, 8, 10, 12, 14, and 16 bins was conducted based on monthly mean precipitation data (Fig. S3). To compare spatial patterns of variability based on the Colwell index to those based on traditional methods, a coefficient of variation representing seasonality and variability for each extreme index and monthly mean precipitation was computed using the same input data. A seasonal coefficient of variation (CV_S) was computed by 1) averaging monthly precipitation data (means and extremes) over a 62-yr period to obtain the respective mean for each month of a year, 2) computing the standard deviation (std dev) and the mean of the 12-month data, and 3) calculating CV_S by using std dev/mean. The coefficient of variation for precipitation variability (CV_V) was computed by 1) taking the mean and std dev of the 62-yr monthly precipitation data and 2) calculating CV_V by using std dev/mean. For simplicity, only one intensity-based wetness index (i.e., RX5D), one duration-based wetness index (R20L), and one duration-based dryness index (i.e., R01S) are provided in the results section. Representations of other indices are provided in Figs. S4 and S5 (based on the Colwell index), and Figs. S6 and S7 (based on the CV method). All interpolation and data visualizations were performed in RStudio (V0.98, RStudio Inc.). Code scripts are available in the supplemental material text 2.

3. Results

Gradual regional transitions of precipitation variability and seasonality are observed across the conterminous United States for the period of 1949–2010 (Figs. 1, 2). Low scores of V indicate high variability, and low scores of S indicate low seasonality. For scores of V (i.e., variability), there is a clear west–east contrast for monthly mean precipitation, with low scores generally distributed in the east and the western ranges and high scores in the interior west, Southwest, and Midwest (region classification in Fig. S2). A similar pattern is observed for R20L, a duration-based wetness index, but with reduced regional heterogeneity in the interior west and Southwest. Such a spatial pattern is still visible for R01S (duration-based dryness index), but the west–east contrast becomes less apparent. For RX5D (intensity-based wetness index), scores of V are higher in the east (i.e., Northeast, Southeast, and Florida) and are generally low in the west. This pattern is consistently observed for all intensity-based wetness indices (Figs. S4 and S5). In comparison, scores of S (i.e., seasonality) for precipitation means and extremes are spatially consistent: they are generally low in the east and the interior west and are high along the western ranges, in parts of Florida, and the Midwest.

Spatial and regionally aggregated patterns of variability and seasonality characterized by CV are provided in Figs. 3 and 4. High scores of CV indicate high variability, and low scores indicate low variability (Fig. 3 colors are adjusted for direct visual comparisons to Fig. 1). As shown, spatial patterns of variability and seasonality are similar for monthly mean precipitation and RX5D: scores of CV_V (variability) are high in the Southwest and low elsewhere; and scores of CV_S (seasonality) are high along the California coast, and low in the east and the interior west. This pattern is consistent for all intensity-based extremes (Figs. S6 and S7). For duration-based wetness indices (e.g., R20L), scores of CV_V are homogenized with some sharp regional heterogeneity in the interior west, and scores of CV_S are low in the east, accompanied by some abrupt CV contrasts in the interior west. For duration-based dryness indices (e.g., R01S), high scores of CV_V are sporadically distributed along the western ranges and in the east, and high scores of CV_S are predominately distributed in the Pacific Northwest coast and Florida.

Spatial distributions of P scores derived by the Colwell index mimic the scores of V across the U.S. landscape for most of the cases (Figs. 2, 5). For monthly mean precipitation and duration-based wetness indices (R20L), P is low in the east and along the western ranges and high in the interior west, Midwest, and Southwest. Similarly, for duration-based dryness indices (e.g., R01S), P is low along the western ranges, is relatively low in the east, and is high in the interior west, Midwest, and Southwest. Finally, for intensity-based wetness extremes (RX5D), P is relatively high in the Northeast and the western ranges and is low in the Southwest.

Furthermore, the V/S ratio reveals the relative contribution of variability compared to seasonality in determining precipitation predictability over the U.S. landscape (Fig. 5). It is evident that, for monthly mean precipitation and all extreme indices, scores of V play a proportionally higher or equal role in regulating scores of P in most grid cells. Scores of V have a much higher role in determining predictability of precipitation means and R20L in the interior west. This regional controlling role of V expands to include parts of the Southwest and the Northeast for R01S and shrinks to the Northeast for RX5D. Scores of S are proportionally larger than scores

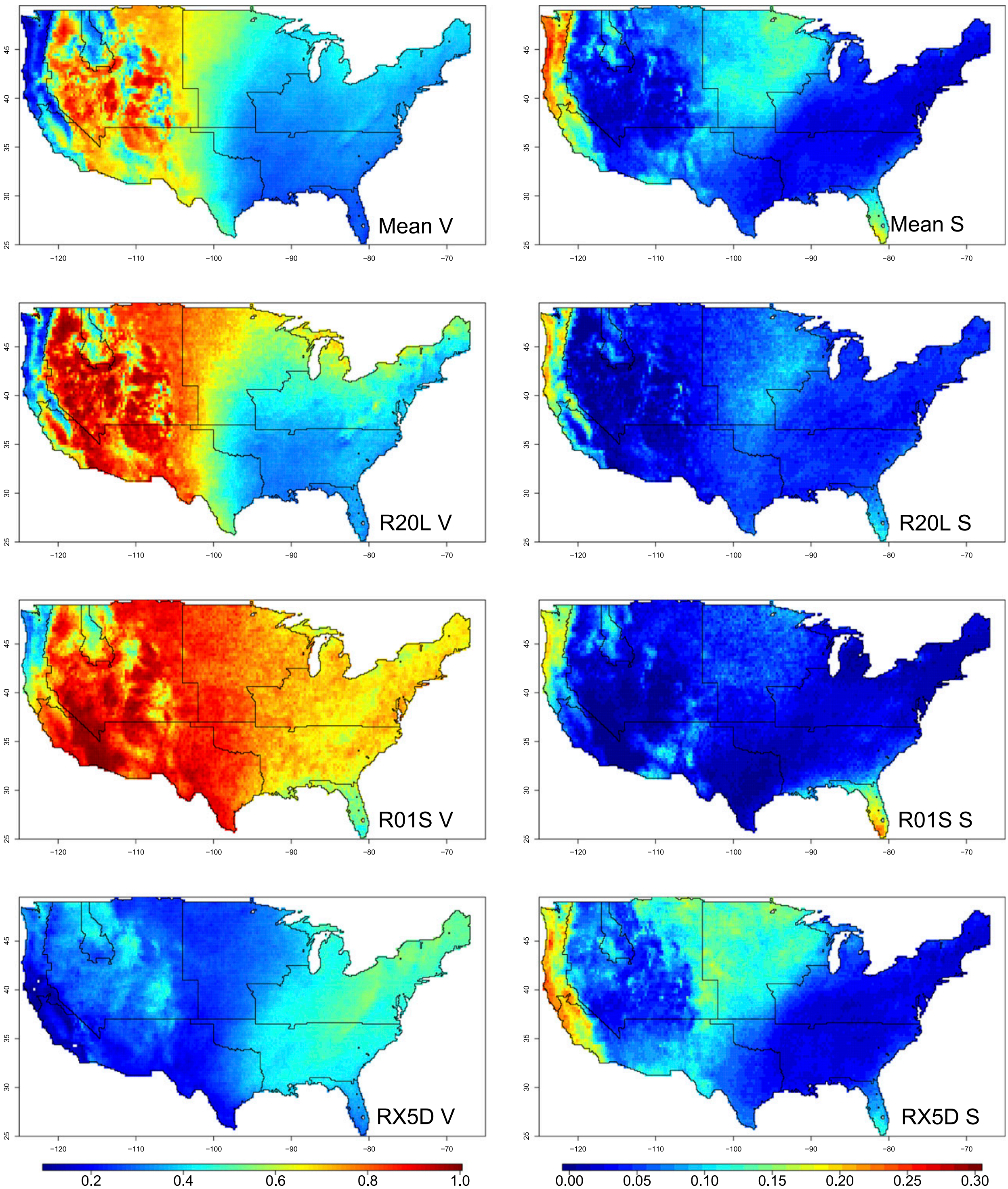

FIG. 1. Spatial representations of (left) variability and (right) seasonality based on the Colwell index for (top)–(bottom) monthly mean precipitation, R20L, R01S, and RX5D. Scores of interannual variability vary inversely with precipitation magnitude fluctuation, while scores of intra-annual seasonality vary positively with seasonality. Data were calculated based on gridded daily precipitation in 1949–2010.

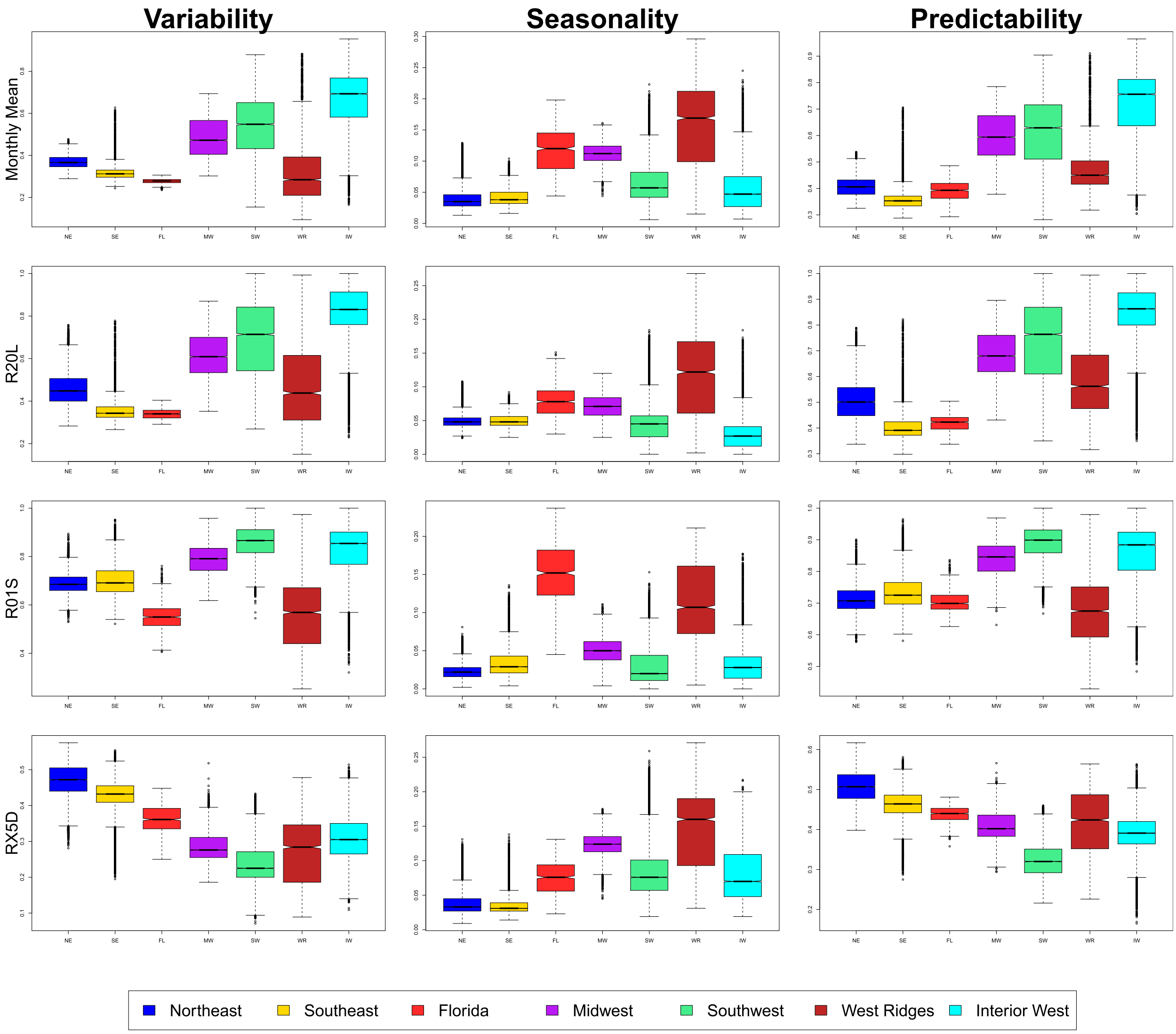

FIG. 2. Box plot of the regionally aggregated scores for variability, seasonality, and predictability, computed based on the Colwell index for (top)–(bottom) monthly mean precipitation, R20L, R01S, and RX5D.

of V only in parts of the West Coast (e.g., California coast for RX5D and Pacific Northwest coast for mean monthly precipitation).

4. Discussion and conclusions

a. *Variability of precipitation and precipitation extremes*

Precipitation-related variability, seasonality, and predictability are quantified in this study for the historical period 1949–2010 using the Colwell index. Specifically, clear west–east contrasts of precipitation variability are demonstrated: the variability of mean monthly precipitation and duration-based extremes (i.e., R01S and R20L) is low in the interior west, and high in the east and along the western ranges. Regional studies have provided similar results; for example, Berg and Hall (2015) reported large fluctuations in interannual variability of precipitation in California; Dettinger et al. (1998) demonstrated evidence for large year-to-year precipitation variations in the Pacific Northwest; and Wang et al. (2010) revealed high interannual variability for summer precipitation in the Southeast. Precipitation is relatively low in much of the interior west and the Southwest (e.g., Petrie et al. 2014). Therefore, mean monthly precipitation in the interior west, especially in the Southwest, does not fluctuate as much on an absolute basis as in the wet regions of the east and the coastal west. Similarly, precipitation less than 1 mm day^{-1} is common, and precipitation greater than 20 mm day^{-1} is rare in the dry regions of the west, and therefore

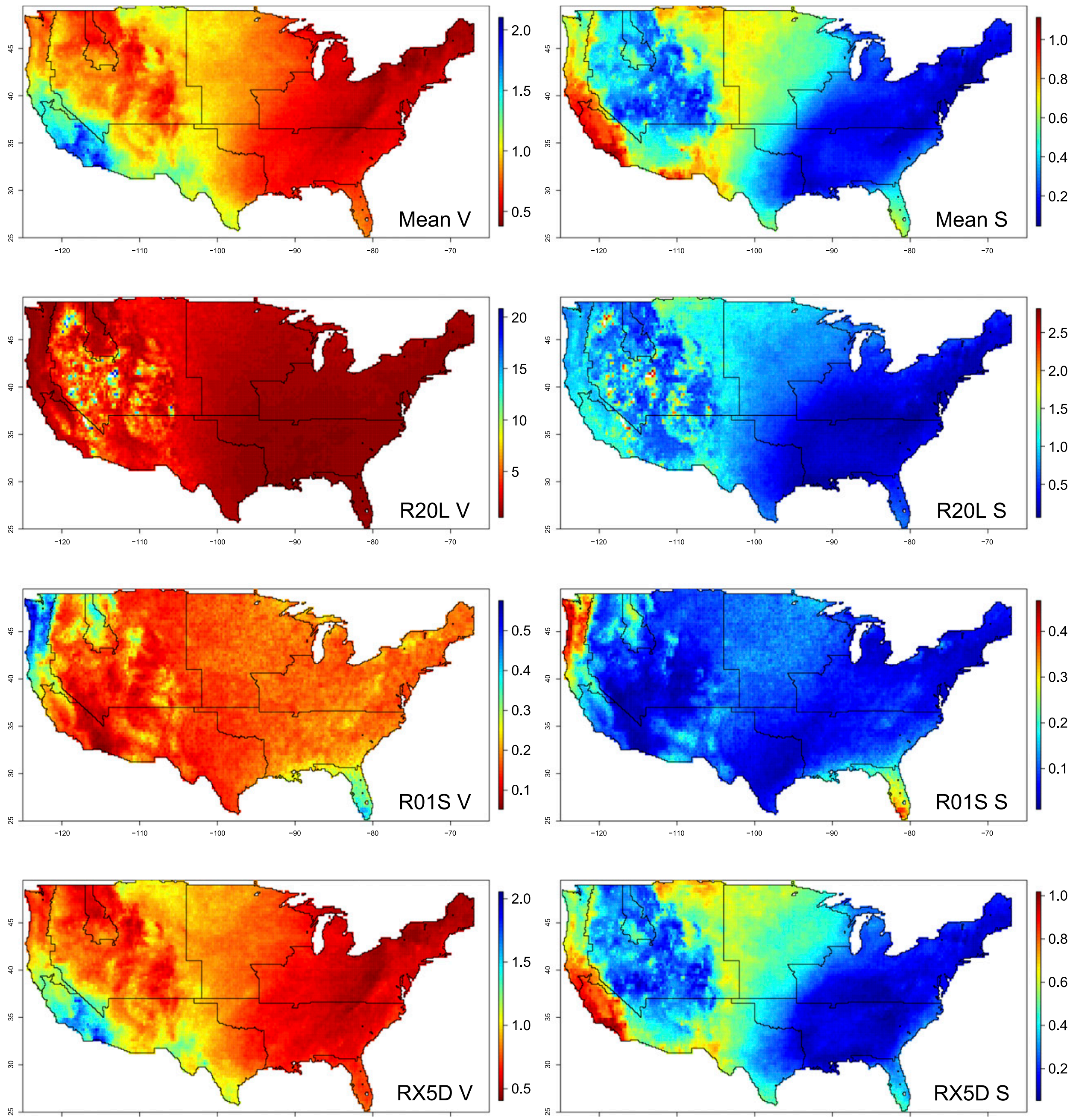

FIG. 3. Spatial representations of (left) variability and (right) seasonality based on CV for (top)–(bottom) monthly mean precipitation, R20L, R01S, and RX5D. Data were calculated based on gridded daily precipitation in 1949–2010.

percentage of a month when precipitation is below 1 mm day^{-1} (i.e., R01S) and percentage of a month when precipitation exceeds 20 mm day^{-1} (i.e., R20L) shows little fluctuation. Compared to the uniform characterization of rainy day fluctuation by De Martino et al. (2013) for the entire United States, our results based on thresholds demonstrate more regionally distinguishable patterns, and as such, our study provides more detailed results to inform regional as well as national management decision-making.

In comparison, a reversed west–east contrast is observed for RX5D—an intensity-based wetness indicator (Figs. 1, 2). It is apparent that RX5D is highly variable in the west and low in the Northeast and the Pacific Northwest. Combining variabilities characterized for monthly mean and duration-based extremes, patterns

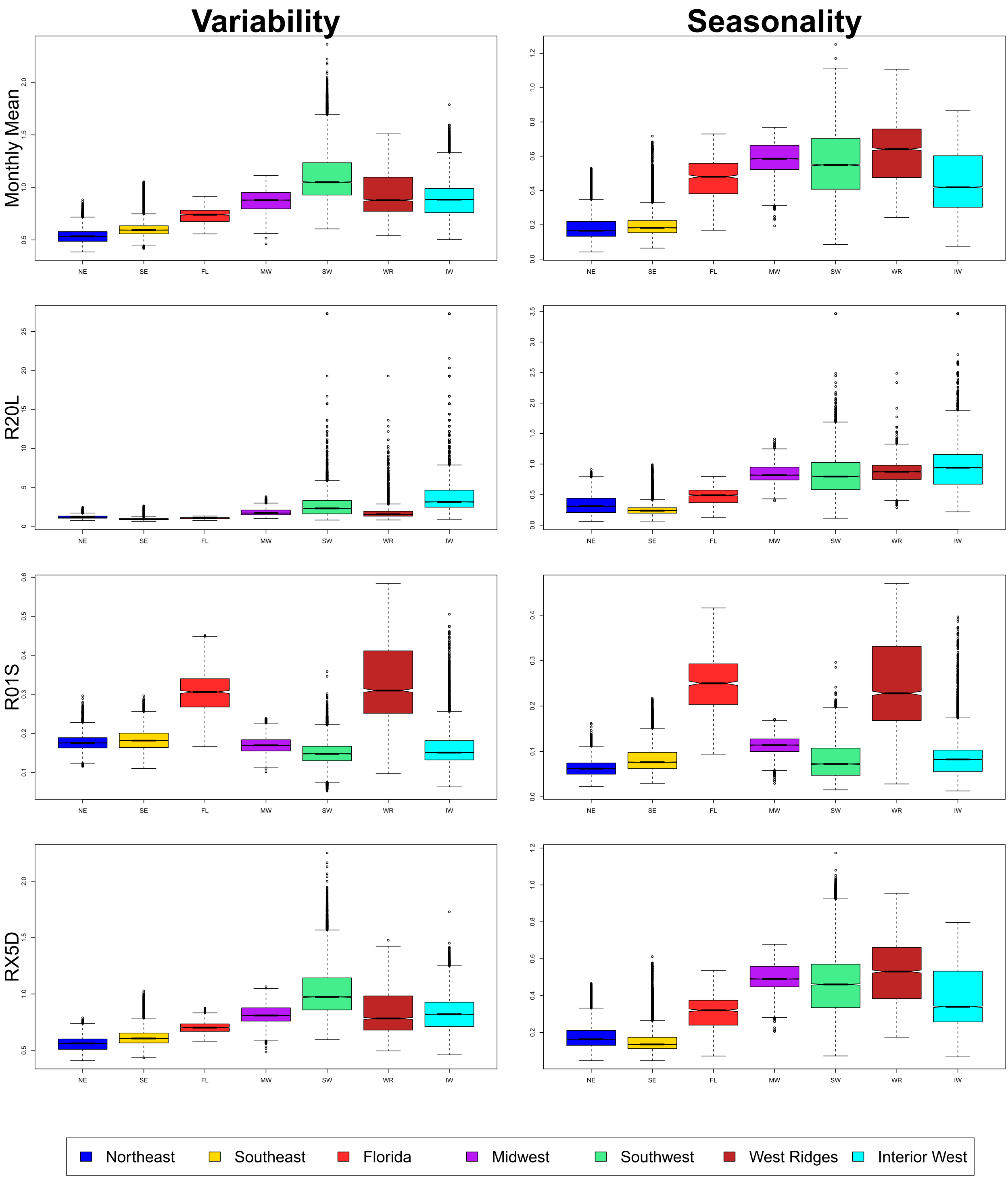

FIG. 4. Box plot of the regionally aggregated scores for variability and seasonality computed based on CV for (top)–(bottom) monthly mean precipitation, R20L, R01S, and RX5D.

start to emerge: across the United States, with the exception of the Pacific Northwest coast, the year-to-year variations of monthly mean precipitation are predominately determined by the occurrences of no precipitation intervals (i.e., R01S) and frequency of heavy precipitation events (i.e., R20L) but not by fluctuations in the intensity of the heaviest precipitation events. In the Southwest, temporal RX5D is highly variable, but occurrences

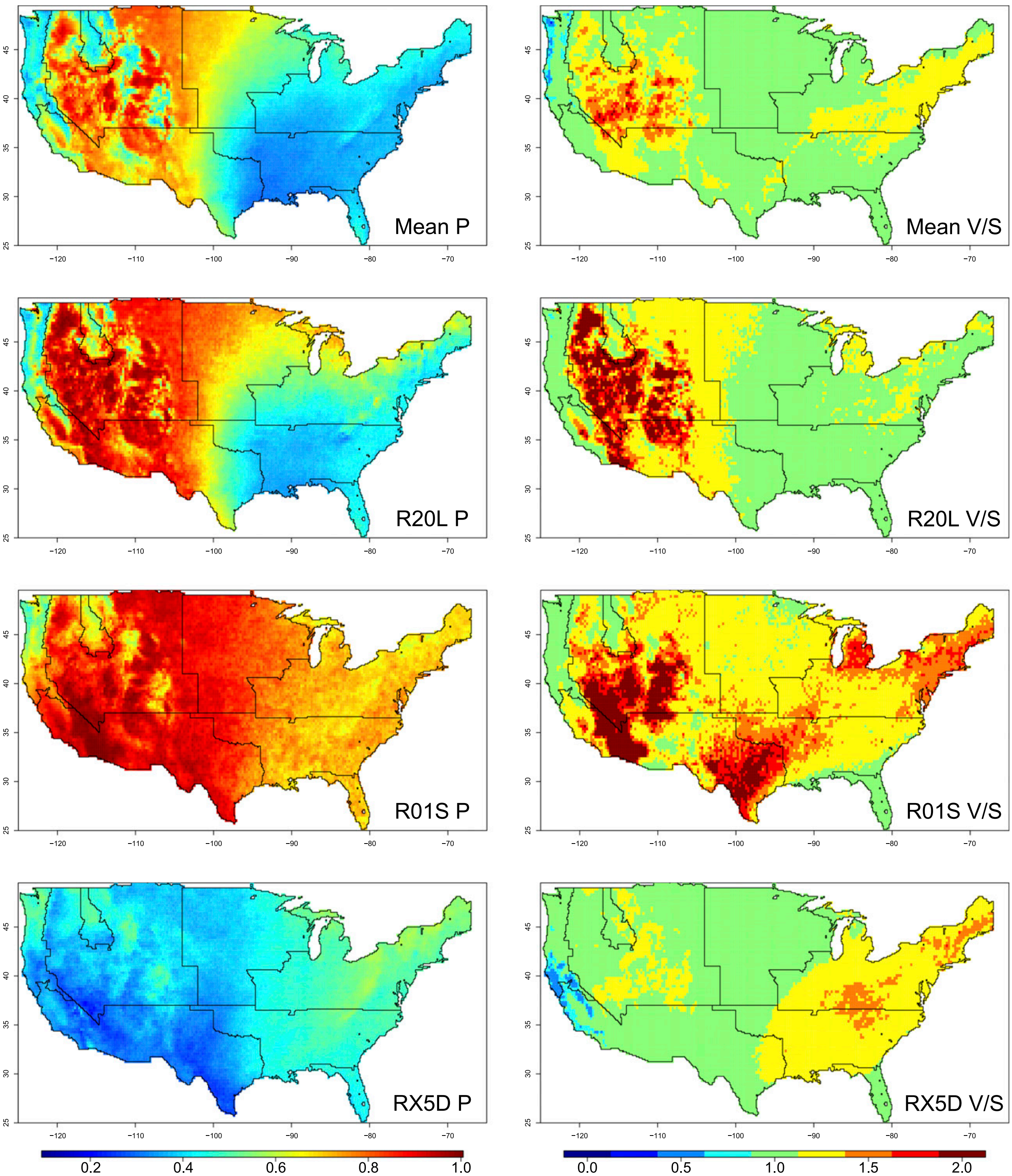

FIG. 5. Spatial representations of predictability and variability/seasonality ratio for (top)–(bottom) monthly mean precipitation, R20L, R01S, and RX5D. For $V/S > 1$, P is characterized more by scores of V; for $V/S < 1$, P is characterized more by scores of S; and for $V/S = 1$, V and S contribute equally. Data were calculated based on gridded daily precipitation in 1949–2010 and were interpolated onto the 1–2 range for V/S larger than 1.

of dry days and extremely wet days are highly persistent, resulting in a highly persistent precipitation variation through time; in the east, intensity of heavy precipitation is highly persistent interannually, but precipitation occurrences and monthly means are not, resulting in highly variable monthly mean precipitation fluctuations. This result agrees well with the findings of Polade et al. (2014), which demonstrated that the total number of dry days plays a dominating role in interannual precipitation variability in the subtropics. Our study indicates that 1) the number of dry days and extremely wet days underpins the temporal precipitation variability over much of the United States, while 2) the intensity of heavy precipitation does not play a significant role. The only exception to this occurred in the Pacific Northwest, where large variations of precipitation means correlate with large variations of heavy downpours, as well as with the number of dry days and wet days.

Furthermore, it is evident that the spatial pattern of V scores is smoother in the east, whereas the spatial pattern of V is much more irregular in the west (Fig. 1). This spatial characterization reflects the different roles that topography and large-scale atmospheric circulation play in regulating local land moisture conditions (e.g., Abatzoglou et al. 2014). In the west, regionalized water vapor content, moisture-adiabatic lapse rate, upward wind velocity, small-scale dynamics, cloud microphysics, temperature profile, and the orientation of storm tracks relative to topography caused by complex terrains may all contribute to the sharp regional contrast of precipitation variability (Dominguez et al. 2012).

For seasonality, mean monthly precipitation agrees with indices of precipitation extremes in that seasonality is uniformly distributed across the U.S. landscape with the exceptions of the western ranges, Florida, and parts of the Midwest, where stronger seasonality is observed (Figs. 1, 2). These regionalized seasonality features are likely the consequence of season-specific meteorological events, such as the known wet and dry seasons in Florida and the Pacific Northwest, which occurred in opposite seasons from each other. For the rest of the United States, where seasonality is low, it is worth noting the contrast of seasonality between wet and dry regions: in wet locations (e.g., Northeast), low seasonality is a likely consequence of persistently high precipitation throughout the year, possibly driven by different meteorological conditions seasonally (e.g., Kunkel et al. 2012), whereas in dry locations (e.g., the interior west), low seasonality of absolute precipitation is a likely consequence of consistently low precipitation throughout the year.

The spatial representations of variability computed on the basis of the Colwell index do not agree with those computed based on the CV method. Taking monthly mean precipitation as an example, the Colwell index indicates that the temporal variability of precipitation is high in the east and low in the interior west, whereas CV_V estimates that precipitation fluctuation is high only in the Southwest. Essentially, precipitation variation is standardized to the mean monthly precipitation data of the 62-yr for each grid point by the CV method. Low mean and high variances therefore result in a high CV estimation for the Southwest. In contrast, precipitation variation is standardized to the precipitation range of the entire United States under the Colwell approach. Consequently, precipitation variability is inherently lower in drier regions than wet regions. In summary, estimates of variability are not independent of the methodology.

Nevertheless, broad spatial patterns of seasonality for monthly precipitation means and extremes computed based on the Colwell index agree qualitatively well with those derived based on the CV method within this study (Figs. 1, 3) and agree reasonably well with those derived based on the Precipitation Concentration Index by Fatichi et al. (2012). Regionally aggregated seasonality scores further emphasized this (Figs. 2, 4). Regional differences are observed for the seasonality of monthly means, with the Colwell index indicating the highest seasonality observed in the Pacific Northwest, whereas CV indicates a high seasonality in California. Such a regional difference is also method dependent: in California, monthly precipitation within a year fluctuates as much as does the mean calculated by the CV method (which is the highest standardized fluctuation compared to other parts of the United States), whereas, in the Pacific Northwest, monthly precipitation within a year has the highest absolute fluctuation range as compared to other regions of the United States, and, consequently, the Colwell captures this region to represent the highest seasonality of all.

Combining scores of V and S yields precipitation predictability that provides an implicit estimate of the recurrent likelihood of the described precipitation patterns in the future (Fig. 5). Nationally, distributions of P mimic closely distributions of V. This correlation indicates that the recurrent pattern of precipitation over the period of 1949–2010 is predominately determined by its variability rather than seasonality across the United States. Specifically, monthly mean precipitation and duration-based wetness and dryness extremes in the east and the western ranges are not as predictable as those in the interior west and the Southwest, largely because precipitation is highly variable with a relatively low seasonality. In contrast, heavy precipitation in the east and parts of the western ranges is highly predictable, because heavy precipitation is temporally persistent at a certain level (i.e., low variability), with a relatively high seasonality in the Pacific Northwest and a relatively low seasonality in the east. Exceptions to the dominating role of variability on predictability only occur along the Pacific Northwest coast for monthly mean precipitation and along the California coast for RX5D, where signals of seasonality play a proportionally higher role in determining predictability scores. In these regions, precipitation is temporally variable, whereas seasonality is strong enough to form a recurrent pattern to underpin its overall predictability.

b. *Uncertainties and limitations*

Previous studies utilizing the Colwell index have suggested the possibility of lost precision and information during the process of categorizing continuous time series data into different bins (e.g., Colwell 1974; Gan et al. 1991). This is because the computation of predictability is inevitably dependent upon bin size and because the definition of bins is typically based on numerical manipulation of the data without explicit qualitative knowledge. As such, suggestions have been made that the application of the Colwell index is better suited for nominal or ordinal data (Stearns 1981) or that the Colwell index performs justifiably only if data are standardized with a consistent classification scheme in comparative studies (Gan et al. 1991). The current study standardized the classification schemes for extremes using a consistent log algorithm and tested the effects of varying bin sizes on the spatial patterns of Colwell index. As demonstrated here (Fig. S3), the spatial pattern of the Colwell index is insensitive to various bin classification schemes. With the added simplicity and interpretability, the application of the Colwell index is therefore justifiable in continuous time series data in this study.

Trends imposed by long-term climate change upon precipitation variability within the period of 1949–2010 are not explicitly considered in this study. Climate change has resulted in a general pattern of wetter areas becoming wetter and drier areas becoming drier (Easterling et al. 2000; Sun et al. 2012; Walsh et al. 2014). Similarly, wet seasons have been getting wetter and dry seasons have been getting drier over the past century (Chou et al. 2013). These changes in precipitation distributions across space and time would result in a likely temporal trend on precipitation variability, and the identification of such temporal trends in changes of precipitation variability may provide useful information to facilitate climate change mitigation and adaptation. However, given that only 62 yr of consistent daily precipitation data are available to compute the Colwell index, detection of trends in interannual variability may be unreliable. Moreover, it may be difficult to establish a robust causal–response relationship between anthropogenic climate change and change in precipitation variability within this 62-yr period. For example, within a full cycle of the Pacific decadal oscillation (PDO), there are multidecades of warm phase conditions and other multidecades of cool phase conditions. Given that a switch in PDO from cool to warm took place in 1977 (Mantua and Hare 2002), any temporal shift in precipitation variability cannot rule out the signal of this natural climate variability. Shen et al. (2016) further provided evidence for a centennial precipitation variability shift for the United States, with the period of 1895–1975 considered as dry and 1976–2010 as relatively wet. As such, the relative role of natural versus anthropogenic variability in regulating the trends in precipitation variability requires further investigation based on longer time series than used in this study [e.g., rain gauge observations with century-long data coverages such as those utilized in Kunkel et al. (1999), Kunkel (2003), Shen et al. (2016), and De Martino et al. (2013)]. For those investigations, the computed precipitation variability is inevitably subject to various data quality issues (e.g., missing data and inconsistent observation techniques) as well as local land-use change effects (e.g., Abatzoglou et al. 2014), thus leading to a possible unreliable interpretation of precipitation variability. This study therefore does not consider these temporal changes in precipitation variability.

c. *Broad implications*

The identified patterns of predictability for precipitation means and extremes have important ecological, hydrological, and socioeconomic implications (e.g., Burgess and Marshall 2014; Lawson et al. 2015). The exact extent of the implications, however, depends not on the relative scores of predictability, but on how the system and affected individuals perceive and respond to fluctuations in their environment (Colwell 1974; Hsu et al. 2012; Gherardi and Sala 2015). A highly predictable environment driven by low variability and high seasonality may be highly sensitive to stochastic events. At the same time, a highly unpredictable environment with high variability but low seasonality does not necessarily yield a low sensitivity to stochastic events, such as those driven by changes in precipitation seasonality. Many studies have investigated environmental responses to precipitation variability and have revealed contrary results in some cases. For example, Gherardi and Sala (2015) provided evidence that enhanced interannual precipitation variability increased plant functional diversity, which in turn reduces the negative effects of climate change on productivity. In contrast, Knapp and Smith (2001) suggested that interannual variability in aboveground net primary production is not related to fluctuations in precipitation. This uncertainty highlights the need for rigorous, evidence-based, and case-specific analysis of changes in precipitation predictability and environmental responses so as to maximize the utility of this information toward building sustainable environmental management schemes. The protocols developed and the results outlined in this study could provide useful guidance for future efforts directed toward providing this information to decision-makers and stakeholders.

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