Appendix B: Pacific SST-related teleconnective influences on North American monsoon precipitation within North American Regional Climate Change Assessment Program (NARCCAP) models

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To be submitted to International Journal of Climatology

Version December 7, 2014

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Abstract

Natural climate variability over the North American monsoon (NAM) region is associated with El Niño Southern Oscillation (ENSO) and Pacific Decadal Variability (PDV). Wet and dry conditions over the southwestern U.S. are determined by atmospheric Rossby wave teleconnections driven by the ENSO-PDV, through modulation of the subtropical ridge position. Bukovsky et al. (2013) performed an in-depth analysis of the North American Regional Climate Change Assessment Program (NARCCAP) simulations over the NAM region. They found that NARCCAP regional climate models forced with reanalysis performed well but performance degrades with dynamically downscaled global climate model projections. However, the large-scale forcing mechanism was not evaluated in association with the future NAM precipitation change. This study evaluates the continental-scale patterns of warm season precipitation variability within the NARCCAP simulations. We investigated whether the known dominant mode of warm season precipitation is connected to ENSO-PDV and its associated Rossby wave teleconnection. Multivariate statistics analyses are applied on multiple sea surface temperature and precipitation datasets to determine the dominant modes of variability at a continental scale, with focus on the Southwest. Our analysis shows that NARCCAP simulations are able to portray the spatial pattern in a similar way to observations for the NARCCAP models forced by a reanalysis dataset. However, all simulations forced by fully coupled global climate models from CMIP3, except one, generally fail to reproduce this climate variability. An inevitable question that rises is how relevant is the use of the ensemble model mean. We suggest more physically-based metrics to evaluate model quality are needed in assessment of uncertainty of future climate change. Although including all possible NARCCAP model simulations increases the statistical degree of confidence, not necessary better physical reliability is achieved.
1. Introduction

How the North American monsoon System (NAMS) is going to change in the future is an important and pressing question because of its impact on severe weather and water resources (Garfin et al. 2013, Ray et al. 2007). Climate change projections, based on the global climate models (GCMs) used for the Coupled Model Intercomparison Project version 5 (CMIP5, Taylor et al. 2012), currently project a seasonal delay in NAMS. A more intense subtropical high, or monsoon ridge, leads to greater atmospheric stability and decreased precipitation in early summer (June-July). Increased precipitation in late summer occurs once the atmosphere becomes sufficiently unstable to support convection (Cook and Seager 2013). The CMIP5 NAMS projections conform to the broader paradigm of more abrupt transitions in monsoonal climates (Cook and Seager, 2013), with increased contrast between the dry and wet regimes. However, there are some caveats to this projection. It has been demonstrated that most CMIP models do not faithfully reproduce NAMS intraseasonal variability (Lin et al. 2008, Sheffield et al., 2013). Though CMIP5 models reasonably represent NAMS precipitation during the onset period in early summer, they generally overestimate precipitation during late summer (Geil et al. 2013), precisely the period that is projected to become wetter.

Regional climate models (RCMs), alternatively, may be used to dynamically downscale CMIP GCMs to generate NAMS climate change projections. The principal advantage to the use of a RCM at the scale of tens of kilometers is the value added in the representation of terrain-forced monsoon thunderstorms (Gutzler et al., 2005 and 2009; Castro et al., 2007 and 2012), as this process is not physically represented well within a GCM. Even with enhanced spatial resolution and model physics more appropriate for the
mesoscale, RCMs do not faithfully physically represent the organized propagating monsoon convection that accounts at a distance away from the mountains (e.g. Castro et al., 2012). This paper specifically considers RCM data generated as part of the North American Regional Climate Change Assessment Program (NARCCAP, Mearns et al., 2012), to be described in further detail later. Similar to the aforementioned studies, Bukovsky et al. (2013) showed that when the NARCCAP RCMs were forced with lateral boundary forcing from an atmospheric reanalysis, the climatological evolution of the NAMS is improved. Also Bukovsky et al. (2014) recently considered NARCCAP RCMs that dynamically downscaled CMIP3 data from the A2 emission scenario, to evaluate future changes in mean NAMS precipitation. Consistent with Cook and Seager (2013), they found that mean NAMS precipitation is projected to decrease, considering the ensemble of all NARCCAP RCM-GCM combinations, but that the decrease was not statistically significant. Though the NARCCAP RCMs are forced with CMIP3 GCMs, to date their projections still represent the highest spatial resolution information generated by dynamical modeling.

At least for NARCCAP RCMs, a traditional climate projection approach that equally weights all the models to generate an ensemble mean change suggests that NAM precipitation will not substantially change in the future. Such an approach implicitly favors statistical confidence based on the level of multi-model agreement, over physically-based metrics of model performance of the individual contributing models. What has been absent in the discussion of NAMS climate projections thus far is how the contributing models, whether they be GCMs or RCMs, represent known sources of natural climate variability. Should this also be considered as a physically-based metric to
evaluate model quality? How would such information bear on the projected changes in NAMS precipitation? As we have argued previously in Carrillo et al. (2014a, in preparation), consideration of natural climate variability is extremely important for real-time resource decision making at seasonal timescales and for worst-case scenarios, for example long-term drought.

Our prior work, along with others, has characterized NAMS climate variability in the context of observational analyses, and downscaled atmospheric reanalyses and a global seasonal forecast model (e.g. Castro et al., 2001; Castro et al., 2007; Castro et al., 2012; Bukovsky et al., 2013). In particular, Castro et al. (2012) showed that a downscaled global seasonal forecast model was able to statistically represent the dominant mode of early warm season precipitation in North America. This mode reflects the anti-phase relationship between precipitation in the southwestern U.S. and central U.S., related to an atmospheric teleconnection (quasi-stationary Rossby wave train) emanating from the western tropical Pacific. Variability in the El Niño Southern Oscillation and Pacific Decadal Variability (ENSO-PDV) govern the teleconnection response, such that a positive (negative) phase of ENSO-PDV during early summer is associated with wet (dry) conditions in the central U.S. and a dry and delayed (wet and early) North American monsoon. We assert that a “well performing” climate model should reasonably represent the spatial and temporal structure of this dominant mode of warm season climate variability, especially given that a very recent community assessment of CMIP5 models by Sheffield et al. (2013) has explicitly considered ENSO and PDV-driven winter precipitation variability in North America. They generally
conclude that only a relative few number of CMIP5 models are able to physically represent such variability.

This work evaluates the continental-scale patterns of warm season precipitation variability within the NARCCAP simulations, using similar objective analysis approaches that have been applied to observational data sources in our aforementioned work. Our main research question of interest is: Is the known dominant mode of early warm season climate variability, and its connection to ENSO-PDV, reasonably represented each component NARCCAP RCM? More broadly, is it appropriate to consideration natural climate variability as an additional metric to assess physical uncertainty in NARCCAP model-generated climate projections?

This paper is organized as follows. The methodology and datasets are described in section 2. A review of the climatological behavior of NARCCAP simulation during the warm season is presented in section 3. The warn season SST variability in NARCCAP AOGCMs is described in section 4. The impact of spectral nudging in representing ENSO-PDV warm season precipitation in Phase I NARCCAP simulations is explained in section 5. The ENSO-PDV warm season precipitation response in Phase II NARCCAP RCMS is described in section 6. Concluding points and discussion are presented in section 7.

2. Methodology and datasets

2.1 NARCCAP models

We use regional climate model simulations generated as part of the North American Regional Climate Change Assessment Program (NARCCAP; Mearns et al., 2012), because these data reflect the most comprehensive research effort to date to
generate dynamically downscaled climate projections using multiple global and regional atmospheric models. A summary of NARCCAP model simulations used in this study is shown in Tables 1 and 2. Phase I NARCCAP simulations force six RCMs with NCEP-NCAR Reanalysis 2 (Kanamitsu et al. 2002) boundary conditions during the historical period 1979-2003 to assess RCM sensitivity with “perfect” observed analysis conditions. Phase II simulations use boundary conditions from four different fully coupled atmosphere-ocean global climate models (AOGCMs) from the Coupled Model Intercomparison Project (CMIP3) that are forced by the A2 greenhouse gas emission scenario (Community Climate System Model [CCSM], Third Generation Coupled Global Climate Model [CGCM], Geophysical Fluid Dynamics Laboratory GCM [GFDL], and Hadley Centre Coupled Model version 3 [HadCM3]). There are two periods of simulation, a twentieth century historical (1971-2000) and a twenty-first century climate change period (2038-2070). Eight of the twelve possible AOGCM-RCM combinations were generated (Table 3) with a grid spacing of 50 km. Additional NARCCAP experiments force some of the GCMs with observed sea surface temperatures, as described in Bukovsky et al. (2013), but are not considered here.

In considering how the NARCCAP models represent natural climate variability, it is important to note that two (CRCM and ECP2) of the participating RCMs utilize spectral nudging in both NARCCAP Phases I and II (Mearns et al., 2012). The spectral nudging approach may be advantageous because it preserves the properties of the synoptic-scale circulation of the driving atmospheric reanalysis or AOGCM (Castro et al., 2005 and 2012). When specifically considering NARCCAP Phase I experiments, the spectrally nudged RCMs generally outperform the non-spectrally nudged models with
respect to the representation of the mean climate (Mearns et al., 2012; Bukovsky et al., 2013).

2.2 NARCCAP warm season precipitation

This study considers NARCCAP RCM-generated precipitation during the period of July-August, as the majority of North American monsoon-related precipitation occurs during this time. Precipitation from each RCM is interpolated to a common grid of 0.5° because of the different model grid projections used (Mearns et al., 2012). To consider interannual variability, gridded JA precipitation is converted to a two-month standardized precipitation index (SPI; McKee et al. 1993), following the identical procedures we have used in prior analysis of gridded precipitation products in North America (Castro et al. 2009; Ciancarelli et al. 2013). The gamma distribution of precipitation for SPI computation of NARCCAP Phase II data is obtained independently for the twentieth and twenty-first centuries. Ciancarelli et al. (2013) showed that the dominant spatial modes of warm-season SPI in North America derived from PRISM precipitation data (PRISM Climate Group, 2004) are tied to distinct large-scale atmospheric teleconnections, or quasi-stationary Rossby wave trains. We consider equivalent observed precipitation obtained from a new NOAA precipitation (P-NOAA) product that covers the entire U.S. and Mexico, provided by Dr. Russ Vose. P-NOAA incorporates a terrain interpolation function similar to PRISM. We utilized the P-NOAA precipitation data previously in the evaluation of dynamically downscaled data from the Climate Forecast System (CFS) model, Version 1, reforecast (Castro et al. 2012).

Observed and GCM-derived sea surface temperature is considered only for the early summer (JJ). The main reason for the slight lead in time for SSTs is because of the
relative stronger influence of ENSO-PDV variability on North American warm season precipitation in early summer (Castro et al., 2001). Our guiding premise is that NARCCAP CMIP3 models may have a reasonable representation of the ENSO-PDV forced atmospheric teleconnection response, in reference to what we previously found considering a global atmospheric reanalysis (Ciancarelli et al. 2013). The level of correspondence in the warm season atmospheric teleconnection response may be used as a subjective physically-based measure of NARCCAP model quality. Observed SST is obtained from the two-degree NOAA Extended Reconstructed SST dataset (Smith et al., 2008)

2.3 Dominant spatial modes of variability

Dominant spatial modes of variability JA SPI and JJ SST are determined using two complementary statistical analysis tools. As in Ciancarelli et al. (2013), we apply empirical orthogonal function, principal component analysis (e.g. Wilks, 2006). The dominant principal component (PC) of SPI can be regressed onto 500-mb height and sea surface temperature anomalies, to reveal atmospheric teleconnection patterns and their relationship to SST. Where point source correlation is determined, local significance is determined by a t-test and field significance is determined by a Monte Carlo technique consistent with Livezey and Chen (1983) using 500 iterations. To isolate significant temporal variability in the dominant mode, we apply a multiple taper method (MTM) spectrum. MTM attempts to maximize both spectral resolution and variance by use of a Slepian taper to the data (Mann and Lees 1996). MTM toolkit for spectral analysis was taken from the Theoretical Climate Dynamic group at the University of California, Los
Angeles. The MTM toolkit is explained in further details in Ghil et al. (2002), and can be accessed at http://web.atmos.ucla.edu/tcd//ssa/.

Multi-taper method singular value decomposition (MTM-SVD) is a multivariate method that uses spectral and spatial disaggregation simultaneously. Low-frequency signals are enhanced by applying multiple Slepian data tapers. Conceptually, MTM-SVD first transforms time-space data to spectral domain and then finds dominant spatio-temporal variability by solving a complex eigenvalue problem. The three main outputs of MTM-SVD analysis are: 1) the local fractional variance (LFV) spectrum, similar to a power spectrum of a time series of point source data but applicable to the entire spatial domain, which statistical significance of spectral peaks are assessed by bootstrap resampling (Rajagopalan et al., 1998); 2) the reconstruction time series, determined typically for the specific spectral bands that are statistically significant; 3) the phase pattern map, which provides the phasing information for a spatial pattern in a given frequency band with respect to a designated reference point in the domain and can be shown as a vector plot. In Castro et al. (2009) we applied MTM-SVD in North America during the warm season to gridded observed precipitation (SPI), soil moisture (from National Land Data Assimilation System), and satellite derived normalized difference vegetation index (NDVI). Significant temporal variability in all of these fields was found at interannual to decadal timescales, corresponding to ENSO-PDV forced climate variability. Here, we essentially want to know if similar behavior exists within the NARCCAP AOGCMs and RCMs.
3. Review of climatological behavior of NARCCAP models during the warm season

The climatological behavior of Phase I and II NARCCAP models with respect to their representation of the NAMS during the warm season (JJAS) has been previously evaluated by Bukovsky et al. (2013). Considering the RCMs in the Phase I experiments, these generally showed a salient NAMS in the core region, with a rapid increase in precipitation in early summer and seasonal peak in rainfall in late July and August. However, Arizona was noted as a geographic area that exhibits a dry precipitation bias due to inadequate low-level moisture transport from the Gulf of California. The Phase II NARCCAP RCM simulations do not represent the NAMS well during the twentieth century historical period, in terms of the timing and amount of monsoon precipitation, and there is considerable variation in performance among the various RCM-GCM combinations. The most well-performing NARCCAP Phase II models, by the metrics of NAMS precipitation timing and amount, are CRCM[cgcm3], RCM3[cgcm3], WRFG[cgcm3], and HRM3[hadcm3]. The RCMs that utilized GFDL boundary forcing were by far the worst performing and comparatively a major outlier to other Phase II RCMs simulations, with summer monthly precipitation amounts exceeding observed values by a factor of two to three.

Before we consider the performance of the NARCCAP models with respect to their representation of year-to-year climate variability, we first briefly revisit some aspects of their climatological performance that augment what has already been done by Bukovsky et al. (2013). The most critical issue for the NAMS region is the representation of the annual cycle of precipitation, and this is also true when considering the CMIP3 and CMIP5 models directly (Geil et al., 2013). Figure 1 (left panels) shows the monthly
mean precipitation in the NAMS 2 region (Gochis et al., 2009) during the historical and climate change projection periods for all NARCCAP Phase II RCMs. Corresponding P-NOAA observations are shown in the light blue histogram on the top left panel. The observed precipitation shows an abrupt jump from 0.3 mm day\(^{-1}\) in June to 1.6 mm day\(^{-1}\) in July. Considering the ensemble mean of all NARCCAP Phase II RCMs (thick red line), this abrupt precipitation transition is absent. Removing the four NARCCAP RCMs that have the largest precipitation biases yields a more physically reasonable result, as shown on the right of Figure 1. The better performing NARCCAP RCMs are those forced by CGCM3 and HadCM3 while the poorer performing RCMs are those forced by GFDL and CCSM. This performance evaluation is in concurrence with Bukovsky et al. (2013). However, even the four better performing NARCCAP RCMs do not accurately represent monsoon onset and retreat. Only CRCM-CGCM3 and HRM3-HadCM3 are able to do this. The climatological performance of the NARCCAP RCMs also does not substantially change from the historical to future period (bottom panels of Figure 1). As previously stated, we use JA as our period of analysis for consideration of year-to-year climate variability in the following subsections because monsoon precipitation is maximized at this time and ENSO-PDV is known to significantly influence monsoon precipitation during the onset period in July. Our guiding supposition in the proceeding analyses is that the NARCCAP Phase II models which have the best representation of the NAMS climatology would also have the best representation of year-to-year climate variability.

The spatial distribution of JA precipitation for all eight Phase II NARCCAP models during the historical and future periods, along with the difference, is shown in
Figure 2. These precipitation maps confirm that there is a wide variation in the climatological representation of the NAMS in these RCMs, with some models generating little to no monsoon precipitation at all. As shown by Bukovsky et al. (2013), the ensemble mean difference of Phase II NARCCAP RCMs exhibits little to no change in NAMS precipitation with a low level of confidence due to the lack of model agreement. However, the NARCCAP RCMs that have the best NAMS precipitation climatology (CRCM-CGCM3 and HRM-HadCM3) also show the largest projected decreases in monsoon precipitation during JA. The results from these two particular NARCCAP models are actually the most consistent with recent NAMS projections from CMIP5 models (Cook and Seager, 2013), which as a whole improve the climatological representation of the NAMS in comparison to CMIP3 models.

To further illustrate the spread in NAMS precipitation projections in the NARCCAP models and the potential impact of distinguishing models by their physical performance, Figure 3 shows the JA mean precipitation for NAMS precipitation region 2 (Arizona) for the historical and future periods (yellow and red bars, respectively). The three models that project wetter conditions are highlighted in dark blue and the five models that project drier conditions are highlighted in light blue. Error bars at the top of the histogram are one standard deviation about the mean, as an indication of the degree of spread in the data. The models which project wetter conditions in the future are those with the least faithful climatological representation of the NAMS, forced by GFDL and CCSM. Inclusion of these models in the ensemble mean projection causes the NAMS precipitation change to be negligible. However, if just those models with the best climatological representation of the NAMS are considered (HRM3-HadCM3 and CRCM-
CGCM3), then there is a projected decrease in NAMS precipitation that exceeds one standard deviation in both models. Thus, applying some basic physical performance metrics of NAMS behavior to the NARCCAP models may have substantial bearing on the degree of statistical confidence of a projected climate change.

**Dominance of boundary forcing on NARCCAP interannual climate variability**

Bukovsky et al. (2013) also have previously noted that the sign of projected precipitation changes in the NARCCAP Phase II RCMs is largely consistent with that of the driving AOGCM. To further illustrate the influence of the driving AOGCM on the RCM solutions we consider the time evolution of the NARCCAP RCM simulated SPI for the historical and future periods in Figure 4 for the NAME 2 precipitation region. RCM SPI solutions are grouped according to their parent driving AOGCM. As these are each free running, coupled AOGCMs with their own unique representations of natural climate variability, we do not expect any deterministic correspondence of the SPI time series when comparing NARCCAP RCM simulations forced by different AOGCMs. When comparing RCMs driven by the same parent AOGCM, the SPI time series are always statistically significantly correlated at the 90% level or above in both periods (correlation coefficients shown on plot). The interannual variability of the NARCCAP RCM precipitation solution is largely a slave to the large-scale atmospheric circulation of the driving AOGCM. This is the case irrespective of whether or not spectral nudging is applied to the RCM. We submit that a “well performing” AOGCM-RCM system should reasonably represent the spatial structure of known atmospheric teleconnection patterns and their continental-scale precipitation responses. We reached basically the same
conclusion in our previous consideration of dynamically downscaled global seasonal forecast model data in Castro et al. (2012).

4. Warm season SST variability in NARCCAP AOGCMs

Given that interannual variability of NARCCAP RCM precipitation substantially depends on the imposed boundary forcing from a reanalysis or AOGCM, we consider how each of the four NARCCAP Phase II AOGCMs represent interannual variability in global SSTA in comparison to observations. Figure 5 shows the leading EOF of JJ SSTA (right) and the corresponding MTM spectrum of the principal component. The spatial pattern of the leading model of observed JJ SSTA shows a clear ENSO-PDV signal (top of Fig. 5) with maxima in spatial loading in the eastern tropical Pacific and central North Pacific. This leading mode has statistically significant temporal variability at a typical ENSO timescale of 3-5 years. Additional, but not statistically significant peaks in the MTM spectrum occur between approximately 6-9 years and 12-16 years. All of the NARCCAP AOGCMs have at least some representation of ENSO variability in their corresponding dominant mode. HadCM3 and GFDL appear to have the better representations, with statistically significant peaks in their MTM spectra at a reasonable ENSO timescale of approximately 3-7 years. CCSM incorrectly represents ENSO as a biennial cycle, a problem that has been previously documented in the literature (Hu et al., 2012). CGCM3 has relatively low spatial loading in the eastern tropical Pacific, though the mode peaks at a timescale of 5 years.

A limitation of EOF analysis of global SSTA is that ENSO-PDV variability may be present in more than one dominant mode. We apply MTM-SVD to specifically isolate
ENSO and PDV-related signals at their known timescales of temporal variability. The MTM-SVD analysis of observed SSTA is shown in Fig. 6. Consistent with other analyses of observed global SSTA, statistically significant temporal variability is mostly present in two bands, an ENSO band (2-6 years) and a decadal band (greater than ten years), as highlighted on the LFV spectrum at the top of the figure. As the analysis period considered here is limited to fifty years, the lowest possible resolvable frequency is 25 years. Figs. 6c and 6d shown of both the SSTA patterns associated with these two frequency bands, reference to a grid point in the eastern tropical Pacific (center of the Niño 3.4 region). These reconstructed SSTA pattern maps show a clear distinction between ENSO and PDV signatures in the Pacific Ocean, as compared to just consideration of the dominant EOF in Fig. 5a. Also of note in the reconstructed decadal band is the presence of statistically significant variability in the Atlantic basin, which suggests the Atlantic Multidecadal Oscillation (AMO). The combination of both interannual and decadal SSTA bands is shown in Fig. 6a, revealing the combined ENSO-PDV SSTA signature similar to that of Castro et al. (2007), their Figure 4.

MTM-SVD analysis is similarly applied to global SSTA for the NARCCAP AOGCMs for the historical and future climate periods in Figs. 7 and 8. The number of years considered in these analyses is more than the period of simulation of the NARCCAP RCMs. We use 40-50 year periods as denoted on the figure to resolve any possible statistically significant decadal variability. None of these four AOGCMs have significant temporal variability in their LFV spectra, shown by the yellow bars, beyond a timescale of 10 years. Generally speaking, the only significant SSTA variability in these four CMIP3 models is associated with ENSO, similar to what has been found in prior
studies (Sheffield et al., 2013). For that reason, the figures of reconstructed SSTA patterns associated with significant temporal variability are not so substantially different from the EOF dominant modes presented earlier in Fig. 5. HadCM3 and GFDL both show significant temporal variability in JJ SSTA at an ENSO timescale. The reconstructed SSTA patterns in the 2-6 year bands for these models show a well-defined ENSO signal in the eastern equatorial Pacific. Though CGCM3 and CCSM also have ENSO signals, these occur at a higher frequency and the SSTA signature in the eastern equatorial Pacific is comparatively less extensive. CCSM incorrectly represents ENSO as a biennial oscillation, consistent with the EOF analysis, as has been previously documented (Hu et al., 2012). For the future period, only HadCM3 and GFDL retain significant ENSO-related SSTA variability. There is not statistically significant spatiotemporal variability in SSTA for CGCM3 and CCSM in the future period, though reconstructed SSTA is shown for the bands that were significant in the historical period. HadCM3 shifts ENSO variability to a slightly longer timescale (6-10 years). From these analyses, we conclude that only HadCM3 and GFDL models have reasonable representations of ENSO variability, in terms of frequency and spatial distributions of SSTA. These models also retain ENSO as a statistically identifiable feature proceeding into the future.

**Warm season atmospheric teleconnections**

The next step in assessment of NARCCAP AOGCMs with respect to their representation of warm season climate variability is the examination of atmospheric teleconnection patterns. Fig. 9 shows the regression of ENSO-PDV associated SSTA on JA 500-mb geopotential height anomalies in a band of 2-6 years and greater than 10
years, according to the significant bands in the LFV spectrum of observed SSTA. Consistent with our previous work (Castro et al. 2007; Ciancarelli et al. 2013) there is the signature of a quasi-stationary Rossby wave train emanating from the western tropical Pacific that affects the large-scale atmospheric circulation pattern over North America. The spatial structure of the teleconnection does not appear unique to either of significant temporal bands. The regressed patterns are field significant at the 95% level or above.

The equivalent results during the historical period for the four NARCCAP AOGCMs, for just the 2-6 year band, are shown in Fig. 10 and their pattern correlation with the observed map in Fig. 9 is shown in Table 4. Only two of the NARCCAP AOGCMs have field significant regression of 500-mb height anomalies that statistically compare well to observations. Not surprisingly, these two models are HadCM3 and GFDL, as these two models have the best representations of ENSO SST variability. CGCM3 and CCSM do not exhibit atmospheric teleconnective structures that are field significant. The future period yields similar results, as shown in Fig. 11 and Table 4. The teleconnection in HadCM3 tends to have a weaker statistical relationship to that of the atmospheric reanalysis as compared to GFDL, but is still statistically significant. It is worth noting that we are just considering the warm season atmospheric teleconnections that are associated with ENSO in these AOGCMs, since that is the dominant control on the year-to-year early warm season precipitation variability. We acknowledge that there are higher order warm season teleconnection responses, namely the Circumglobal Teleconnection (CGT; Ciancarelli et al. 2013, Ding and Wang, 2005; Ding et al., 2011), but these likely arise as free stochastic modes. Though these other modes are important as well, they are not considered in this work.
5. Impact of spectral nudging in representing ENSO-PDV warm season precipitation response in Phase I NARCCAP models.

The observed spatial structure of precipitation anomalies associated with ENSO-PDV is determined by regressing SSTA in the significant spectral bands from MTM-SVD analysis. The regressed patterns shown in Fig. 12 reveal the expected antiphase relationship between precipitation in the Southwest and the regions of the central U.S. and northern Rockies. There is also a statistically significant relationship to precipitation in the Southeast U.S. These precipitation patterns are very similar to the dominant mode of early warm season precipitation in the U.S. found by Ciancarelli et al. (2013), their Figures 2 and 3. Note that we choose to orient the maps to reflect a negative phase of ENSO-PDV, with positive precipitation anomalies in the Southwest.

A reasonable expectation would be that the Phase I NARCCAP RCMs are able to reasonably reproduce this dominant spatial pattern of precipitation variability, since they are forced with “perfect” boundary conditions from an atmospheric reanalysis. We have already demonstrated, by dynamically downscaling the NCEP-NCAR reanalysis with the Regional Atmospheric Modeling System (RAMS) for a 50-year period, that this mode can be well reproduced in a RCM simulation (Castro et al. 2007). Given the fact that our previous RAMS model simulations utilized internal nudging, as motivated by findings in Castro et al. (2005) and Rockel et al. (2008), it is also reasonable to assume that those NARCCAP phase I RCMs that incorporate spectral nudging would have the best representation of year-to-year precipitation variability. Mearns et al. (2012) reported that the spectrally nudged Phase I NARCCAP RCMs have the lowest root mean square error when compared with observed precipitation. The two NARCCAP RCMs that incorporate
spectral nudging are CRCM and ECP2. Fig. 13 shows the correlation maps between ENSO and PDV associated SST and RCM-generated JA SPI, in the identical manner as done for observed precipitation in Fig. 12. Results combining ENSO-PDV are shown in Fig. 14. The spatial correlation (r) from these model generated precipitation results to the corresponding observed precipitation result is included on each plot. A value of r that exceeds 0.3 is considered statistically significant at the 90% level or above, given the sample size of the data.

For the ENSO band, the spectrally nudged models yield the closest result to the observed precipitation pattern, with r = 0.54 for CRCM and r = 0.36 for ECP2. HRM3 (r = 0.3) also exhibits significant pattern correlation. For the PDV band, the pattern correlations in WRFG (r = 0.33) and CRCM (r = 0.36) are statistically significant, with ECP2 and MM5 being the next best (r = 0.24). There may be two reasons why the PDV-associated precipitation pattern has generally less of a correspondence with observations. The observed pattern has relatively high spatial loading in the Great Plains (Fig. 12b), and RCMs generally have a problem in representing organized, propagating convection there (Castro et al., 2012). The length of record considered also may not be long enough to robustly assess decadal variability. In any case, those models which are not spectrally nudged generally present a lower correspondence with observed precipitation patterns associated with ENSO-PDV variability in the warm season (combined mode shown in Fig. 14). If spectral nudging is not included, RCMs will not be able to reproduce as well the observed, continental-scale spatial patterns of precipitation variability that are driven by atmospheric teleconnection responses.
6. ENSO-PDV warm season precipitation response in Phase II NARCCAP RCMs

The relatively short period of the NARCCAP Phase II RCM data limits the range of observable frequencies when considering year-to-year precipitation variability. Decadal variability is not temporally well resolved in a thirty year period and none of the NARCCAP GCMs exhibited significant SST variability at the decadal timescale. For these two reasons, we only can consider the relationship of Phase II NARCCAP RCM-generated precipitation within the temporally significant ENSO-related band in the general range of 2-6 years (with some minor variation therein among the models). We repeat the same type of analysis as in the previous section, regressing Phase II NARCCAP model simulated JA SPI on ENSO-band associated SSTA from MTM-SVD analysis in Section 3.3. The regressed SPI patterns for all Phase II NARCCAP RCMs are shown in Fig. 15 along with the pattern correlation (r) with the equivalent observed precipitation pattern as shown in Fig. 12a. The pattern correlations for Phase II NARCCAP RCMs, overall, are generally lower than what we found for the Phase I RCMs, and this is to be expected since the Phase I RCMs utilize “perfect” reanalysis boundary forcing. Considering first the historical period, the best performing model by the metric of pattern correlation is HRM3-HadCM3 (r = 0.38), and this value of pattern correlation actually slightly exceeds the equivalent Phase I NARCCAP RCM (r = 0.3). This is the only exception to the aforementioned general behavior of the pattern correlation in Phase II NARCCAP results. All of the other NARCCAP Phase II models in the historical period are not able to reproduce the spatial pattern of JA precipitation anomalies associated with ENSO variability. RCM3-CGCM3 does capture the nature of the antiphase relationship in precipitation between the southwest U.S. and the regions of
the Great Plains and Northern Rockies, but incorrectly represent the phasing of the precipitation anomaly in the Southeast. The worst performing model by the pattern correlation metric is CRCM-CCSM ($r = -0.33$), which has totally opposite phase of precipitation anomalies to the observed pattern and therefore a statistically significant, but negative value.

We attribute the good performance of HRM-HadCM3 with respect to its representation of warm season precipitation variability the fact that: 1) the driving AOGCM HadCM3 has a reasonable representation of the ENSO warm season atmospheric teleconnection response and 2) HRM-HadCM3 has one of the best climatological representations of the NAMS. For the future period, recall that only two of the NARCCAP Phase II AOGCMs are able to simulate significant temporal variability SST at the ENSO timescale (HadCM3 and GFDL). If just the RCMs which utilize these two GCMs as boundary forcing are considered, HadCM3-HRM3 retains the highest pattern correlation ($r = 0.25$). Though the value of the pattern correlation exceeds 0.3 for CRCM-CGCM3 and RCM3-CGCM3, the driving CGCM3 AOGCM does not exhibit any significant ENSO-related SST variability and does not capture the associated warm season atmospheric teleconnection response. Though these two RCMs do capture the spatial pattern of the ENSO-related precipitation response at least from the standpoint of statistical correspondence, they do so with incorrect underlying physics that would cause the response, at least as we presently understand that within the observed instrumental record.
7. Concluding points and discussion

This work has evaluated whether or not NARCCAP models can reasonably represent the continental-scale pattern of North American monsoon precipitation variability associated with ENSO-PDV. Per previous studies of the observational record, this pattern is basically the anti-phase relationship in precipitation between the southwest U.S. and Central U.S. that is dominant in the early part of the warm season. NARCCAP Phase I models with imposed reanalysis boundary forcing can represent it in a manner that similar to observations, consistent with our previous findings considering a dynamically downscaled 50-year retrospective reanalysis (CASTRO et al. 2007). However, when Phase II NARCCAP models are considered with boundary forcing imposed from CMIP3 GCMs only one of them (HRM3-HadCM3) is able to satisfy this condition. This particular NARCCAP model simulation exhibits a correct pattern and phasing of precipitation anomalies and a statistically significant atmospheric teleconnection that has a clear tie to Pacific SST forcing, in both the historical climate and climate change projection periods. HRM3-HadCM3 is also one of the most well performing Phase II models with respect to the climatology of warm season precipitation, in accordance with our hypothesis posed in Section 2.

Generally speaking, NARCCAP Phase I models are able to better represent the influence of large-scale atmospheric teleconnections in the warm season when spectral nudging in the RCM is applied. The nudging ensures that the structure of the large-scale, or synoptic-scale, atmospheric circulation as it exists in the driving GCM is preserved, especially and including the teleconnective structures. It also ensures that there is still added value on mesoscale by a better representation of diurnally-generated convective
precipitation. Even if spectral nudging is applied for a Phase II model, if the known dominant atmospheric teleconnections that drive warm season precipitation are absent in that driving GCM, there would be absolutely no hope of representing the associated continental-scale precipitation response in any RCM. We basically came to the same conclusion in Castro et al. (2012) with respect to dynamically downscaled warm season seasonal forecasts from the Climate Forecast System model. Though we are considering free-running, fully coupled atmosphere-ocean global climate models in the case of CMIP3, the paradigm is essentially the same.

We have suggested in this work that an appropriate standard for a “well performing” NARCCAP Phase II model for North American monsoon is that the model simulations have a reasonable representation of warm season precipitation climatology and year-to-year variability driven by natural climate variability. Again, only HRM3-HadCM3 mostly satisfies these criteria by the analysis presented here. With respect to the latter criterion, let us presuppose that CMIP3 models should be expected to at least represent ENSO and its associated atmospheric teleconnection responses, but probably not the other coupled ocean-atmosphere modes that vary on decadal timescales (PDO, AMO). These expectations would conform to recent overviews of CMIP5 performance in North America (Sheffield et al. 2013). In our case, only two of the four NARCCAP CMIP3 GCMs meet this condition (GFDL and HadCM3). But the errors in the climatological representation of warm season precipitation in the Phase II NARCCAP RCMs with GFDL imposed boundary forcing are quite large relative to the NARCCAP RCMs forced with the other three GCMs and observations. In our own experience working with water resource providers in Arizona, we have concluded it is problematic to
use the GFDL-forced RCMs in a climate change impacts assessment, as they simulate more than twice the normal amount of monsoon precipitation and it erroneously occurs mostly during September (Shamir et al., 2014).

NARCCAP does provide a unique source of dynamically downscaled climate change projection data from an ensemble of models. As it represents the best presently available, community generated source of such information in North America, it has been employed to estimate changes in mean climate in North America in the context of regional climate change assessments (e.g. Garfin et al. 2013). We do not disagree with the well established paradigm that a multimodel ensemble approach is necessary to robustly characterize statistical uncertainty. However, we question the notion that adding more models to ensemble mean projections should be done because this helps “cancel out” the errors among models due to their varying representations of natural variability and parameterized physics (Pierce et al., 2009). If we do so, a more statistically confident climate change projection can achieved, but it may not be based on models with robust physical performance. It is even more important to establish a well-defined standard of physical performance in dynamically downscaled climate change projections, since overarching purpose of the dynamical downscaling is to add value with respect to mesoscale meteorological processes that are more dependent on the surface boundary conditions, like convective precipitation. If RCM-GCM combinations are ultimately shown to be physically unreasonable, then why proceed with considering them as part of a model ensemble within climate change impacts assessment analyses? In the case of North American monsoon precipitation, Bukovsky et al. (2013) established that there is little statistical confidence in projected changes in North American monsoon
precipitation, based on the level of model agreement. We would add that from the work presented here that there is low physical confidence in these projected changed as well, because the wide variation in Phase II results is attributable in great part to an inadequate representation of the warm season precipitation climatology and natural climate variability (ENSO-PDV). We acknowledge that our conclusion is somewhat disconcerting from the perspective of climate change impacts assessment for the southwest U.S., given the pressing need for more confident North American monsoon climate projections. We also would emphasize it is not universally applicable across the entire NARCCAP simulation domain. Areas of the western United States that are not influenced by North American monsoon precipitation exhibit a much greater level of model agreement with respect to projected decreases in warm season precipitation.

It may be possible to differentially weight GCMs or RCMs, using physically based metrics, prior to constructing the ensemble mean climate projection. In the case of North American monsoon precipitation simulated by NARCCAP GCM-RCM model combinations, the historical performance of HRM-HadCM3 far exceeds that of the other NARCCAP combinations—which would limit the value of weighting. We hope that CMIP5 models are able to better physically represent natural climate variability during the warm season, and North American warm season precipitation; this would make constructing an ensemble mean climate projection that would include physically “well performing” GCMs, per the criteria established here, more practicable. The results of Cook and Seager (2013) and Geil et al. (2013) collectively suggest that the climatology of North American monsoon precipitation has been improved in CMIP5, especially in models with higher spatial resolution. It remains to be seen, though, if the CMIP5
models can reasonably represent warm season atmospheric circulation variability. We hope our work here provides guidance for future analysis of dynamically downscaled CMIP5 models from the North American Coordinated Regional Climate Downscaling Experiment (NA-CORDEX; Mearns et al., 2013), in a continuing effort for more statistically and physically confident projections of the North American monsoon in the future.

Acknowledgments
This research was funded by the City of Tucson Office of Conservation and Sustainable Development and the National Science Foundation (NSF). Additional funding was provided by both the Water Sustainability Graduate Student Fellowship Program and the Climate Assessment for the Southwest (CLIMAS) at the University of Arizona. We thank NARCCAP for providing the dataset. NARCCAP is funded by the NSF, the U.S. DOE, NOAA, and the U.S. EPA. We are grateful to Drs. Russ Vose and Richard Heim for access to the gridded precipitation dataset.

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chronologies in the Southwest U.S. *International Journal of Climatology.* To be submitted.


### Tables

<table>
<thead>
<tr>
<th>Model</th>
<th>Description</th>
<th>Nudging Type</th>
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<tbody>
<tr>
<td>CCSM</td>
<td>Community Climate System Model</td>
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<tr>
<td>CGCM3</td>
<td>Third Generation Coupled Global Climate Model</td>
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<tr>
<td>GFDL</td>
<td>Geophysical Fluid Dynamics Laboratory GCM</td>
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<tr>
<td>HadCM3</td>
<td>Hadley Centre Coupled Model, Version 3</td>
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**Table 1: General Circulation Models**

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<th>Model</th>
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<td>CRCM</td>
<td>Canadian Regional Climate Model</td>
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<td>ECP2</td>
<td>Experimental Climate Prediction Center Regional Spectral Model</td>
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<td>Hadley Regional Model 3</td>
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<td>Regional Climate Model Version 3</td>
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<td>WRFG</td>
<td>Weather Research &amp; Forecasting Model</td>
<td>Non-spectral nudged</td>
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<td>MM5I</td>
<td>PSU/NCAR mesoscale model at Iowa State University</td>
<td>Non-spectral nudged</td>
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**Table 2: Regional Climate Models**

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<tr>
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<tr>
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<td>CRCM-CGCM3, CRCM driven by CGCM3</td>
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<td>ECP2-GFDL, ECP2 driven by GFDL</td>
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<td>7</td>
<td>WRFG-CCSM, WRFG driven by CCSM</td>
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<td>8</td>
<td>HRM3-HadCM3, HRM3 driven by HadCM3</td>
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</tbody>
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**Table 3: NARCCAP simulations**

<table>
<thead>
<tr>
<th>Model</th>
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<th>21C</th>
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<td>GFDL</td>
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<td>0.72</td>
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**Table 4: correlation of spatial patterns of 500-mb GPHA between observed and NARCCAP GCMs.** 500-mb GPHA patterns were obtained by regressing original GPHA against the SST ENSO mode obtained with MTM-SVD.
Figure Captions

**Figure 1:** Upper panel: annual cycle of NARCCAP precipitation for the NAM region for all the NARCCAP models (left) and selected models which best represent the monsoon (right) both for the 20th century. Histogram is for observed precipitation. Lower panel: as in upper panel but for the 21st century.

**Figure 2:** Seasonal mean (July-August) of NARCCAP precipitation for the 20th century (left panel), 21st century (central panel), and difference between 20th minus 21st century (right panel) for each NARCCAP model. The units for the mean and difference precipitation is mm/day.

**Figure 3:** Seasonal mean (July-August) of NARCCAP precipitation for individual NARCCAP simulations for the 20th century (yellow bars) and the 21st century (red bars). Dark blue background highlight positive change (wet) and light-blue background negative change (dry). In grey background are the multi-model ensemble mean for both cases: all models (ALL) and well-performing (WELL). The area average is highlighted by the blue box in the upper right corner. Error bars are calculated as ±1 standard error of the mean for each case.

**Figure 4:** SPI area average time series for each NARCCAP model for the 20th century (left panel) and the 21st century (right panel). NARCCAP simulations with same GCM boundary condition forcing are grouped with same color. Correlation between a time series and the leader of the group is indicated in the plot by $\sigma$.

**Figure 5:** Right panel: EOF leading mode of spatial variability for observed (top) and IPCC GCM SST (below: gfdl, hadcm3, cccm, and cgcm3) for summer (JJ) SST for the 1951-2000 period—but 1968-2008 for hadcm3. Left panel: MTM spectrum of the temporal leading mode, PC1, of the cases defined in the right panel. Significance levels of 90% and 99% confidence are superimposed in cyan lines.

**Figure 6:** Upper: LFV spectrum of the spatiotemporal leading MTM-SVD mode for observed JJ SST (a). Lower: Spatial correlation between the JJ SST gridded dataset and the MTM-SVD reconstructed temporal pattern of JJ SST for the ENSO spectral band (b), the PDV spectral band (c), and the combined ENSO-PDV band (d). Local significance is shown with oblique lines and field significance in percentage in lower left corner.

**Figure 7:** LFV spectrum of the spatiotemporal leading MTM-SVD mode for JJ SST for each IPCC GCMS used to force NARCCAP models during the 20th century: from 1951 to 2000—but from 1968 to 2008 for hadcm3. Peaks statistically significant passing the 90% level of confidence are highlighted with yellow. Right panel: Spatial correlation between the JJ SST gridded dataset and the MTM-SVD reconstructed temporal pattern of JJ SST for the ENSO spectral band. Local significance is shown with oblique lines and field significance in percentage in lower left corner.
**Figure 8:** Similar to Fig. 7 but for the 21st century: from 2021 to 2070.

**Figure 9:** Spatial correlation between the JA GPHA at 500 mb and the MTM-SVD reconstructed temporal pattern of JJ SST for the ENSO (a) and combined ENSO-PDV (b) spectral bands. Local significance is shown with oblique lines with oblique lines and field significance in percentage in lower left corner.

**Figure 10:** Spatial correlation between the JA NARCCAP GPHA at 500 mb and the MTM-SVD reconstructed temporal pattern of JJ NARCCAP SST for the ENSO spectral band: cgcm3(a), hadcm3(b), gfdl(c), and ccsm(d) during the 20th century. Local significance is shown with oblique lines with oblique lines and field significance in percentage in lower left corner.

**Figure 11:** Similar to Fig. 10 but for the 21st century.

**Figure 12:** Spatial correlation between the JA SPI gridded dataset and the MTM-SVD reconstructed temporal pattern of JJ SST for the ENSO spectral band (a), the PDV spectral band (b), and the combined ENSO-PDV spectral band (c). Local significance is shown with oblique lines.

**Figure 13:** Spatial correlation between the JA SPI for each NARCCAP model dynamically downscaled with NCEP-Reanalysis and the MTM-SVD reconstructed temporal pattern of JJ NCEP-Reanalysis SST for the ENSO (left panel) and PDV (right) spectral bands. Local significance is denoted with oblique lines and spatial correlation with the corresponding observed spatial pattern (from Figs. 12a and 12b) are indicated in the lower right corner. The bottom two panels are the spectral nudged cases: CRCM and ECP2.

**Figure 14:** As in Fig. 13 except for the combined ENSO-PDV mode.

**Figure 15:** Similar to Fig. 13 but for JA SPI for each NARCCAP model dynamically downscaled with IPCC GCMs for the 20th century (left panel) and 21st century (right panel). For both centuries only ENSO spectral band spatial pattern is shown.
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