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Objective determination of monsoon season onset, withdrawal, and length

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[1] Using daily precipitation data from a network of weather stations across mainland Thailand, we apply a two-phase linear regression model to objectively determine the onset, withdrawal, and length of the summer monsoon season for the years 1951–2005. Our onset metric compares favorably with an independent determination of onset. Both onset and withdrawal are associated with expected wind and geopotential height anomalies in the lower atmosphere. Comparisons between stations show no coherent spatial variability in either onset or withdrawal, and trends at each station are small and statistically insignificant at the $p < 0.05$ level. When averaged across all stations, onset, withdrawal, and season length all show significant correlations with sea surface temperatures (SST) in the Indian ocean, tropical Pacific, and in the North Pacific regions with relatively well understood connections to monsoon variability. Additionally, there are also significant correlations with SSTs in the South Atlantic and North Atlantic, teleconnections that have been previously suggested but remain controversial. Compared to other methods for deriving the onset and withdrawal of the monsoon, our method provides one of the most objective techniques available using data readily available from most meteorological stations.

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1. Introduction

[2] The onset and withdrawal of the Asian summer monsoon is characterized by rapid seasonal transitions in atmospheric circulation and precipitation over a large area of the Asian continent [*Hsu et al.*, 1999]. Objectively defining the timing of the onset and withdrawal of the monsoon, however, has been a difficult task, often being based on atmospheric variables exceeding some arbitrary threshold given with little (and sometimes no) explicit justification. Example thresholds for calculation of monsoon onset include (1) the day on which a 5 day running mean rainfall index exceeds 5 mm d^{-1} and persists continuously for 5 days while, over the next consecutive 20 days, the number of days with rainfall greater than 5 mm/d exceeds 10 days [*Zhang et al.*, 2002]; (2) wind speeds in excess of 8 m s^{-1} for more than 7 consecutive days [*Taniguchi and Koike*, 2006]; (3) increases in precipitable water above the "Golden Ratio" [*Zeng and Lu*, 2004]; and (4) normalized (+1 to −1) vertically integrated moisture transport rising above 0 [*Fasullo and Webster*, 2003]. Even fewer studies [*Goswami and Xavier*, 2005] have attempted to calculate monsoon season length and withdrawal. These remain valuable contributions and highlight the variety of methods and variables that can be used to diagnose monsoon season transitions. Still, a more objective determination of monsoon onset and withdrawal, without the requirement of a priori selected thresholds and critical values, would be valuable.

[3] We use two-phase linear regression, applied to daily precipitation data from a network of stations across mainland Thailand, to calculate the onset dates, withdrawal dates, and length of the summer monsoon rainy season. The advantages to our approach are two-fold: objective determination of these metrics without a priori selection of arbitrary thresholds and the use of data readily available from meteorological stations throughout the world. We also estimate uncertainty using a maximum entropy bootstrap resampling procedure, an additional contribution as few other studies investigating monsoon timing provide any uncertainty estimates. Because of our parsimonious approach (i.e., a simple algorithm applied to widely available data), this methodology is readily applicable to any region with a pronounced seasonal cycle in rainfall. Our results compare favorably with other onset measures, and demonstrate statistically significant and physically consistent teleconnections to known and suspected drivers of monsoon variability in southeast Asia.

2. Data

[4] Our study is focused on Thailand because of the quality and availability of data, although the techniques

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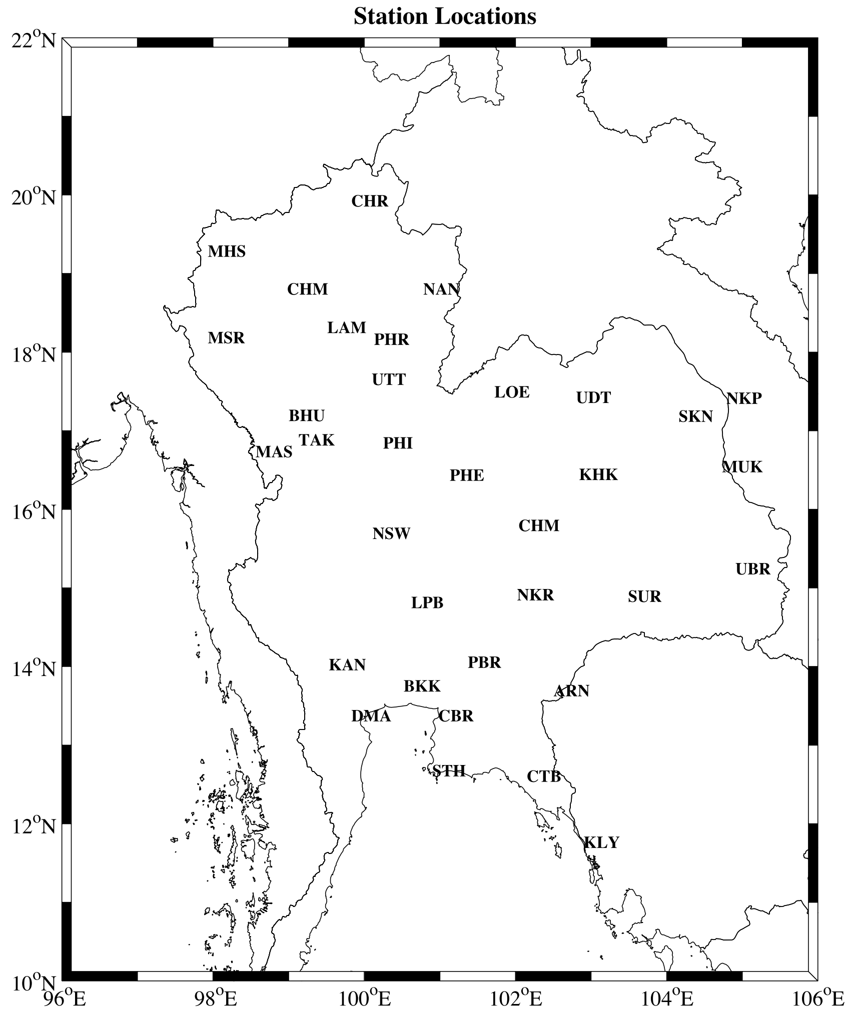

Figure 1. Map of station locations used in our analysis. Station codes from Tables 1 and 2.

and analyses described here are easily transportable to other regions. We use daily precipitation data from a network of 34 meteorological stations from across mainland Thailand (Figure 1). Data from these stations have been used in previous studies over the region [*Kripalani et al.*, 1995; *Singhrattna et al.*, 2005; *Zhang et al.*, 2002]. Prior to our analysis, the data were subjected to a series of homogeneity and quality control tests [*Komojinda*, 2003]. The stations provide good spatial and temporal coverage, and include daily records of maximum and minimum temperatures, precipitation, and relative humidity, covering the time period 1951–2005. Years with 30 or more missing values (days) were excluded from the analysis. For all other years, missing days were filled in with climatological values from the same station. We also use a data set of land and sea surface temperatures to compare with our derived indices [*Rayner et al.*, 2003].

3. Methodology

[5] Two-phase linear regression is used extensively to objectively locate undocumented change points and nonlinearities in meteorological time series [*Lund and Reeves*, 2002; *Solow*, 1987]. The regression model follows the form:

$$
\begin{aligned}
X_t &= \mu_1 + \alpha_1 t + \epsilon_t, 1 \leq t \leq c \\
X_t &= \mu_2 + \alpha_2 t + \epsilon_t, c < t \leq n,
\end{aligned}
\tag{1}
$$

where $\mu_{1,2}$ and $\alpha_{1,2}$ are the regression parameters, t is the time series under consideration and n is the length of the time series. The optimal change point, c, is determined through iterative fitting of the two-phase regression model from time $t = 3$ to $t = n - 3$: the change point is selected from the model that minimizes the sums of squares of the residuals. In other words, c is taken from the "best fit" of all possible two-phase regression models. As an example, we show the application of this method to daily precipitation from Chiangmai station for the year 1951 (Figure 2, left). Early and late in the year, before and after the monsoon season, there are scattered and intermittent rainfall events. These are often associated with midlatitude frontal systems or local convective activity but are distinct from precipitation related to monsoon dynamics. At the beginning of the monsoon season, usually in early to mid-May, the frequency

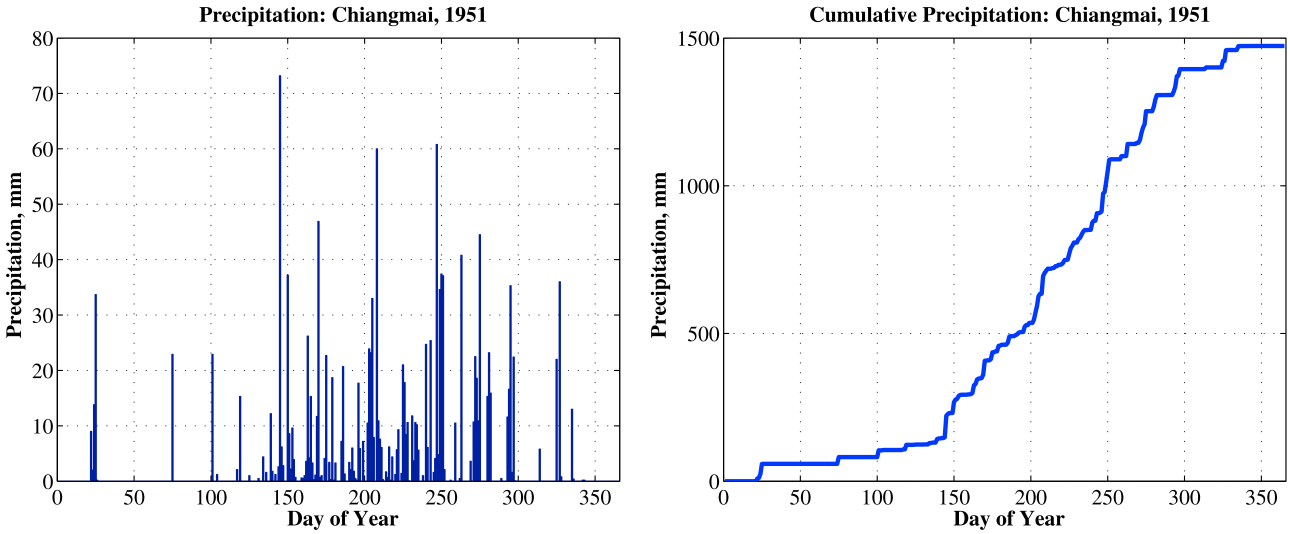

Figure 2. Precipitation from Chiangmai station, 1951. (left) Daily precipitation (mm) and (right) cumulative precipitation over the year (mm).

of precipitation events increases substantially and remains high, relative to the dry season, until the end of the summer monsoon period. These features become even more clear if we calculate the cumulative annual rainfall starting from January 1 through to the end of the year (Figure 2, right). The premonsoon and postmonsoon periods are characterized by a near-zero slope, indicating few precipitation events. During the summer monsoon period, however, consistent and frequent rainfall leads to a steep slope in the cumulative rainfall distribution. To take advantage of these features in the cumulative precipitation, we fit separate two-phase linear regression lines to the first and second half of the cumulative rainfall time series (Figure 3). The optimally selected change points correspond to the onset and withdrawal of the monsoon season, and the monsoon season length is calculated as the difference between these two dates. For our Chiangmai example, onset occurs on day of year (DOY) 144, withdrawal occurs on DOY 292, and the monsoon season length is 148 days. For our study, we calculate onset, withdrawal, and season length separately for each year and each station, and then average our monsoon indices across all stations to minimize local effects. The station-averaged monsoon time series are then compared against an alternate measure of onset [*Zhang et al.*, 2002] and a monthly gridded data set of land and sea surface temperatures [*Rayner et al.*, 2003].

[6] To estimate uncertainty in our estimates of onset and withdrawal, we use the maximum entropy bootstrap (MEB) [*Vinod*, 2004, 2006] to resample from the original cumulative precipitation time series. In the MEB procedure, the original data series is sorted in increasing order, and the ordering index is retained. Intermediate points are computed for the order statistics and the maximum entropy density within each interval is calculated. *N* number of uniform

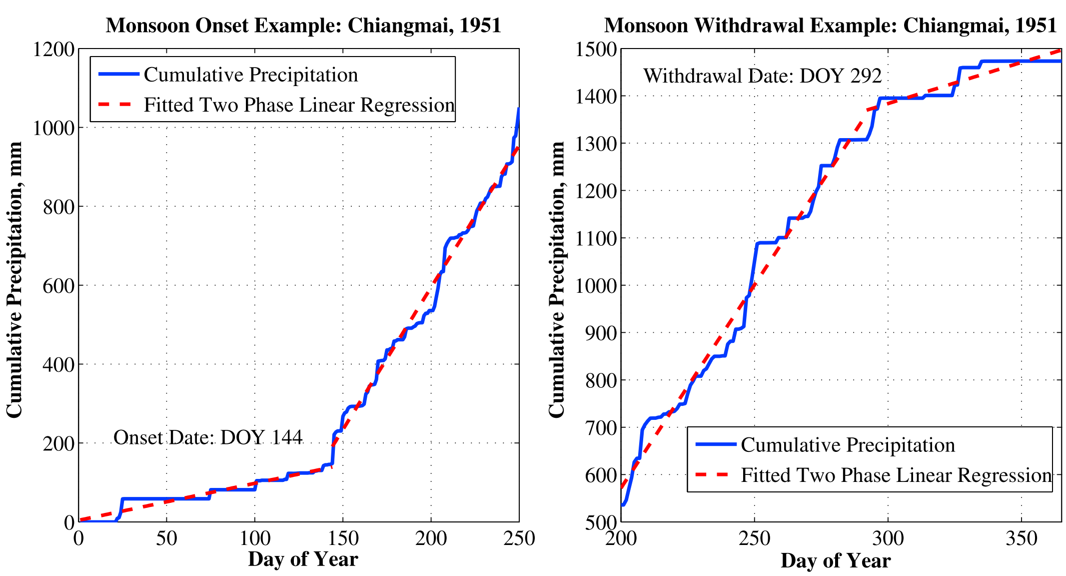

Figure 3. Fitted regression model and calculation of (left) onset and (right) offset for Chiangmai, 1951.

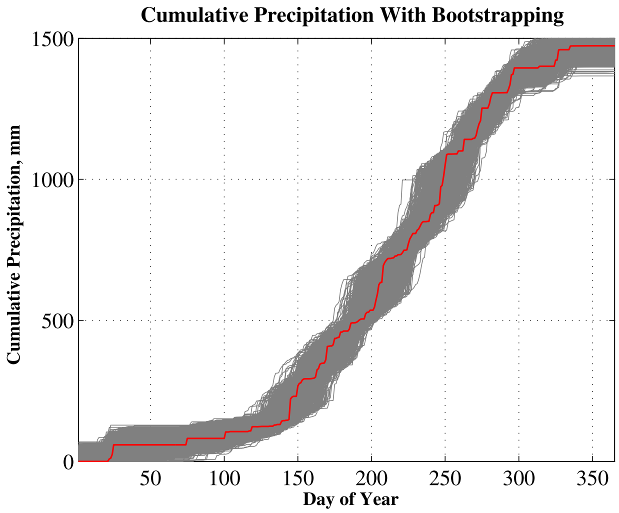

Figure 4. Cumulative precipitation from observations and 1000 resampled time series using MEB for Chiangmai, 1951.

random values are generated (between 0 and 1), where *N* is equal to the number of points in the original data series. These random numbers are then used to compute sample quantiles of the maximum entropy density and then sorted using the ordering index from the first step, recovering the time dependence of the original data. The MEB technique provides several distinct advantages over standard bootstrapping: it satisfies both the ergodic and central limit theorems, resamples consistent with the time variant behavior of the underlying time series, and preserves the autocovariance structure. This method is therefore ideal for nonstationary time series or data sets, including data that have a pronounced seasonality, such as precipitation in monsoon regions. Additional details and full description of the MEB method can be found from *Vinod* [2004, 2006].

[7] For each station and year of data, we use the MEB to resample from the original cumulative precipitation time series and generate 1000 new series. We then recalculate monsoon onset and withdrawal for each of the bootstrapped time series and use these new estimates to bracket our uncertainty. An example of the resampling is shown in Figure 4 for Chiangmai, 1951. In red is the cumulative precipitation from the data, with 1000 resampled time series shown in grey. The bootstrapping does a reasonable job

Table 1. Interannual Onset Mean, Standard Deviation, Percentile of Precipitation on Day of Onset, and Bootstrap Confidence Limits for Monsoon Onset

Station	Code	Mean	Standard Deviation	Percentile of Precipitation	Confidence Limits[a] (days) 25	75
Aranyaprathet	ARN	124.71	17.65	0.122	−7	10
Bangkok	BKK	127.77	23.10	0.099	−7	8
Bhumibol	BHU	124.48	22.95	0.096	−6	8
Chaiyaphum	CHM	122.52	28.10	0.114	−6	10
Chantaburi	CTB	133.00	17.32	0.105	−6	10
Chiangmai	CHM	128.04	23.53	0.078	−6	10
Chiangrai	CHR	134.98	25.31	0.110	−7	9
Chonburi	CBR	125.15	29.67	0.115	−6	11
Donmuang	DMA	126.82	20.06	0.086	−6	10
Kanchanaburi	KAN	118.96	25.64	0.093	−6	9
Khlongyai	KLY	146.08	13.75	0.142	−8	9
Khonkaen	KHK	127.96	22.31	0.120	−5	11
Lampang	LAM	124.25	22.69	0.082	−6	10
Loei	LOE	124.43	23.08	0.134	−7	9
Lopburi	LPB	120.24	21.31	0.089	−6	10
Maehong	MHS	124.68	14.46	0.059	−5	10
Maesariang	MSR	127.92	15.70	0.063	−5	9
Maesot	MAS	143.31	21.09	0.100	−6	9
Mukdahan	MUK	133.69	22.89	0.129	−8	9
Nakhon Phanom	NKP	143.92	18.00	0.143	−8	9
Nakhon Ratchisima	NKR	124.54	30.23	0.133	−7	10
Nakhon Sawan	NSW	129.85	25.81	0.116	−7	8
Nan	NAN	128.62	29.57	0.125	−7	10
Phetchabun	PHE	123.24	20.93	0.122	−6	12
Phitsanulok	PHI	129.76	22.31	0.094	−6	10
Phrae	PHR	121.48	26.10	0.089	−5	12
Prachinburi	PBR	130.73	23.13	0.121	−8	11
Sakon	SKN	126.98	20.49	0.125	−6	11
Sattahip	STH	113.43	40.19	0.134	−6	10
Surin	SUR	122.50	18.54	0.091	−6	10
Tak	TAK	129.56	18.31	0.098	−5	9
Ubon	UBR	129.63	14.71	0.097	−6	11
Udon	UDT	129.64	17.82	0.123	−7	10
Uttaradit	UTT	130.47	23.22	0.101	−6	9
All stations ensemble		128.27	23.51	0.107	−6	10

[a]Units for confidence limits are days relative to initial predicted onset date.

Table 2. Interannual Withdrawal Mean, Standard Deviation, Percentile of Precipitation on Day of Withdrawal, and Bootstrap Confidence Limits for Monsoon Withdrawal

Station	Code	Mean	Standard Deviation	Percentage of Precipitation	Confidence Limits[a] (days) 25	75
Aranyaprathet	ARN	264.96	25.44	0.731	−15	7
Bangkok	BKK	251.00	25.98	0.597	−11	13
Bhumibol	BHU	244.27	18.56	0.528	−7	14
Chaiyaphum	CHM	248.05	23.90	0.621	−10	10
Chantaburi	CTB	267.13	21.17	0.784	−12	6
Chiangmai	CHM	260.74	25.98	0.682	−13	7
Chiangrai	CHR	260.35	15.97	0.744	−13	5
Chonburi	CBR	252.09	24.84	0.598	−11	12
Donmuang	DMA	251.97	21.99	0.629	−12	13
Kanchanaburi	KAN	251.41	19.82	0.550	−9	13
Khlongyai	KLY	259.21	17.87	0.806	−10	7
Khonkaen	KHK	253.51	19.37	0.700	−11	8
Lampang	LAM	260.71	20.67	0.672	−13	7
Loei	LOE	255.35	26.39	0.702	−12	7
Lopburi	LPB	252.76	22.87	0.640	−13	11
Maehong	MHS	266.70	17.60	0.778	−12	7
Maesariang	MSR	271.79	15.72	0.823	−12	5
Maesot	MAS	254.52	21.68	0.806	−8	7
Mukdahan	MUK	252.75	13.99	0.780	−10	8
Nakhon Phanom	NKP	251.50	13.23	0.823	−9	6
Nakhon Ratchisima	NKR	246.69	21.70	0.592	−9	12
Nakhon Sawan	NSW	259.25	22.55	0.650	−12	9
Nan	NAN	259.28	19.30	0.755	−12	5
Phetchabun	PHE	264.47	20.09	0.763	−13	6
Phitsanulok	PHI	262.46	20.46	0.706	−14	6
Phrae	PHR	255.46	18.95	0.664	−14	4
Prachinburi	PBR	264.73	18.42	0.758	−12	6
Sakon	SKN	253.44	16.71	0.787	−9	6
Sattahip	STH	253.27	24.48	0.583	−7	14
Surin	SUR	256.31	22.29	0.716	−11	10
Tak	TAK	245.42	22.36	0.564	−7	14
Ubon	UBR	263.25	15.95	0.811	−11	7
Udon	UDT	255.93	15.43	0.791	−11	7
Uttaradit	UTT	256.92	22.14	0.684	−11	7
All stations ensemble		257.17	21.41	0.701	−11	8

[a]Units for confidence limits are days relative to initial predicted withdrawal date.

preserving the characteristics of the original time series, including low values and low slope in the premonsoon season, a rapid increase during the monsoon season, and high values and low slope postmonsoon.

4. Results and Discussion

[8] Results for each station, including bootstrapped confidence limits, are summarized in Table 1 (for onset) and Table 2 (for withdrawal). Station-averaged cumulative precipitation percentile on dates of onset and withdrawal are 0.107 and 0.701, respectively. The spread across stations, however, is wide. For onset, precipitation percentiles on dates of onset range from 0.059 to 0.142; for withdrawal the spread is even wider, 0.528–0.823. This implies, at least at the station level, that using static thresholds or similar thresholds across stations may be inappropriate for diagnosing monsoon transitions.

[9] Confidence limits are calculated as the interquartile range (25 and 75 percentiles) of the 1000 bootstrapped estimates, relative to the initially predicted dates of onset and withdrawal. We use this nonparametric estimate of spread because we found the resulting distributions would not fit to a theoretical probability distribution (e.g., Gaussian, Laplace). When results from all stations and all years are pooled together, the mean monsoon onset is DOY 128 with an interannual standard deviation of $\sim$24 days; for withdrawal, the mean is DOY 257 with a standard deviation of $\sim$21 days. Confidence limits from the pooled stations (Figure 5) are smaller for onset (−6 to +10 days) than for withdrawal (−11 to +8 days). Monsoon withdrawal in our study is more gradual than the onset, a result consistent with other studies [*Fasullo and Webster*, 2003].

[10] Climatological dates for onset and withdrawal at each station are shown in Figure 6. In general, there is no coherent spatial pattern to monsoon onset or withdrawal based on precipitation, a result found in other monsoon regions [*Marteau et al.*, 2009]. While a lack of any spatially coherent monsoon advancement or retreat may seem odd, we note that our study domain is a much smaller area than in many monsoon studies, and we might expect a more organized and discernible advance and retreat of the monsoon across a larger region, such as the Indian subcontinent or Eastern Asia. Trend tests, using least squares linear regression, showed no significant trends in onset, withdrawal, or monsoon season length at any of the stations (at a significance level of $p < 0.05$).

[11] Because of the relatively small spatial domain of our study, and in order to minimize noise and compare against

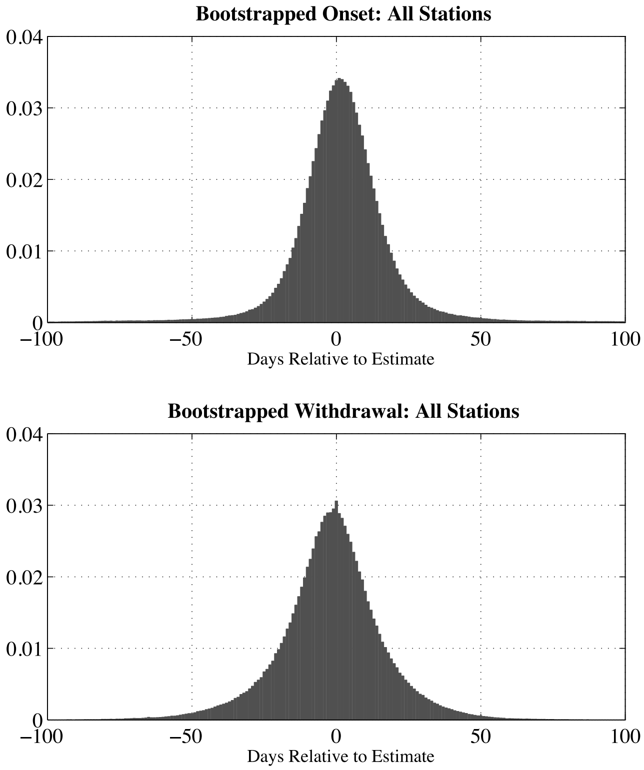

Figure 5. Pooled bootstrapped estimates of monsoon onset and withdrawal for all years and all stations. Values are relative to the original estimated dates.

other climate data sets, we average onset, withdrawal, and monsoon season length across all stations (Figure 7). We also compare against the onset index from *Zhang et al.* [2002] (hereafter Z02) plotted in Figure 7 (top) for comparison and described in section 1. The Z02 index is based on daily precipitation rates using many of the same stations from mainland Thailand we used, as well as several stations from peninsular Thailand. Some disagreement, therefore, will be expected. Despite differences in methodology and data, our onset index correlates well with Z02 (Spearman rank correlation, $\rho = 0.746$, $p < 0.0001$), although our estimate of onset has a somewhat diminished amplitude compared to Z02. There are no significant temporal trends in any of the three monsoon time series. Another way to check the efficacy of our onset and withdrawal indices is to see if our dates sync with dynamical transitions in the monsoon system, such as wind fields and geopotential heights. To do this, we use daily winds and geopotential heights from the National Centers for Environmental Prediction–National Center for Atmospheric Research reanalysis [*Kalnay et al.*, 1996]. Using the station-averaged indices, we difference (after onset and withdrawal minus before onset and withdrawal) 14 day averaged 850 hPa and 1000–850 hPa averaged winds. Our onset is associated with negative 850 hPa geopotential height anomalies over much of monsoon Asia, as will as low-level southwesterly wind anomalies developing over the Arabian Sea, the Bay of Bengal, and the South China Sea (Figure 8). For withdrawal, these anomalies are reversed (Figure 9), with positive 850 hPa geopotential height anomalies and northeasterly winds, indicating the start of the winter monsoon.

[12] Remote patterns of climate variability have long been investigated for their influence on monsoon dynamics across the Asian monsoon region, especially sea surface temperatures (SSTs) in the Indian and Pacific oceans [*Webster et al.*, 1998; *Zhang et al.*, 2002] and the El Niño–Southern Oscillation (ENSO) [*Krishnamurthy and Goswami*, 2000; *Lau and Wu*, 2001; *Singhrattna et al.*, 2005; *Wang et al.*, 2001]. To analyze how these remote patterns may affect the monsoon season over Thailand, we compare our station-averaged index against the Hadley Center Climate Research Unit variance adjusted monthly surface temperature record [*Rayner et al.*, 2003]. We use Spearman rank correlations to compare our indices against spring (March–April–May (MAM)) surface temperatures, conditions just prior to and during the transition into the summer monsoon season. Correlations for the preceding winter (December–January–February (DJF)) are similar, though diminished and are not shown for brevity.

[13] Results from the correlation analyses are shown on the basis of two separate time periods, 1951–1979 (Figure 10) and 1980–2005 (Figure 11), with insignificant

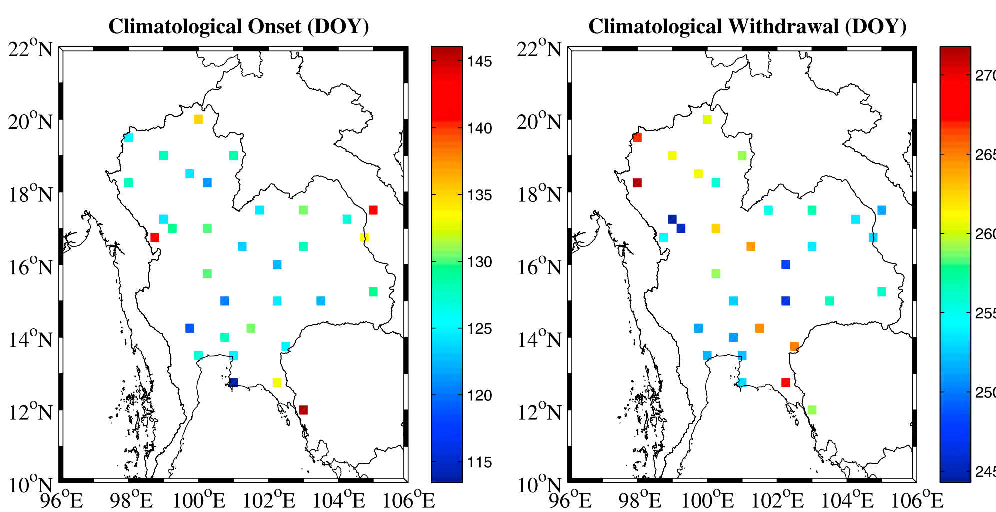

Figure 6. Climatological dates for monsoon onset and withdrawal for each station.

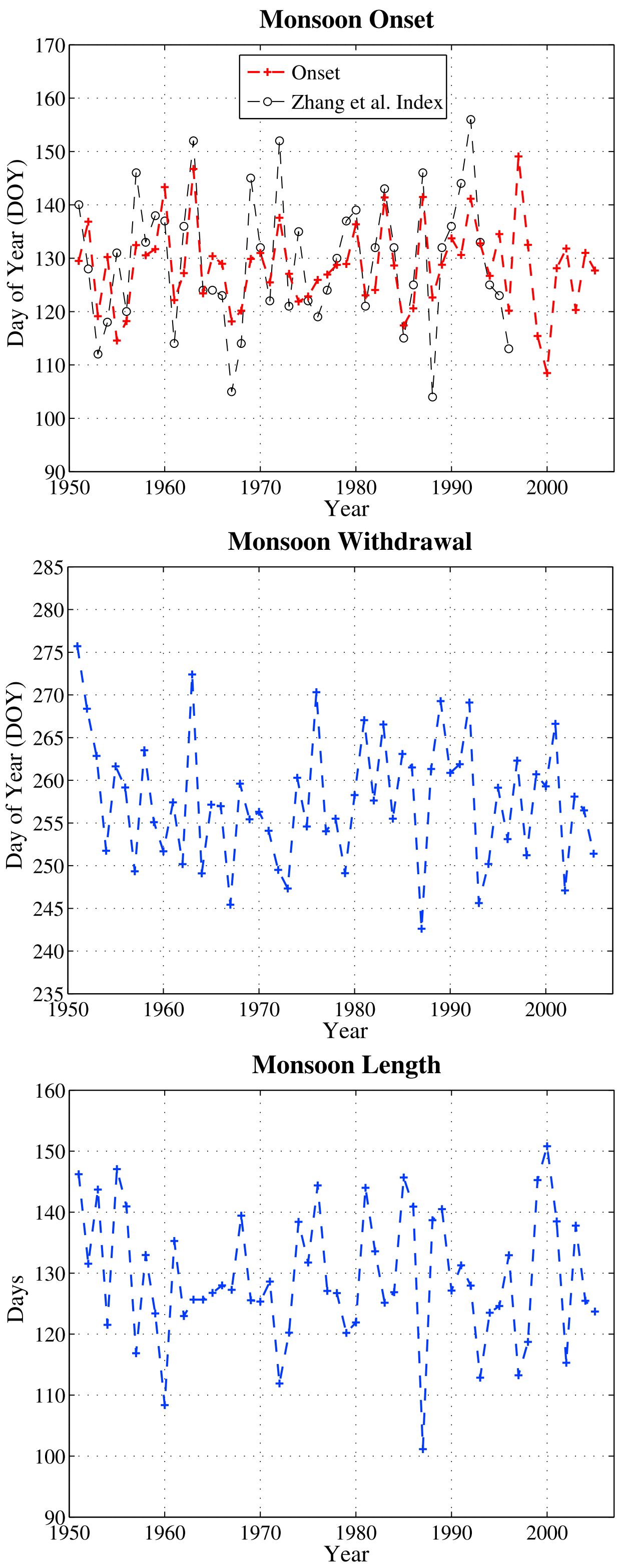

Figure 7. Monsoon season (top) onset, (middle) withdrawal, and (bottom) length, averaged across all Thailand meteorological stations. For comparison, monsoon onset estimated by *Zhang et al.* [2002] is also plotted in Figure 7 (top).

($p > 0.05$) correlations masked out. This division in time approximately marks the period (beginning in the late 1970s) when the relationship between ENSO and the monsoon over the Indochina peninsula began to strengthen [*Singhrattna et al.*, 2005]. Indeed, for the period 1951–1979, there is weak correlation between the monsoon indices and SSTs in the ENSO region, although other significant correlations are apparent. Significant correlations in the Indian ocean and Bay of Bengal indicate warm SSTs in this region associated with a delayed onset, an earlier termination, and a shorter monsoon season. Mechanistically, this is consistent with previous studies that show warm SST anomalies in the Indian Ocean lead to a weaker monsoon and delayed monsoon onset over this region [*Zhang et al.*, 2002]. There also appear to be significant signals in the North Atlantic (withdrawal and monsoon length) and the South Atlantic (monsoon onset) during this time period. The signal in the North Atlantic supports recent work suggesting a connection between surface temperatures in the North Atlantic region and the Asian monsoon [*Chang et al.*, 2001; *Goswami et al.*, 2006]. *Goswami et al.* [2006] show that the Atlantic Multidecadal Oscillation, combined with variability in the northern annual model, can modify the meridional tropospheric temperature gradient, helping to weaken or strengthen the Asian monsoon circulation. More recently, a paper combining observational analysis and modeling [*Kucharski et al.*, 2008] demonstrated a plausible mechanism for a South Atlantic influence on the Asian monsoon, where anomalously warm SSTs in the South Atlantic stimulate a Rossby wave response leading to decreased Asian monsoon precipitation.

[14] In the latter part of the record (1980–2005), the strongest correlations are found in the equatorial and North Pacific. The pattern looks similar to ENSO, although there is some evidence for a distinct and separate influence of the North Pacific on the Asian monsoon system [*Lau et al.*, 2004]. To confirm an ENSO impact, we also separately correlate our indices against the Multivariate ENSO Index (MEI), a multivariate measure of ENSO variability with high values indicating El Niño–like conditions and low values indicating La Nina–like conditions [*Wolter and Timlin*, 1998]. During this latter period, monsoon onset and length both correlate strongly (Spearman rank correlations, $p < 0.001$) with the MEI (ρ = 0.716 and ρ = −0.701, respectively), indicating a warm tropical Pacific (El Niño) leading to delayed monsoon onset and a shorter overall monsoon season. Also of interest appears to be an apparent consistency across both time periods in the pattern of correlation with a gradient in SSTs spanning from the Bay of Bengal, across Indochina, to the South China Sea. This manifests as a significant positive correlation in the Bay of Bengal during the early period (1951–1979) and a significant negative correlation in the South China Sea during the latter period (1980–2005). This suggests that, independent of singular forcing from either the Bay of Bengal or the South China Sea, the gradient in SSTs between these two regions may be a robust driver of variability in monsoon onset across Indochina.

5. Conclusions

[15] The literature discussing the timing of monsoon transitions showcases a wide array of methods and variables

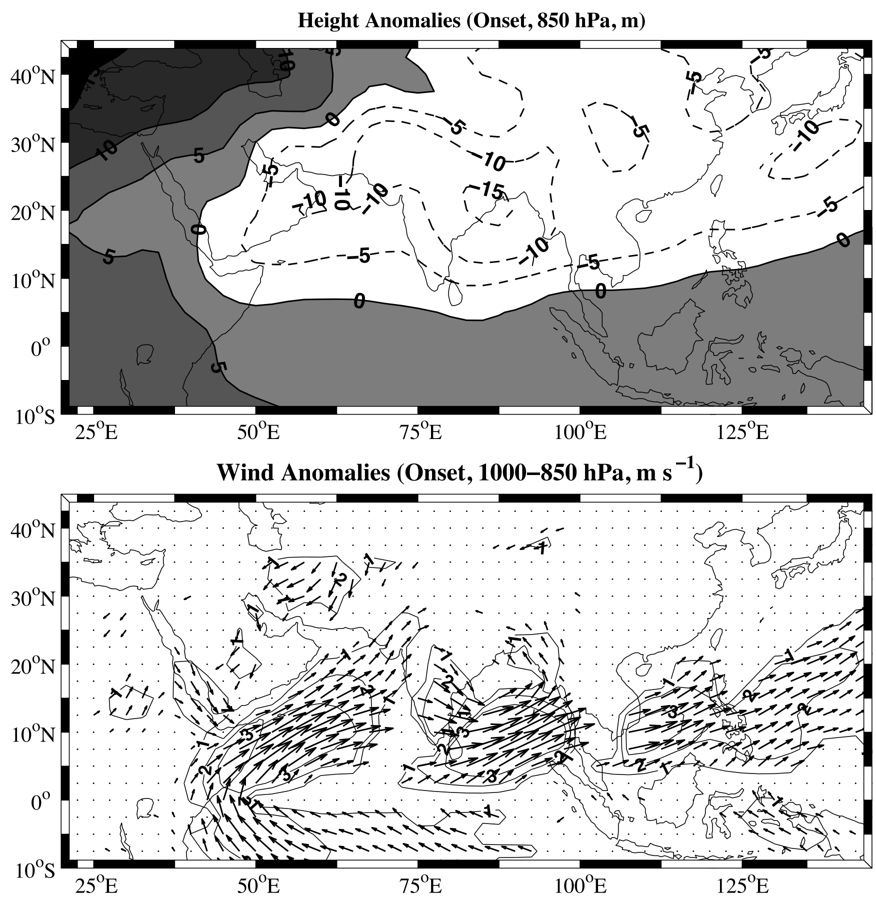

Figure 8. Maps showing mean differences (1951–2005) between 14 day averaged 1000–850 hPa winds and 850 hPa heights associated with station averaged monsoon onset (after onset minus before onset). For the winds, insignificant ($p > 0.05$) differences are masked.

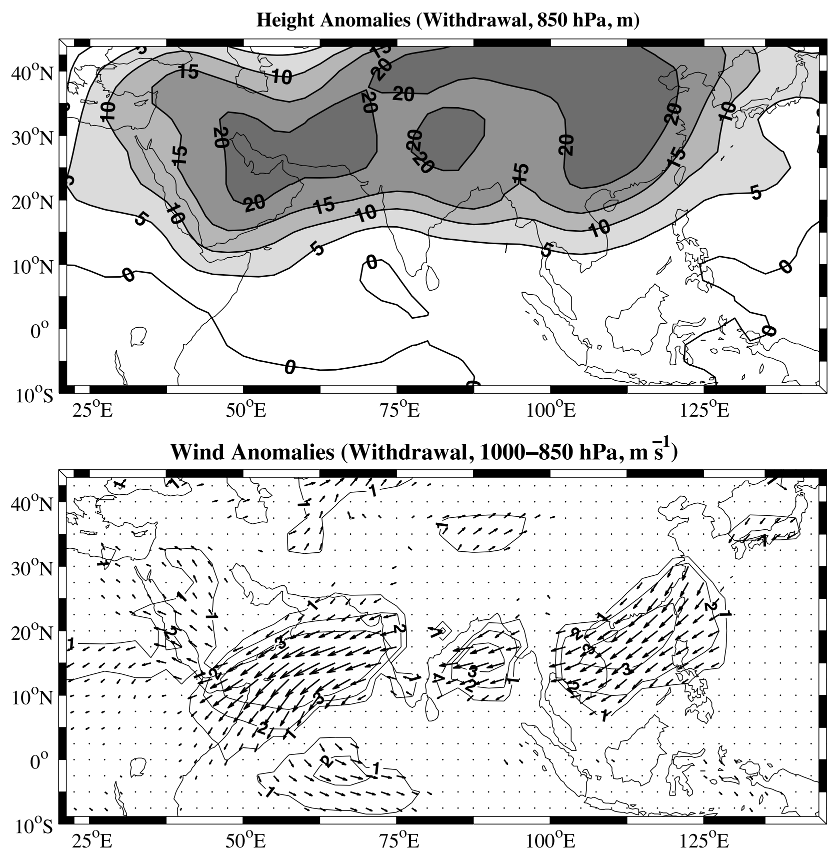

Figure 9. Maps showing mean differences (1951–2005) between 14 day averaged 1000–850 hPa winds and 850 hPa heights associated with station averaged monsoon withdrawal (after withdrawal minus before withdrawal). For the winds, insignificant ($p > 0.05$) differences are masked.

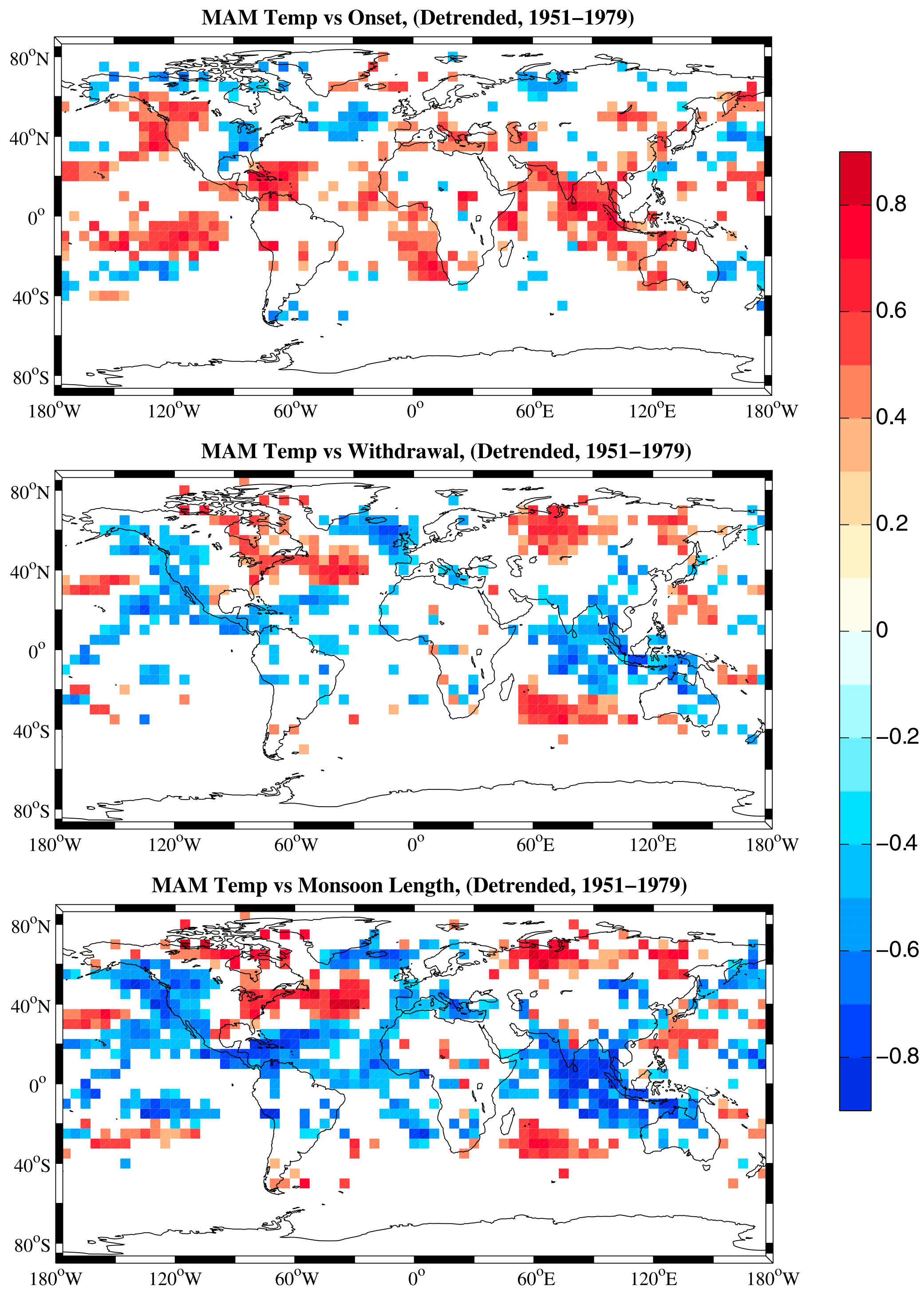

Figure 10. Correlations between onset, withdrawal, and length of the monsoon season for years 1951–1979.

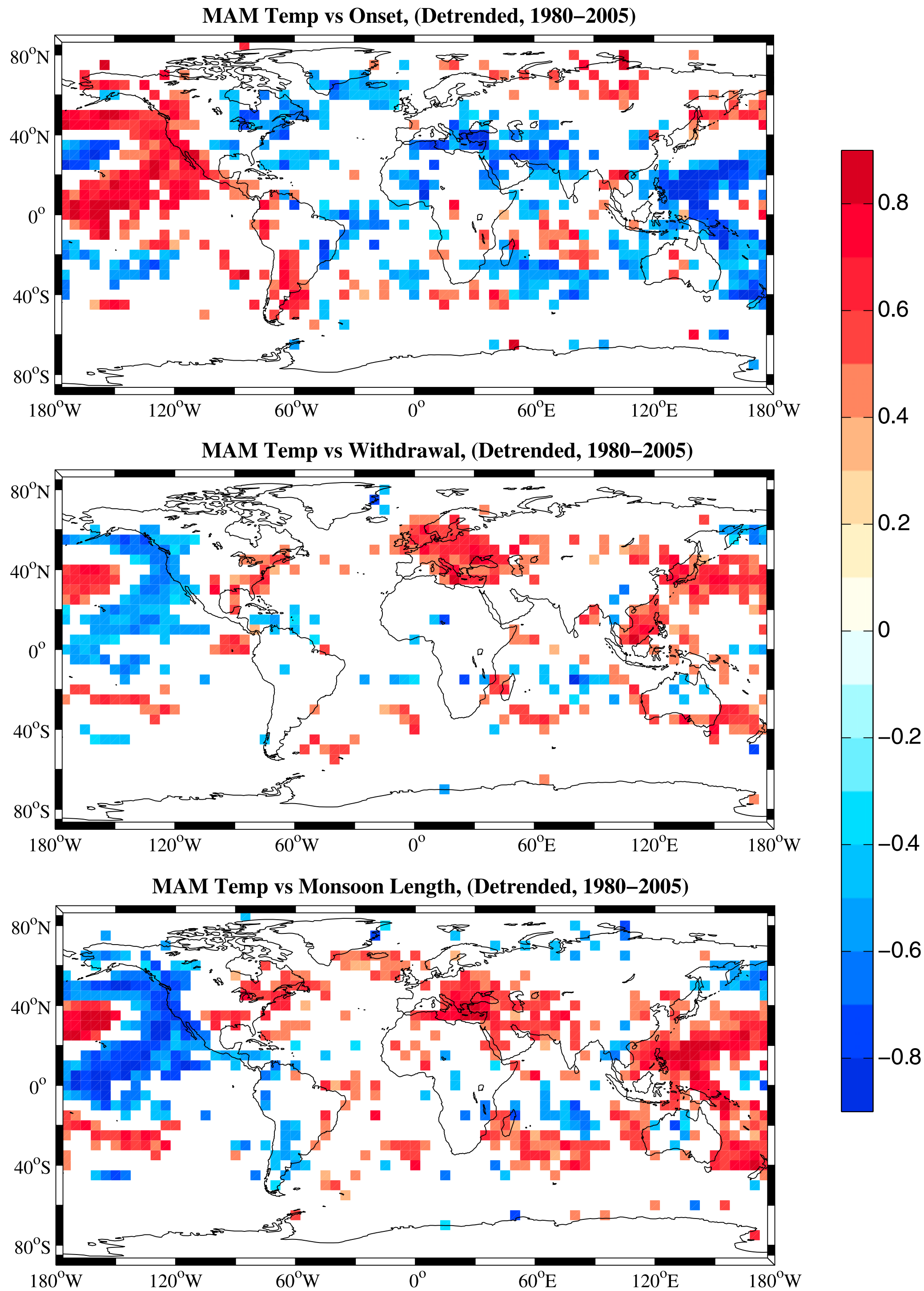

Figure 11. Correlations between onset, withdrawal, and length of the monsoon season for years 1980–2005.

used to define onset and withdrawal. Our methodology represents an additional contribution to this body of work by offering two major advantages over some other methods: (1) an objective determination of monsoon onset and withdrawal, without the requirement of a priori setting arbitrary, and often subjective, thresholds and (2) the use of daily precipitation data, normally readily available from any meteorological station. This makes our method widely applicable and dependent only on the time series properties of the data rather than a best guess of what constitutes a physically meaningful threshold. Our onset and withdrawal series pick up monsoon-related transitions in the lower atmosphere, demonstrated in the 850 hPa height anomalies and low-level winds, and show significant, and physically consistent, correlations with temperatures in areas with established and suspected monsoon teleconnections. Of note are significant correlations between ENSO and our onset and withdrawal indices, teleconnections that are widely assumed but rarely quantified [*Fasullo and Webster*, 2003]. Additionally, our application of the maximum entropy bootstrap to estimate uncertainty may provide a new way to compare the precision of various methods, and allow for placing confidence bounds on published and future monsoon onset and withdrawal time series. Our method provides for an objective and diagnostic retrospective determination of the timing of the monsoon season. While this may not be applicable for operational forecasting, it does give another way to look at monsoon variability and provides a new method for comparison against other monsoon indices, as well as allowing for division of data into physically meaningful seasons.

[16] **Acknowledgments.** This work was supported by NSF award 0908971 (dynamics of coupled natural and human systems). The authors wish to thank two anonymous reviewers for valuable comments that have greatly improved this manuscript, as well as E.R. Cook for suggesting the use of the maximum entropy bootstrap. Lamont contribution 7310.

References

Chang, C., P. Harr, and J. Ju (2001), Possible roles of Atlantic circulations on the weakening Indian monsoon rainfall–ENSO relationship, *J. Clim.*, *14*, 2376–2380.

Fasullo, J., and P. Webster (2003), A hydrological definition of Indian monsoon onset and withdrawal, *J. Clim.*, *16*, 3200–3211.

Goswami, B., M. S. Madhusoodanan, C. P. Neema, and D. Sengupta (2006), A physical mechanism for North Atlantic SST influence on the Indian summer monsoon, *Geophys. Res. Lett.*, *33*, L02706, doi:10.1029/2005GL024803.

Goswami, B., and P. Xavier (2005), ENSO control on the south Asian monsoon through the length of the rainy season, *Geophys. Res. Lett.*, *32*, L18717, doi:10.1029/2005GL023216.

Hsu, H., C. Terng, and C. Chen (1999), Evolution of large-scale circulation and heating during the first transition of Asian summer monsoon, *J. Clim.*, *12*, 793–810.

Kalnay, E., et al. (1996), The NCEP/NCAR 40-year reanalysis project, *Bull. Am. Meteorol. Soc.*, *77*, 437–471.

Komojinda, S. (2003), An analysis of rainfall, temperature and relative humidity in north Thailand: Application to paleoclimatology, Master's thesis, Mahidol Univ., Salaya, Thailand.

Kripalani, R., S. Singh, N. Panchawagh, and M. Brikshavana (1995), Variability of the summer monsoon rainfall over Thailand—Comparison with features over India, *Int. J. Climatol.*, *15*, 657–672.

Krishnamurthy, V., and B. Goswami (2000), Indian Monsoon–ENSO relationship on interdecadal timescale, *J. Clim.*, *13*, 579–595.

Kucharski, F., A. Bracco, J. Yoo, and F. Molteni (2008), Atlantic forced component of the Indian monsoon interannual variability, *Geophys. Res. Lett.*, *35*, L04706, doi:10.1029/2007GL033037.

Lau, K., and H. Wu (2001), Principal modes of rainfall–SST variability of the Asian summer monsoon: A reassessment of the monsoon–ENSO relationship, *J. Clim.*, *14*, 2880–2895.

Lau, K., J. Lee, K. Kim, and I. Kang (2004), The North Pacific as a regulator of summertime climate over Eurasia and North America, *J. Clim.*, *17*, 819–833.

Lund, R., and J. Reeves (2002), Detection of undocumented changepoints: A revision of the two-phase regression model, *J. Clim.*, *15*, 2547–2554.

Marteau, R., V. Moron, and N. Philippon (2009), Spatial coherence of monsoon onset over western and central Sahel (1950–2000), *J. Clim.*, *22*, 1313–1324.

Rayner, N. A., D. E. Parker, E. B. Horton, C. K. Folland, L. V. Alexander, D. P. Rowell, E. C. Kent, and A. Kaplan (2003), Global analyses of sea surface temperature, sea ice, and night marine air temperature since the late nineteenth century, *J. Geophys. Res.*, *108*(D14), 4407, doi:10.1029/2002JD002670.

Singhrattna, N., B. Rajagopalan, K. Kumar, and M. Clark (2005), Interannual and interdecadal variability of Thailand summer monsoon season, *J. Clim.*, *18*, 1697–1708.

Solow, A. (1987), Testing for climate change: An application of the two-phase regression model, *J. Clim. Appl. Meteorol.*, *26*, 1401–1405.

Taniguchi, K., and T. Koike (2006), Comparison of definitions of Indian summer monsoon onset: Better representation of rapid transitions of atmospheric conditions, *Geophys. Res. Lett.*, *33*, L02709, doi:10.1029/2005GL024526.

Vinod, H. (2004), Ranking mutual funds using unconventional utility theory and stochastic dominance, *J. Empirical Finan.*, *11*, 353–377.

Vinod, H. (2006), Maximum entropy ensembles for time series inference in economics, *J. Asian Econ.*, *17*, 955–978.

Wang, B., R. Wu, and K. Lau (2001), Interannual variability of the Asian summer monsoon: Contrasts between the Indian and the western North Pacific–East Asian monsoons, *J. Clim.*, *14*, 4073–4090.

Webster, P., V. Magaña, T. Palmer, J. Shukla, R. Thomas, M. Yanai, and T. Yasunari (1998), Monsoons: Processes, predictability, and the prospects for prediction, *J. Geophys. Res.*, *103*, 14,451–14,510.

Wolter, K., and M. Timlin (1998), Measuring the strength of ENSO: How does 1997/1998 rank?, *Weather*, *53*, 315–324.

Zeng, X., and E. Lu (2004), Globally unified monsoon onset and retreat indexes, *J. Clim.*, *17*, 2241–2248.

Zhang, Y., T. Li, B. Wang, and G. Wu (2002), Onset of the summer monsoon over the Indochina Peninsula: Climatology and interannual variations, *J. Clim.*, *15*, 3206–3221.

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