The Relationship between Tibetan Snow Depth, ENSO, River Discharge and the Monsoons of Bangladesh

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The Relationship between Tibetan Snow Depth, ENSO, River Discharge and the Monsoons of Bangladesh

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Abstract

We examine the interannual variability of the monsoon rains of Bangladesh, an area greatly affected by land surface hydrologic processes including Himalayan snow pack size, snowmelt river flooding, and Bay of Bengal storm surge. For the 20th century, we find Bangladesh monsoon rainfall (BMR) to be uncorrelated with the All-Indian Monsoon Index. This result is consistent with previous findings for shorter time records. We next use a 9-year record of satellite estimates of April snow depth for the Himalayan region and concurrent seasonal El Niño-Southern Oscillation (ENSO) conditions in the equatorial Pacific to develop an empirical model that explains a high percentage of BMR interannual variability. Inclusion of late spring river discharge levels further improves empirical model representation of BMR for June-September. These results, though for a limited record length, suggest that BMR interannual variability is constrained by concurrent ENSO conditions, spring Himalayan snow pack size and land surface flooding. The 20th century analysis indicates that BMR should be considered independently of Indian monsoon rainfall.

1. Introduction

The impact of Eurasian snow cover and land surface hydrologic processes on the monsoons of South Asia has been studied for over a century. Blanford (1884) first suggested that climate conditions over India could be affected by the size of the Himalayan snow pack. Differences in the extent of this snow pack alter the heating of the land surface
and overlying atmosphere. Given the relative constancy of Indian Ocean sea surface
temperatures (SSTs), such changes in land surface heating can strengthen or weaken the
land-sea temperature gradient controlling monsoon winds and the landfall of rain.

The most intense south Asian monsoon rains occur over Bangladesh and the
adjacent eastern portions of India (e.g. Assam). This area records some of the highest
annual rainfall totals in the world. Bangladesh lies to the immediate south of the
Himalayas on the delta confluence of the Ganges, Brahmaputra and Meghna Rivers above
the Bay of Bengal. During much of the northern hemisphere summer, large portions of the
country are under water. Monsoon rains, the confluence of Himalayan meltwaters, and
surging, windswept waters from the Bay all contribute to these flood conditions.

Much study heretofore has focused upon monsoon rains in India, southeast Asia, or
China at the exclusion of Bangladesh. In fact, the Indian monsoon is often used as proxy
for the entire South Asian monsoon. In this study, however, we focus exclusively on the
monsoons over and immediately around Bangladesh. This country’s unique position as a
locus of so much intense hydrologic activity warrants analysis independent of other
components of the South Asian monsoon system. Furthermore, previous studies have
shown that rainfall recorded at individual station sites in Bangladesh was not significantly
correlated with Indian monsoon rainfall during 1901-1977 (Kripalani et al. 1996a) and that
monsoon rainfall in neighboring Assam was not significantly correlated with All-Indian
Summer Monsoon Rainfall during 1951-1980 (Krishna Kumar et al., 1995). In this study
we will examine the effect of three variables on the monsoons of Bangladesh: Himalayan
snowpack size, El Niño-Southern Oscillation (ENSO) conditions, and river discharge
levels.
Snow and the South Asian Monsoons

An inverse relationship between snowfall on regions of the Eurasian continent and the Indian summer monsoon has been both observed (Hahn and Shukla, 1976; Dickson, 1984; Ropelewski and Halpert, 1989; Bamzai and Shukla, 1999) and modeled (Barnett et al 1989; Meehl, 1994; Bamzai and Marx, 2000). An increased snowpack increases land surface albedo; incident solar radiation that would otherwise have heated the land surface instead melts and sublimes the snowpack. The melting snow also increases land surface wetness, so that subsequent evaporation further cools the land surface. (In addition, more energy is required to evaporate surface wetness; the specific heat of ice and land are about the same, but the specific heat of water is double that amount.) These effects conspire to reduce the land-sea summer thermal gradient between the Eurasian continent and the Indian Ocean.

Studies have explored the effects of both Eurasian snow cover and snow volume (depth) on the Indian monsoons. Observational investigations have demonstrated inverse relationships between Eurasian snow cover and subsequent summer rainfall over India (Hahn and Shukla 1976; Sankar-Rao et al. 1996). Kripalani et al. (1996b) used Nimbus 7 Scanning Multichannel Microwave Radiometer (SMMR) satellite estimates of snow depth and found an inverse relationship between snow depth over areas of the former Soviet Union and Indian Monsoon Rainfall (IMR). Similarly, Bamzai and Shukla (1999) found some evidence of a relationship between snow depth over central Eurasia and June-September IMR. Others have noted a dipole effect, with less western/European Russia
snow depth and more central Siberia snow depth associated with greater Indian rainfall in
the following season (Kripalani and Kulkarni, 1999; Ye and Bao 2001).

In model simulations, Eurasian snow cover has been shown to impact both albedo
and rates of latent heat transfer. Barnett et al. (1989) found that heavy Eurasian snow
increased evaporative rates and reduced land and overlying atmospheric temperatures.
This reduction of the land-ocean contrast inhibited monsoon activity. In a prior study
Barnett et al. (1988) ran the European Centre for Medium-range Weather Forecast
(ECMWF) general circulation model (GCM) with double and half snow over Eurasia and
found that these runs mimicked weak and strong monsoons respectively. Because the
model Indian Ocean SSTs changed little, these GCM simulations supported Blanford’s
hypothesis that the land-sea thermal gradient is controlled by Eurasian snow amount.
Similar model results have since been demonstrated by Vernekar et al. (1995), Douville
and Royer (1996), and Dong and Valdes (1998).

**ENSO and the South Asian Monsoons**

The covariability of the Indian monsoons and ENSO has been explored in
numerous studies (Walker, 1918; Rasmusson and Carpenter, 1983; Ropelewski and
Halpert, 1987; Webster and Yang, 1992; Mehta and Lau, 1997; Webster et al., 1999).
During an El Niño event, subsidence over South Asia generally increases (Krishna Kumar
et al., 1999b). This anomalous subsidence suppresses convection over South Asia and is
thought to produce the weaker monsoons that often develop during El Niño events, though
recently this relationship has broken down (Krishna Kumar et al., 1999a). In a recent
model study, Dong and Valdes (1998) found evidence that El Niño conditions lead to increased snow mass on Eurasia.

\textit{Land Surface Evaporative Feedbacks}

For Bangladesh, local wetting of the land surface, due to flooding, could also play a role in determining the strength of the monsoons. GCM simulations have found that land-based precipitation is partially controlled by land surface evaporative rates (Koster and Suarez, 1995; Reale and Dirmeyer 2001a,b; Hong and Kalnay, 2000), that precipitation variability over land is controlled in part by land surface evaporative variability (Dirmeyer, 2001), and that improved land surface modeling improves forecast of climate anomalies (Dirmeyer et al., 2000). No doubt, the extent of land surface flooding partly determines land surface evaporative rates over Bangladesh. Local river runoff levels (in addition to rainfall and storm surge) are an important indicator of this local flood potential. In fact, the seasonal flooding of the Bangladesh land surface may be of large enough scale to function as a catalyst, inducing the landfall of low-pressure systems from the Bay of Bengal. Yasunari et al. (1991) found evidence in a GCM experiment of such interactions at mid-latitudes. For these reasons we included the effects of late spring river discharge in our analysis.

2. Data and Methods
Snow Depth Data. Both model and observational studies have shown that snow volume, or depth, is a better predictor of monsoon intensity than snow coverage (Barnett et al. 1989; Kripalani and Kulkarni 1999; Ye and Bao 2001). In this study we restrict our analyses with snow to estimates of snow depth from Nimbus 7. This satellite sensor was in operation from November 1978 through August 1987, after which it began showing signs of failure. Its passive microwave data can be used to measure snow extent and calculate snow depth on an areal basis using the difference between brightness temperatures in the 18 and 37 GHz channels (Chang et al., 1987). This algorithm has been shown to be as accurate as more recent Nimbus 7 SMMR algorithm estimates of April and May snow depth over Eurasia (Foster et al. 1997).

In this study we focus on Himalayan snow pack depth during the northern hemisphere spring season. This plateau region (the Himalayas and Tibetan Plateau) lies directly north of Bangladesh and supports a summertime high pressure ridge and the warmest summertime upper tropospheric temperatures on the planet (Li and Yanai 1996). The upper tropospheric temperature gradient between the Himalayas and the Indian Ocean and the summertime heating of the Tibetan Plateau has been shown to be associated with the onset of the South Asian monsoons (Luo and Yanai, 1984; He et al. 1987; Yanai et al. 1992; Yanai and Li 1994; Li and Yanai 1996). Furthermore, the temperature gradient between the Tibetan Plateau and equatorial Pacific has been shown to be associated with Indian monsoon rainfall (Fu and Fletcher, 1985). We therefore anticipated that the strength of this upper troposphere high pressure ridge and of the summer meridional upper troposphere temperature gradient between the Himalayas and the Indian Ocean, and thus monsoon rainfall over Bangladesh, would be sensitive to spring snow pack size. It has also
been suggested that the inverse snow-monsoon relationship should be most strongly associated with spring snows, which delay the end of winter (Ramage, 1983). This postulant is further supported by model studies, which have shown that the largest variability of Eurasian snow mass occurs in April (Dong and Valdes 1998). Average monthly spring season snow depth anomalies for the area 25N-35N and 75E-100E (the Himalayas and Tibetan Plateau) were therefore determined and used. The time series of April snow depth anomalies is shown in Figure 1.

*River Data.* Monthly river discharge data is from the Bahadurabad Transit station site (SW46.9L) on the Brahmaputra River for 1979-1987. Data for June 1983 is missing. Monthly anomalies were calculated, and the June monthly anomalies are shown in Figure 1.

*ENSO Data.* NINO3 (5N-5S, 150W-90W) was the index of ENSO used for this study (Kaplan et al. 1998). A time series of JJAS seasonal anomalies is shown in Figure 2a.

*Rainfall Data.* Two time series measuring Bangladesh monsoon rainfall (BMR) were employed. 1) We averaged monthly rainfall data from all NCDC Global Historical Climatology Network (GHCN) stations between 21N-26N and 87E to 93E for 1900 through 2000. Monthly and seasonal anomalies were then constructed based on this record. 2) Optimally interpolated (OI) monthly rainfall was also used. These data were constructed by reduced space optimal interpolation of the raw GHCN station data. The method is similar to the sea level pressured analysis presented in Kaplan et al. (2000). The OI data are gridded at 4x4 degree resolution (Kaplan et al. 2001). Monthly and seasonal anomalies for 1900-2000 from the grid box centered at 24N and 90E were employed for
this study. Times series of these BMR records is presented in Figure 2b. The increased
variability evident in the GHCN record during last decade, due to changes in the number
and location of stations in operation, is reduced by the optimal interpolation.

For purposes of comparison we also employed the All-India Monthly Rainfall data
of the Indian Institute of Tropical Meteorology (Parthasarathy et al. 1995) and compiled
these data for JJAS, 1900-2000 as seasonal anomalies (Figure 2c). Four of the 29
subdivision employed in the construction of this index lie partially or wholly within the
domain of the GHCN BMR.

3. Results

Table 1 provides correlations among NINO3, OI BMR, GHCN BMR, and the All
India Monsoon Index for JJAS for 1900-2000. For this 101-year time period, the
Bangladesh rains are positively associated (p<0.05) with NINO3, whereas the All-India
rains are more strongly negatively correlated with NINO3 (p<0.001). Thus, within the
region, there seem to be differing responses to events in the Pacific: IMR is suppressed
during an El Niño event, but BMR increases. The OI BMR rains are also weakly
negatively correlated with the All-India rains, though not at statistically significant levels.

Table 2 shows correlation coefficients for 1979-1987 between BMR (for JJAS) and
monthly snow depth anomalies in the preceding April, the concurrent NINO3 index, and
June Brahmaputra river discharge levels. The Nimbus 7 snow data and Brahmaputra
discharge data records are of limited length (9 and 8 years respectively), so these findings
must be considered provisional.
For this short period of record, April snow depth is significantly positively correlated with JJAS NINO3 but significantly negatively correlated with June Brahmaputra discharge. The BMR records are not associated with any of the other measures at statistically significant levels; however, the tendencies of the BMR correlations are intriguing. Both BMR indices are negatively correlated with April snow depth but positively correlated with JJAS NINO3. This latter association is consistent with the longer 101-year analysis in which NINO3 is also positively associated with both BMR indices. While the correlations of April snow depth and JJAS NINO3 with BMR are opposite, JJAS NINO3 and April snow depth are themselves positively associated. Thus, April snow depth and JJAS NINO3 could be masking each other’s effects on BMR so that simple correlation analysis may be inadequate for revealing their effect on BMR. We therefore developed models of BMR using multiple regression analysis. Per such analysis, we accepted a predictor when the correlation between residuals was significant.

Multiple Regression Model

Regression of BMR rain for June-September on April snow and concurrent NINO3 accounts for 72% (GHCN) and 87% (OI) of BMR variance. Both explanatory variables are statistically significant (each variable at p < 0.002 for OI BMR; p < 0.05 for GHCN BMR). Within these multiple regression models increased April snow leads to decreased BMR, and increased JJAS NINO3 SSTs results in increased BMR. These tendencies are consistent with the results presented in Table 2 for simple correlation; however, unlike the results for simple correlation, both April snow depth and JJAS NINO3 are statistically
significant in the multiple regression model. This statistical significance is the correct consequence of the multiple regression analysis, which considers the orthogonal contribution of each explanatory variable. Because April snow and JJAS NINO3 are themselves positively correlated but their effects on BMR are opposite, each masks the other’s effect when subjected to simple correlation with BMR; however, when these explanatory variables are considered in conjunction within the multiple regression model they are both shown to be statistically significant.

Given the limited data set (9 years), these model fittings were further examined by leave-one-out ordinary cross validation (OCV). Correlations among the omitted data points and OCV regression equations were significant for the OI BMR ($r=0.85$, $p<0.002$) and near significant for the GHCN BMR ($r=0.56$, $p=0.08$). Figure 3 shows a plot of the normalized OI BMR and the values predicted by OCV. We also subjected the rainfall, snow depth and ENSO data to an EOF analysis and confirmed that the BMR predominantly lies in the plane delineated by April Tibetan Plateau snow depth and JJAS NINO3 (93% of variance). These analyses indicate that our statistical findings are consistent and robust, and that though the record length is short, it would be extremely unlikely for the association between BMR, April snow depth and JJAS NINO3 to have occurred solely by chance.

We also performed the regression of BMR rain for June-September on April snow, concurrent NINO3 and June Brahmaputra discharge (only eight years). The inclusion of June Brahmaputra discharge is statistically significant only for the OI BMR ($p<0.05$). Both April snow depth and JJAS NINO3 remain significantly associated with both the OI BMR ($p<0.002$) and the GHCN BMR ($p<0.05$). 96% of OI BMR variance is accounted
for with this three-variable regression model. These model fittings were again confirmed by OCV. Correlations among the omitted data points and OCV regression equations were significant for both the OI and GHCN BMR data sets (r=0.91, p<0.001; r=0.67, p<0.05, respectively).

Figure 4 deconstructs the regression model fit for the OI BMR. Regression values are shown with April snow alone, April snow and JJAS NINO3, and all three variables; also shown are the OI BMR anomaly values.

4. Discussion

Our findings show that the All-India monsoon index and BMR are not well correlated; if anything they vary inversely, though not at statistically significant levels. This result is similar to findings of Kripalani et al. (1996a), showing that monsoon season rainfall at individual stations in Bangladesh had no significant relationship with All India Monsoon Rainfall (Kripalani and Singh, 1993).

The correlation between NINO3 and BMR is positive, but negative between NINO3 and the All India Monsoon Rainfall. Furthermore, the correlation analysis shows NINO3 for JJAS to be positively associated with April Himalayan snow pack depth estimates, and although not significant at 95%, a positive association also holds true for April NINO3 (r=0.49, n=9). These correlations suggest that Himalayan snow pack depth is tied to conditions in the Pacific, and that increased Himalayan snow pack depth decreases BMR. (This is true both for the simple correlation and within the regression model.) However, within the multiple regression model, in which the common effects of
Himalayan snow pack depth are removed, BMR and NINO3 are significantly and positively associated. It thus appears that ENSO indirectly suppresses BMR through links with Himalayan snow pack depth, but directly, or through other yet unidentified mechanisms, enhances BMR.

The empirical regression model suggests that knowledge of April snow depth on the Tibetan plateau and forecast of JJAS conditions in the equatorial Pacific could provide a good predictive model of seasonal BMR. Inclusion of June river discharge levels can further tune such forecasts for the remainder of the monsoon season. However, given the short records lengths of the Nimbus 7 SMMR snow depth estimates and the Brahmaputra discharge, these results must be considered preliminary.

We also explored using the longer National Snow and Ice Data Center (NSIDC) snow cover data in place of the satellite estimates of snow depth. However, the NSIDC snow cover data had a low correlation (r=0.403) with the Nimbus 7 snow pack depth estimates for the coincident period of record (1979-1987). The NSIDC data did not possess the same interannual variability, and regression models developed using the NSIDC Himalayan snow cover data were not statistically significant.

In an area of year-round snow cover, snow depth variability is presumed to have a larger effect on the local energy balance than snow cover variability. A deep snow pack not only reduces incident solar radiation by increasing land surface albedo, but more absorbed radiation is also used to melt snow rather than heat the land surface. In addition, the wetter land surface has a higher specific heat than dry land and evaporation of surface moisture keeps the land and overlying air column cool.
Our findings suggest that analysis of the regional variability of rainfall throughout all of South Asia is warranted. In addition, an examination of the moist energy budget for Bangladesh might be highly revealing.

5. Conclusions

By virtue of its location at base of Himalayas and on the floodplain of the Meghna, Ganges, and Brahmaputra rivers, Bangladesh is an area greatly affected by hydrologic processes, both land-atmosphere and ocean-atmosphere. Monsoon rainfall over Bangladesh is not significantly correlated with the All India Monsoon Index. We find that a large percentage of the interannual variability of BMR is explained by a simple multiple regression model using satellite estimates of April Himalayan snow pack depth, an ENSO index and June Brahmaputra river discharge. Because of the short time record examined, these results should be viewed as preliminary. Future operational satellite estimates of snow depth (e.g. MODIS) will offer the opportunity to test these findings further.

Acknowledgments

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References


Table 1. Correlation coefficients among NINO3, BMR, and Indian monsoon rainfall indices, 1900-2000. * p<0.05; ‡ p<0.001

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<th>OI BMR</th>
<th>GHCN BMR</th>
<th>All-India</th>
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<tr>
<td>NINO3</td>
<td>1.00</td>
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<td>0.19*</td>
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<td>GHCN BMR</td>
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<td>All-India</td>
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Table 2. Correlation Coefficients among April Tibetan snow depth anomalies, NINO3, OI and GHCN BMR, and June Brahmaputra Discharge. All correlations are for the 9-year period 1979-87, except those with June Brahmaputra for which 1983 is missing. * p<0.05

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<th>OI Rain</th>
<th>GHCN Rain</th>
<th>June Brahmaputra Discharge</th>
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**Figure 1.** Time series plot of April Tibetan Plateau snow depth anomalies as calculated from Nimbus 7 SMMR satellite measurements and June Brahmaputra river discharge anomalies. All records are shown in normalized units of standard deviations.
**Figure 2.** Time series plots of 101-year index records. a) JJAS NINO3 anomalies; b) JJAS OI and GHCN BMR rainfall anomalies; c) JJAS OI BMR and All-India Monsoon Rainfall anomalies. All records are shown in normalized units of standard deviations.
Figure 3. Time series plot of normalized OI BMR and OCV predicted values. Error bars (plus or minus 2 standard error), estimated from each OCV regression are also presented.
Figure 4. Reconstruction of the OI BMR from a regression model with 3 explanatory variables. Regression model values are shown with April Tibetan snow depth alone, April Tibetan snow depth and concurrent NINO3, and all three variables; also shown are the OI BMR anomaly values.