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Increasing frequencies of warm and humid air masses over the conterminous United States from 1948 to 2005

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[1] Time series of individual climate variables, such as air temperature and precipitation, have been thoroughly examined to evaluate climate change, but few studies have evaluated how air masses have varied over time. We use the Spatial Synoptic Classification air mass approach to classify multivariate meteorological surface variables into discrete groups and examine trends in air mass frequencies over the period 1948–2005 for the continental United States. We observe increases in warm, moist air masses at the expense of cold, dry air masses, consistent with expectations in an atmosphere with increasing greenhouse gas concentrations. Temporal variations in the North Atlantic Oscillation, Pacific/North American teleconnection pattern, Arctic Oscillation, and El Niño–Southern Oscillation partially explain some of these observed trends in winter.
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1. Introduction

[2] In the context of studying climate change and variability, the time series of individual variables, such as air temperature and dew point temperature, have been examined in great detail [e.g., *Intergovernmental Panel on Climate Change* (*IPCC*), 2007], but much less attention has been afforded to the temporal changes of groups of weather variables. This is arguably a more important concern with respect to climate change impacts, as systems and organisms typically do not respond to a single variable (such as temperature) but to the entire suite of variables that affect, for example, the exchange of heat, mass, and moisture at the Earth's surface. One common method for investigating these kinds of changes is the examination of air masses. Various procedures have been devised to categorize air mass conditions over time and space. One current approach that has become quite commonly used in the biometeorological community is the Spatial Synoptic Classification 2 (SSC2) owing to its versatility, simplicity, and reliance upon readily available surface data [*Sheridan*, 2002]. This is an air mass classification system that categorizes each day into one of six discrete air mass types (dry polar (DP), dry moderate (DM), dry tropical (DT), moist polar (MP), moist moderate (MM), moist tropical (MT)), or a transition (TR) category that accounts for a significant air mass change over a 24-hour period. This system uses commonly-measured surface meteorological variables sampled four times daily, including air temperature, dew point temperature, scalar components of the surface wind vector, mean sea level pressure, and cloud cover.

[3] Prior researchers have used air mass changes to quantify climate variability. *Kalkstein et al.* [1990] employed such an approach to detect decreasing frequencies of the coldest air masses and increasing frequencies of the warmest air masses in the Arctic regions of North America, and *Ye et al.* [1995] found similar results in the Russian Arctic. *Schwartz* [1995] utilized an approach that categorized days based on air trajectory analysis and 850-hPa temperature-moisture characteristics and found decreases in the coldest winter days and increases in the hot and humid spring and summer days in the north central United States from 1958–1992. Using an earlier version of the SSC [*Kalkstein et al.*, 1996] to evaluate the character and frequency changes of air masses for 100 United States cities from 1948–1993, *Kalkstein et al.* [1998] found increases in the moist tropical air mass type in the summertime and decreases in the frequency of transition days during the winter across the nation. As such, they concluded that the use of an air mass-based approach reveals more about climate change than the analysis of individual meteorological variables. More recently, *Sheridan* [2003] used the SSC2 to link air mass frequencies to the North Atlantic Oscillation and the Pacific/North American teleconnection patterns. The SSC2 has also recently been implemented in Europe as a method to analyze air mass trends and teleconnections [*Bower et al.*, 2007].

[4] Our work is an update to *Kalkstein et al.* [1996] but is based on the SSC2. Both the original SSC and SSC2 classify days based on predetermined seed days, which are actual days in the observed record that contain meteorological characteristics typical of a particular air mass type at a given location. The SSC2 is more advanced than the SSC because its year-round calendar better accounts for seasonality [*Sheridan*, 2002]. Our study also includes more than ten additional years of data that encompass a period of rapid increase in atmospheric greenhouse gas concentrations.

[5] Our objectives are (1) to evaluate air mass frequency changes over the contiguous United States from 1948–2005

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using the SSC2 and (2) to determine whether the air mass changes are consistent with fluctuations in atmospheric circulation during winter.

2. Data and Methods

[6] We use daily SSC2 air mass classifications for 42 stations across the conterminous United States over the period 1948–2005. Variables include four times daily air temperature and dew point depression values, the diurnal ranges of air temperature and dew point temperature, scalar components of the surface wind vector, mean sea level pressure, and mean cloud cover. A manual identification of air masses determines the paradigm weather types, and then all other days are automatically classified into one of six air mass types or a transition category using a simple z-scoring procedure (Table 1). Seed days are selected to represent each weather type for a particular air mass, station, and time of year. For complete details on the SSC2, please refer to *Sheridan* [2002] or http://sheridan.geog.kent.edu/ssc.html. The SSC2 separates MT days into three different categories, primarily for use in heat/mortality research. For our purposes, we aggregate these subsets into one MT category.

[7] The color bars displayed in Figure 1 show the 42-station network (selected from the 225 continuous United States stations available). Stations are selected primarily based upon completeness of SSC2 data while striving for even spatial coverage, but the resolution is sparser west of the Mississippi River. They generally are located at major airports with a long and complete data record. We determine the frequency (percent) of each air mass type for each year, on both an annual and seasonal (DJF, MAM, JJA, SON) basis.

[8] We subdivide each air mass's frequency for each station into segments with homogeneous trends using the change-point detection algorithm developed by *Menne and Williams* [2005]. This method employs a likelihood ratio test and multi-phase regression to identify both trends and change points in time series data. We apply this approach to both annual and seasonal air mass frequencies.

[9] We use ordinary least-squares (OLS) regression to examine the temporal behavior of air mass frequencies over the period of record. Because of our relatively small sample size in some cases (dependent upon the number of change points in a given time series), we bootstrap the regression slopes to develop confidence bounds and evaluate statistical significance. To do this for each location, we randomly draw x-y data pairs (with replacement) from our sample. Using these randomly drawn data pairs, we perform OLS regression to estimate the regression slope parameter. We repeat this procedure 10,000 times, thus developing a 10,000-point distribution for the simple least-squares regression trend for each location and determine the two-tailed statistical significance based upon the 2.5th percentile and 97.5th percentile observations in the ordered list of 10,000 regression slopes. The temporal trend at each location is the mean regression slope of the 10,000 replications. This trend is deemed statistically significant if the 2.5% and 97.5% values are of the same sign.

[10] If the frequency of one air mass type decreases over time, another air mass (or air masses) must increase. To examine air mass trend interactions, we compute the Pearson correlation coefficient between the frequencies of different air masses for each station on both annual and seasonal bases. Values are considered statistically significant at the 95% confidence level. We also test for correlations between air mass frequencies and teleconnection index values in a similar manner for the winter season to determine the linkages between large-scale atmospheric circulation patterns to air mass frequency trends. Teleconnections included are the North Atlantic Oscillation (NAO, data source: Climate Prediction Center, CPC), Pacific/North American teleconnection pattern (PNA, data source: CPC), Arctic Oscillation (AO, data source: CPC), and the Multivariate ENSO Index (MEI, data source: Earth System Research Laboratory).

Table 1. Descriptions of the SSC2 Air Mass Types[a]

Air Mass	Description
Dry Polar	Synonymous with traditional continental polar; cool or cold dry air with northern Canada and Alaska as the typical source regions
Dry Moderate	Synonymous with Pacific weather type; mild and dry, generally appears in U.S. with zonal flow aloft permitting air to dry and warm adiabatically on east side of Rocky Mountains
Dry Tropical	Synonymous with continental tropical; hottest, sunniest, and driest conditions; southwest U.S. and Mexico are the typical source regions; also from regional subsidence
Moist Polar	Cool, cloudy, and humid with light precipitation; source regions are North Pacific or North Atlantic but can also arise when there is frontal overrunning
Moist Moderate	Cloudy but warm and humid; generally south of moist polar air closer to a warm front
Moist Tropical	Synonymous with maritime tropical; warm, humid air; source regions are the Gulf of Mexico or tropical Atlantic or Pacific Oceans
Transition	Represents a day in which one air mass yields to another; indicative of frontal passages

[a] See *Sheridan* [2002].

3. Results

[11] Each map in Figure 1 displays air mass frequency trends over the period of record for each station. Horizontal red and blue bars represent increasing and decreasing trends, respectively, over time (moving left to right). A vertical line identifies a statistically significant change point. There are consistent decreases in the DP air mass frequency in the West, Midwest, and along the East coast (Figure 1b). Seasonally, these trends are largely driven by the winter and spring months. MM air mass frequencies increase across most of the nation, with the exception of the Southeast (Figure 1d). For MM, all seasons contribute to the overall trend. MT air masses generally increase over most of the United States with all seasons contributing to these trends (Figure 1f). Figure 1a shows that no trend is evident across much of the nation for DM air masses, as positive and negative trends are spatially inconsistent. DT air masses exhibit only spatially-irregular upward trends in a few stations, primarily early in the record (Figure 1c). Figure 1e shows that MP air masses decrease in frequency in the West and increase in the Midwest, driven largely by the winter and fall seasons. Finally, there is a striking overall decline in the frequency of the transition category (i.e., days best characterized as air mass changes) across most of the

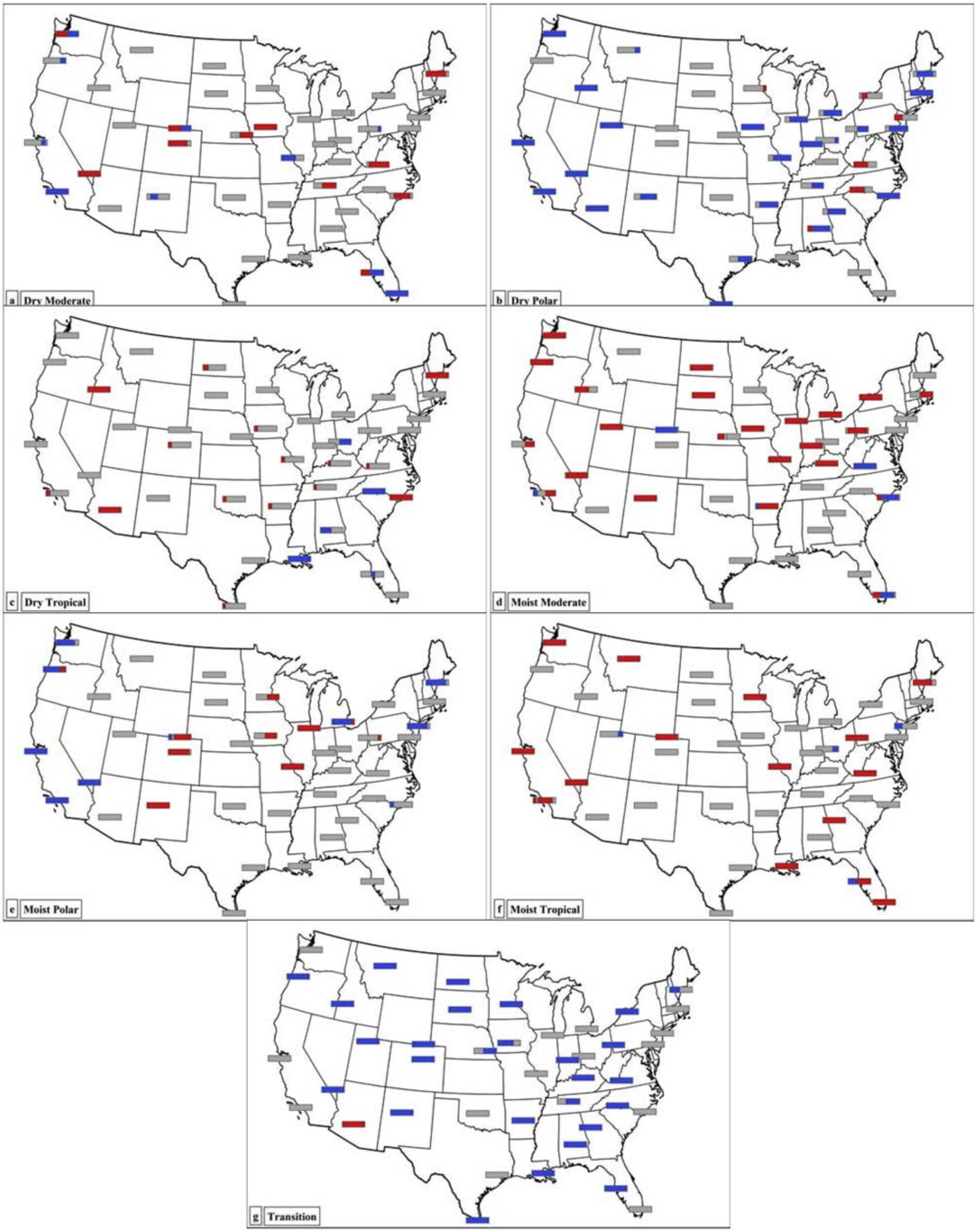

Figure 1. Trends in the frequency of (a) DM, (b) DP, (c) DT, (d) MM, (e) MP, (f) MT, (g) TR. Each horizontal bar denotes time the time period 1948–2005 with time increasing from left to right. Red indicates statistically significant positive trends, blue indicates statistically significant negative trends, and gray indicates no trend. A statistically significant change point is present where two colors are adjacent.

Table 2. Number of Station-Pairs With Statistically Significant Pearson's Product-Moment Correlations of Frequencies for All Possible Combinations of Air Mass Types[a]

	DM		DP		DT		MM		MP		MT		TR	
	Pos	Neg	Pos	Neg	Pos	Neg	Pos	Neg	Pos	Neg	Pos	Neg	Pos	Neg
TR	**1**	**12**	14	3	3	3	2	18	1	14	8	12	-	-
MT	4	15	0	34	1	10	16	6	2	19	-	-		
MP	2	26	11	1	0	22	10	5	-	-				
MM	2	22	0	20	0	32	-	-						
DT	21	4	0	20	-	-								
DP	4	16	-	-										
DM	-	-												

[a] Statistically significant at alpha=0.05. Values are the sum of the number of stations positively and negatively correlated (statistically significant) for each air mass type pair. The maximum possible value of each positive-negative pair is 42 (the number of stations included in the study). For example, entries in bold type indicate that the DM and TR annual frequencies show significant positive correlation for 1 of 42 stations. Similarly, 12 stations exhibit a significant negative correlation.

United States, except perhaps the east and west coasts (Figure 1g). This trend is largely driven by declines during winter.

[12] Table 2 summarizes the number of statistically significant positively and negatively correlated air mass pairs over the 42 stations. We find high consistency among stations, as correlations are generally either mostly negative or positive for each air mass pair. Nearly half of the stations display statistically significant correlations for several air mass pairs. Negative correlations are far more prominent than positive correlations. DM and DT are positively correlated at 21 stations. Negatively correlated air mass pairs include DM and MM (22 stations), DP and MM (20 stations), DP and MT (34), DT and MM (32 stations), and DT and MP (22 stations). In general, by comparing results from Figure 1 and Table 2, there is evidence for a temporal shift toward warm and moist air masses at the expense of the cold and dry air masses. A broader characterization of air masses by temperature and moisture supports this finding, with negative correlations between warm and cold air mass frequencies at 40 locations, between moderate and cold air mass frequencies at 27 stations, and between moist and dry air mass frequencies at all locations (Table 3).

[13] Next we examine correlations between air mass type frequencies and winter teleconnection indices to determine if recurring and persistent, large-scale atmospheric patterns account for some of the observed trends in air mass frequencies. During the positive (negative) phase of the NAO, there is a stronger (weaker) pressure gradient in the North Atlantic between the Icelandic low and Azores high [e.g., *Hurrell et al.*, 2001]. The eastern United States experiences mild and wet winters during the positive phase and more outbreaks of cold weather and more snow during the negative phase [e.g., *Hurrell et al.*, 2003]. In recent decades, the NAO moved from the negative phase to the positive phase [*Hurrell et al.*, 2001], so we would expect a warming in the eastern United States according to this teleconnection. We find that the NAO is negatively correlated with DP and MP across nearly all of the eastern United States, while it is positively correlated in the same region with the warmer MT, DT, MM, and DM air masses (Table 4). Therefore, NAO phase shifts are accompanied by the expected changes in frequencies of the air masses (increases in the warmer air mass types).

[14] The PNA is associated with fluctuations in the meridionality of flow across the eastern Pacific and North America. Especially during the winter, there are high correlations between the Index and regional temperatures in the United States—above-average (below-average) temperatures in the West and below-average (above-average) temperatures in the Southeast during the positive (negative) phase [*Leathers et al.*, 1991]. In the Southeast, we find MT to be negatively correlated with the PNA as expected, while DM is positively correlated with the PNA. MP is negatively correlated with the PNA along the West Coast, while MT is positively correlated in this region (Table 4). Thus, since the PNA has generally moved from the negative phase to the positive phase over the period of record (from CPC), this may explain some of the trends in air mass frequencies in the West. Since MT increases across the Southeast over the period of record, changes in the PNA do not provide a relevant explanation for MT trends (Table 4).

[15] The AO characterizes the strength of the polar vortex aloft [*Thompson and Wallace*, 1998]. Higher temperatures in the eastern United States are associated with increases in the Index [*Wettstein and Mearns*, 2002]. In the eastern half of the United States, we find AO to be positively correlated with MT, DT, MM, and DM and negatively correlated with MP and DP (Table 4). For much of the period of record, the AO shifts from the negative to the positive phase, though it decreased within the positive phase in the late 1990s [*Polyakov and Johnson*, 2000]. Thus, our finding that air masses shift from colder to warmer classifications is also consistent with changes in the AO.

[16] The MEI incorporates measurements of sea level pressure, surface wind, surface air temperature, and total cloudiness over the Pacific Ocean. Above-normal precipitation is associated with positive MEI values over the southeastern United States, the Great Basin region, and the western United States [*Ropelewski and Halpert*, 1986]. We observed spatially consistent positive correlations between the MEI and MM across much of the country, negative correlations for the transition category, and negative correlations in the Southeast for MT (Table 4). It is difficult to draw definite conclusions for the MEI as we did with the previous teleconnections because the time scale of the oscillations is much shorter. Overall, however, the early portion of the period of record is characterized by more years in the negative phase, whereas more of the recent years have fallen in the positive phase [*Lluch-Cota et al.*, 2001]. Therefore, changes toward the more positive phase of the MEI may be a reasonable explanation for increasing MM frequencies. Also, since more rainfall is associated with the positive phase of the MEI, it may have been a contributing factor to the increased frequency of moist air

Table 3. Same as but With Air Mass Types Grouped According to Thermal (Warm, Moderate, or Old) and Moisture (Dry or Moist) Properties

	Dry		Moist		Warm		Moderate		Cold	
	Pos	Neg	Pos	Neg	Pos	Neg	Pos	Neg	Pos	Neg
Cold	7	7	8	6	0	40	2	27	-	-
Moderate	10	2	4	5	6	19	-	-		
Warm	6	8	9	5	-	-				
Moist	0	42	-	-						
Dry	-	-								

Table 4. Results From the Pearson's Correlation Test Between Air Mass Type Frequency and Teleconnection Index Value During Winter (December, January, February)[a]

	NAO		PNA		AO		MEI	
	Pos	Neg	Pos	Neg	Pos	Neg	Pos	Neg
				East Subset				
DM	5	1	4	0	8	2	2	0
DP	0	16	1	0	0	16	0	0
DT	6	0	0	0	11	0	0	2
MM	11	0	2	2	10	1	9	0
MP	0	11	4	0	0	11	2	0
MT	15	0	0	9	13	0	1	7
TR	0	3	2	12	0	2	2	7
				West Subset				
DM	4	0	11	1	4	0	5	0
DP	0	13	0	7	0	7	0	6
DT	2	0	5	0	2	0	0	6
MM	4	0	6	0	1	0	14	0
MP	1	1	3	4	0	2	5	2
MT	3	0	4	4	3	2	5	4
TR	0	3	0	16	2	3	0	15

[a] Values are the sum of the number of stations with significant positive or negative correlations (alpha = 0.05). East and West subsets are divided by the Mississippi River.

mass categories. Overall patterns of the MEI do not provide an explanation for increases in the MT air mass in the Southeast.

4. Conclusion

[17] We identify statistically significant changes in the air mass climate of the United States from 1948–2005, with an increase in the frequency of warm and moist air masses at the expense of cold and dry air masses. These results are consistent with a previous study that utilized slightly different methods over a shorter time period [*Kalkstein et al.*, 1998]. The increasing frequency of warm and moist air masses is consistent with expected changes from increasing greenhouse gas concentrations [*Karl and Trenberth*, 2003] and is also consistent with the temperature [*IPCC*, 2007] and moisture [*Robinson*, 2000] increases observed in the continental United States. Equipment changes or local changes in land cover may also contribute to some of the overall trends in air masses for certain stations (i.e. the increasing DT frequency in Phoenix, Arizona) [*Sheridan*, 2002]. One intriguing and as of yet unexplained result is the decline in transition air masses over most of the study region. In principle, this suggests an overall decline in the number of frontal passages.

[18] Many of these air mass trends are also correlated with several teleconnection patterns. Changes in the NAO, for example, are consistent with the frequency trends in warm versus cold air mass types in the eastern United States. One possible explanation is that large-scale circulation changes are linked to different air mass frequencies via regional changes in synoptic-scale advection patterns. On the other hand, warm and/or moist conditions may change the air mass classification of a given day (MM to MT, for example). Whatever the underlying cause, our results demonstrate a clear trend toward higher frequencies of warm and moist air masses in the continental United States over the last half-century.

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