An investigation of warm-season cloud patterns and related precipitation across Maryland and the Delmarva Peninsula

Heather Richelle Hyre

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AN INVESTIGATION OF WARM-SEASON CLOUD PATTERNS AND RELATED PRECIPITATION ACROSS MARYLAND AND THE DELMARVA PENINSULA

By
Heather Richelle Hyre

A Thesis
Submitted to the Faculty of
Mississippi State University
in Partial Fulfillment of the Requirements
for the Degree of Master of Science
in Geosciences
in the Department of Geosciences

Mississippi State, Mississippi
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By

Heather Richelle Hyre
AN INVESTIGATION OF WARM-SEASON CLOUD PATTERNS AND RELATED PRECIPITATION ACROSS MARYLAND AND THE DELMARVA PENINSULA

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Surface heterogeneities cause differential heating that can generate mesoscale convective boundaries, sometimes leading to cloud development and enhanced localized precipitation. A preferred cloud pattern has been identified across Maryland and the Delmarva Peninsula region from 1998-2006 through the detection of cumuliform clouds on days when synoptic-scale forcing is weak. Hourly visible Geostationary Operational Environmental Satellite (GOES) imagery data are used to identify convective cloud masses. This allows quantitative description of the frequency and spatiotemporal extent of the clouds, helping forecasters gain insight into when and where they are likely to develop. Despite the inability to determine the underlying causes of the distinct cloud pattern, primarily due to the complex land cover, results indicate that the land receives significantly higher average total cloud cover than the Chesapeake Bay with Delaware receiving the highest average total cloud cover per state. Average total precipitation amounts follow this same trend on synoptically-weak days.
DEDICATION

First and foremost, I would like to dedicate this thesis to my undergraduate advisor, at Salisbury University, Dr. Brent Skeeter for providing me with the utmost inspirational and collegial basis of knowledge in understanding the basic principles of meteorology. Secondly, I would like to dedicate this thesis to my long time best friend, Lucas Hanson, for the selfless love and support he has provide me with these past two years despite being 977 miles apart. Lastly, and most importantly, I dedicate this thesis to my family, who in the face of economic hardship and family turmoil, have provided me with an indescribable amount of love, motivation, passion, and sense of worthiness which has gotten me where I am today.
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CHAPTER I
INTRODUCTION

1.1 Problem Setting

It has been well documented that land surface discontinuities of soil type, soil moisture, vegetation cover, coastline curvature, anthropogenic landscapes, and topography influence the development of convective boundaries that form clouds, and also aid in the production of precipitation on days when synoptic scale forcing is weak (Clark and Arritt, 1995; Lynn et al., 1997; Pielke et al., 1998; Baker et al., 2000). A synoptic scale forcing is any atmospheric mechanism found in the lower troposphere that is on a scale of a couple of hundred kilometers wide but not larger than 1,000 km wide. Examples of a synoptic-scale forcing include cold fronts, warm fronts, mid-latitude cyclones, and hurricanes. Synoptic scale forcings would disrupt any mesoscale (10-100 km) convective circulation to form. Only days when synoptic scale forcings are weak will be of interest while trying to identify mesoscale convective boundaries across the study region.

Broad surface heterogeneities cause differential heating, which generate mesoscale convective boundaries that often produce distinct convective cloud patterns and sometimes precipitation. Particular surface areas will heat up and cool down faster than those surrounding them. For example, the Florida peninsula heats up much faster...
during the day while the water surrounding it does not due to differences in the sensible and latent heat fluxes. Differential surface heating therefore causes a circulation to develop over Florida nearly every day during the summer and accounts for much of their total rainfall (Burpee and Lahiff 1983; Wilson and Megenhardt 1997). The existence of the contrasting surface characteristics has even changed the climate of some regions (e.g. the Florida peninsula; Clark and Arritt, 1995). Areas of enhanced convergence, and thus the production of clouds, have been found all across the U.S. in places such as Illinois, Georgia, and the Carolina’s due to the mesoscale convective boundaries set up by differences in land cover, land use, and soil type respectively (Boyles et al., 2007, Brown and Arnold 1998, Dixon and Mote, 2003).

Surface characteristics undoubtedly play a role in mesoscale convective behavior in the atmosphere, thus making some areas more favorable to cloud development and sometimes precipitation (Brown and Arnold 1998, Dixon and Mote, 2003). The goal of this research is to identify convective clouds through the use of GOES satellite imagery for areas across Maryland and the Delmarva Peninsula in which mesoscale convective circulations, assumed to be triggered by heterogeneities including soil type, soil moisture, vegetation cover, coastline curvature, anthropogenic landscapes, and topography, yield a preferred cloud pattern. In identifying distinct areas of cloud cover on synoptically-weak days, improvements can be made in forecasting temperature, small scale winds, cloud type, and even air mass thunderstorm development. Additionally, precipitation enhanced
by convective boundaries (cloud boundaries) can be quantified to help improve water resource management and agricultural irrigation plans.

1.2 Objectives

The primary objective of this research is to identify areas where convective clouds are most likely to occur across Maryland and the Delmarva Peninsula region on synoptically-weak days assumed to be caused by some underlying surface characteristic. The secondary objective of this research is to quantify average total cloud cover and precipitation across the study region. Due to the complex nature of surface heterogeneities across the study region, it is unlikely that the identification of any one preferred cloud pattern be directly related to any one surface discontinuity. While some areas of cloud cover can be explained as a result of some convective boundary at the surface, such as clouds along a coastline caused by the sea breeze phenomena, this research will not provide such evidence but rather recognize areas most susceptible to cloud development on synoptically-weak days.

1.3 Study Area

Maryland is often referred to as “Little America” because it exhibits a broad variety of physiographic regions. Maryland is divided by the Chesapeake Bay into two geographical regions; to the west of the bay is the western shore and to the east, the eastern shore. Neighboring the eastern shore of Maryland is the state of Delaware.
Delaware and portions of Maryland and Virginia make up what is known as the Delmarva Peninsula (Figure 1).

Figure 1: Study region: Maryland and the Delmarva Peninsula (Delaware and parts of Maryland and Virginia)

Maryland and the Delmarva Peninsula region contain five physiographic provinces and can be identified by many contrasting surface characteristics of land cover, land use, coastline curvature, and soil type (Figure 2) (USGS, 2010).

The Delmarva Peninsula and portions of the western shore of Maryland adjacent to the Chesapeake Bay are within the Atlantic coastal plain province. This region is
termed the ‘countryside’, where numerous small towns are scattered between large agricultural areas.

The western shore of Maryland and a small portion of northeastern Delaware are within the Piedmont province, which is adjacent to the Atlantic Coastal Plain and stretches through central Maryland (USGS, 2010). Characteristics of this region include low rolling landscapes and fertile valleys. Notable cities such as Annapolis, Baltimore, Silver Spring and the District of Columbia (D.C.) metropolis area are heavily developed areas located on the western shore.

West of the Piedmont region lies the Blue Ridge province, which can be identified by its narrow, mountainous terrain between the Piedmont and the Appalachian Ridge and Valley. The mostly forested Appalachian Ridge and Valley includes the Great Valley and has elevations as high as 609.6 meters (USGS, 2010). This region is mainly characterized by its hay/pasture land cover.
Figure 2: Landcover across Maryland and the Delmarva Peninsula (NLCD 2001).
Maryland has the greatest ratio of farmland preserved to total land mass by any state in the United States (U.S. Department of Agriculture, 2010). Heavy in corn and soybean production, agricultural sustainability is vital in Maryland and Delaware. In 2008, $555,038,000 was the estimated value of production dollars for field and miscellaneous crops in Maryland, and $193,298,000.00 in Delaware (U.S. Department of Agriculture, 2010). The main contributor to production dollars, for both Maryland and Delaware, is corn for grain. A total of $292,670,000 production dollars, in 2008 were made off of corn for grain alone. Agriculture is vastly dependent on climatological variables related to the surface energy and water budgets, placing local meteorological patterns at the top of the list when determining short term forecasts for agricultural production.

1.4 Convective Boundaries

Meteorological convection is the vertical transport of atmospheric gases and particles due to buoyancy caused by changes in atmospheric density (Emanuel K. A. 1994). Convection can be found almost anywhere in the atmosphere, especially near the Earth’s surface where strong vertical heat fluxes occur. The near-surface part of the atmosphere is known as the boundary layer. The boundary layer is characterized by surface friction and varies in thickness between a few hundred meters and about 2 kilometers. Turbulent mixing, caused by friction, creates a distinct layer to form between the Earth’s surface and what is known as an inversion, characterized by a sharp temperature gradient separating this layer from the free atmosphere. The temperature
inversion acts as a cap, trapping both turbulence and aerosols, but also more importantly, heat and moisture. Sensible and latent heat fluxes are, therefore, limited to near surface areas.

The rate at which convection transports energy is based on the energy and moisture gradient as well as mixing efficiency in the boundary layer (Emanuel K. A. 1994). Mixing of the boundary layer occurs during the day when surface heating is present. When a parcel of air at the surface becomes warmer than the surrounding air, it will begin to rise due to a decrease in density. The Earth’s surface heats up as a whole at different rates dependent upon characteristics of the surface, such as albedo and moisture content. Albedo is important in determining convection rates because lower albedos result in higher absorption of shortwave radiation and thus a greater longwave radiation flux from the surface. The higher the amount of long wave radiation being emitted by surfaces with relatively low albedos, will yield an increase in temperature above the particular surface and trigger convection. Convection rates also depend on the moisture content of the source; a moist surface will undergo latent heat absorption due to evaporation. The actual temperature of the soil will decrease, however, the energy absorbed through evaporation from the soil is now held by the water vapor released from the surface. As that water vapor is transported by convection, it will eventually condense and thus release latent heat. This energy transfer is important to note for moist surfaces because a latent heat exchange is much more powerful than a sensible heat exchange (dry
surface). While both heat fluxes (sensible/latent) are important, a latent heat flux is more efficient at transporting energy through the atmosphere.

Convective circulations form in the atmosphere because adjacent contrasting surfaces heat up differently relative to one another (Aguado E. and Burt J. E. 2004). Convection thus occurs at different rates dependent upon the characteristics of its underlying surface (i.e. moisture content of the surface and/or albedo of the surface). When temperature increases, density decreases. As a parcel at the surface becomes relatively warmer than the surrounding air, it will begin to rise. A parcel will continue to rise until it reaches a layer in the atmosphere that is relatively less dense (i.e. the top of the boundary layer commonly referred to as the cap). This process results in a relative low pressure forming near the surface. Now there exists a pressure gradient between the relative low pressure and the surrounding pressure of the air. Therefore, winds will flow towards the low pulling air from adjacent areas. This begins a convective circulation best described by the sea breeze phenomena. Surfaces that provide stronger convective potential usually are those areas where air is more likely to rise while those surfaces that provide weaker convective potential are those areas where air is more likely to subside (i.e. sea breeze).

Synoptic-scale events such as mid-latitude cyclones produce dominate wind patterns that prevent any localized circulation from forming; therefore, localized circulations are most likely to occur on synoptically-weak days. Strong solar heating at the surface, unaffected by synoptic forcings, result in an increase in convection and the
production of thermals (buoyant air parcels). Natural, or free, convection influences a variety of weather phenomena such as cloud development and growth, temperature, precipitation, and small scale winds. The diversity of surface characteristics in Maryland and the Delmarva Peninsula region presents a location where all variables such as contrasts in coastal boundaries, soil type, land cover, and land use, could develop distinct convective boundaries.
2.1 Land/Water Convective Boundaries

One of the most recognized convective boundaries is the sea breeze (Baker et al. 2000), which is produced because land heats up faster than water. A parcel of air over land will tend to heat and rise faster than a parcel over water, thereby beginning the convective circulation known as the sea breeze. Sea breezes strongly affect the development of deep cumulus convection over coastal regions such as the Florida peninsula, and are accountable for approximately 34 - 40% of the south Florida summer rainfall (Burpee and Lahiff 1983; Wilson and Megenhardt 1997).

The sea breeze phenomenon can be observed as a day-to-day occurrence in Florida and often affects daily precipitation, temperature, wind speed, and cloud cover over the area. Identification of sea breeze induced-precipitation at other coastal locations would allow researchers to quantify the amount of precipitation produced by sea breeze circulations (Burpee and Lahiff, 1983). McPherson (1970) used numerical weather models to simulate sea breeze occurrence in the presence of a bay or other large indentation of a coastline that produces a landward distortion of a sea breeze convergence zone. McPherson (1970) found that the most intense convergence and upward motion develops to the northwest and northeast corners of a square model bay. Such research
suggests the importance of a bay on the convective processes that take place while solar heating is most intense. Enhanced convection in the presence of a bay should yield deep cumulous cloud growth and possibly precipitation.

Convective boundaries are likely to form in the presence of water/land contrasts but may also be affected by coastline concavity. Baker et al. (2000) used numerical simulations and found precipitation to occur earlier with curved coastlines versus linear coastlines. Changes in the curvature of coastline result in differences in confluence/diffluence patterns (Figure 3).

Numerical simulations reveal that convex coastlines maintain strong convergence, due to confluence patterns, while concave coastlines experience sea breeze divergence due to diffluence patterns created by the shape of the coastline (McPherson, 1970). Baker et al. (2000) therefore suggests that higher amounts of precipitation would occur over convex coastlines due to stronger, concentrated convergence. Coastline irregularity strongly affects the location of precipitation and may be a primary factor in determining rainfall intensity (Baker et al., 2000).

The Delmarva Peninsula should not only act as the Florida peninsula, but since the peninsula holds convex characteristics, there may also be a noticeable effect on enhanced convergence, thus resulting in precipitation modification. Findings should also support the presence of stronger convergence to the northwest and northeast of the Chesapeake Bay based on simulations revealed by McPherson (1970).
2.2 Land Cover and Soil Convective Boundaries

Contrasts in land cover can also produce convective boundaries induced by differential surface heating. Discontinuities in land cover have been found to generate convective circulations that are as strong as a sea-breeze (Pielke et al., 1998). Brown and Arnold (1998) show statistical spatial clustering of free convective cloud masses influenced by the land-cover-type and soil-order boundaries in the state of Illinois on days with weak synoptic-scale flow. The three most dominate cloud masses were found above the following contrasting boundaries: (i) the agricultural and mixed forest-agricultural boundaries, (ii) along the urban/suburban Chicago metropolitan area and agricultural boundary, and (iii) along the agricultural and agricultural-mixed forest boundary (Brown and Arnold 1998). Similar contrasts in surface characteristics can be found in Maryland such as the city of Baltimore neighboring the Chesapeake Bay;
however, these contrasts have not yet been proven to produce spatial clustering of free convective cloud masses.

Computer simulations have also been used to suggest that convective circulations may be triggered by discontinuities in land cover. The Carolina Sandhills, located in North and South Carolina, are characterized by sharp contrasts from the dense clay soils in the Piedmont region to coarse sandy soils in the Sandhills (Boyles et al., 2007). Boyles et al. (2007) incorporates a combination of soil and vegetation patterns, using computer simulations to locate areas of enhanced convergence over the Sandhills and conclude that local changes in soils are associated with the dynamics needed to produce convection strong enough to yield precipitation. Heterogeneities between land cover induce differential surface heating, which in turn affect localized temperature and pressure gradient and induces circulations similar to a sea breeze (Boyles et al., 2007).

To explore the affects of vegetation on a sea breeze, Segal et al. (1998) use atmospheric models and compare dry bare soil versus wet soil with dense vegetation next to a water body and conclude a reduction in the intensity of the sea breeze with the presence of adjacent dry bare soil. Segal et al. (1998) also find convective circulations comparable to a sea breeze with the presence of a bare soil surface adjacent to a vegetated wet soil surface. Furthermore, the intensity of the circulations stays the same whether there is a sharp thermal contrast between the vegetated soil versus bare soil or a gradual change, within 30 kilometers, from vegetation to bare soil.
Surface circulations can also be triggered by contrasts in surface heat fluxes caused by wet versus dry ground (Lynn et al., 1997). Baker (2000) simulated the ways in which horizontal variations in soil moisture can result in strong convective mesoscale circulations. A similar study (Clark and Arritt, 1995) used numerical simulations to reproduce the effects of soil moisture and vegetation cover on the development of deep convection and concluded that most rainfall associated with deep convection occurs over moist vegetated surfaces, while the least rainfall occurred over bare-dry ground. Moist soil enhances evaporation, allowing cloud formation and thus, enhanced precipitation. In opposition to these findings, other research shows peak precipitation amounts six times larger for dry soil than for moist soil (Xu et al., 1996), which could be the result of hotter temperatures over drier soil causing more rising air and thus more convergence. Regardless of contrasting findings, soil moisture does have an effect on the distribution of precipitation. Simulations conducted by Baker et al. (2000) reveal that the distribution of initial soil moisture influences the timing and location of precipitation, particularly heavier precipitation over areas with more moist soil. More importantly, soil type determines the capacity of soil moisture, and may be more effective in identifying areas of soil heterogeneity to reveal locations susceptible to convective boundaries that produce cloud cover and possible precipitation.
2.3 **Land Use Convective Boundaries**

The presence of anthropogenic landscapes adjacent to rural areas also generates differential surface heating, which produces mesoscale convective boundaries. Buildings, concrete sidewalks, and asphalt heat up much faster than surrounding, grassy, aggregated, rural areas. The presence of multiple high rise buildings cause solar radiation to become trapped between the buildings and unable to escape as easily as it would in an open field. Asphalt from parking lots and/or roads have a lower albedo and are more efficient at absorbing radiation from the Sun. Much like the sea breeze phenomenon, the air over large cities heats at a faster rate, thus becoming less dense and rising before the air overlying open rural (vegetated) areas, setting up convective boundaries. Urban heat islands and their production of convective circulations have been a popular research subject in recent years (Cenedese and Monti, 2003, Dixon and Mote, 2003, Yoshikado 1990). It should also be noted that most of these urbanized areas can be found along coastlines, which may aid in the strengthening or weakening of sea breeze circulations (Cenedese and Monti, 2003).

Findings by Dixon and Mote (2003) demonstrate that convection initiated by the Atlanta urban heat island affects the total precipitation downstream of the major metropolitan area, especially an increase during late summer months. Yoshikado (1990) used computer simulations to show that the presence of a city with a width of 10 km or greater strongly influenced the intensification of the sea-breeze velocity and decreased as the city was moved inland. Sea breeze circulations are enhanced when urban heat islands
are set further back from the shoreline because this allows maximized heating of the land before the arrival of the sea breeze (Yoshikado, 1990). Such research suggests that the placement of urban areas on coastal regions would influence the strength of sea breeze circulations, thus creating more intense convergence and the production of clouds and precipitation. Maryland’s western shore is more urbanized than the eastern Shore, thus it is likely that stronger mesoscale convective boundaries exist, aiding the development of clouds and if strong enough, produce precipitation.

Convective boundaries that form as a result of diverse surface characteristics across Maryland and the Delmarva Peninsula region should yield a distinct cloud pattern that can be identified on synoptically-weak days. Differential heating caused by discontinuities in land use, land cover, and land/water surfaces yield differences in convective strength. Surfaces with relatively stronger convective potential provide environments better capable of cloud development on synoptically-weak days. The influence from the underlying surface characteristics should therefore generate unique cloud patterns across the region based on convective potential.

2.4 Hypothesis

Null Hypothesis

1. No preferred convective cloud patterns exist across Maryland and the Delmarva Peninsula region on synoptically-weak days.
2. Convective cloud frequency and precipitation depth are not different over land and the Chesapeake Bay.
CHAPTER III
DATA AND METHODOLOGY

3.1 Synoptically-weak Days within the Study Period (1998-2006)

3.1.1 Sounding Data Collection

To represent the synoptic conditions across the domain spanning from 74ºW to 78ºW and 36ºN to 40ºN, rawinsonde data are obtained from National Weather Service (NWS) for all dates that fall within 1998-2006. The sounding sites used to represent Maryland and the Delmarva Peninsula were Wallops Island, Virginia (KWAL) and Sterling, Virginia (KIAD) (Figure 4).

The two sounding site locations are the two nearest to the study region and are chosen to capture synoptically-weak flow (calm and from the west). Sterling, VA lies just west of the study area and Wallops Island, VA is located on the Delmarva Peninsula to avoid any influence the Chesapeake Bay may have. Data collected by these sounding sites are representative of the weather Maryland and the Delmarva Peninsula received on those days. Sounding data are obtained for both 00z and 12z to ensure full 24-hour coverage of the area.
3.1.2 Determining Synoptically-Weak Days

Synoptic scale forcings would act to lessen the likelihood of any localized convective circulations to form; therefore, to be included for analysis as a study day, a set of criteria is met for the entire 24-hour period. These criteria are determined through the use of rawinsonde sounding data collected for 0000 UTC and 1200 UTC for all days within 1998-2006 and are used to identify wind speeds for the following atmospheric conditions...
levels: 700, 500, and 250 hPa. The 700, 500, and 250 hPa pressure levels are representative of: 1) the atmospheric characteristics closest to the surface that are unaffected by the boundary layer 2) the central pressure level of the atmosphere 3) the polar jet stream pattern, respectively. These levels ensure that the entire atmospheric columns during times closest to the observation are taken into account. The frequency distribution of windspeed data were used to determine breaks and bin intervals for wind speeds at 700, 500, and 250 hPa (Figure 5).

![Wind Speed Frequencies (1998-2006)](image)

Figure 5: Distribution of wind speeds at 700hPa, 500hPa, and 250hPa from the Sterling, VA and Wallops Island, VA sounding sites for all dates from 1998-2006.

The first quartile’s maximum value determines the maximum wind speed at each atmospheric pressure level that will be used in determining synoptically-weak criteria.
Synoptically-weak wind speed criteria (maximum value from the first quartile) are as follows: 700 hPa: \( \leq 16 \) knots, 500 hPa: \( \leq 22 \) knots, and 250 hPa: \( \leq 39 \) knots. To be considered synoptically-weak, criteria must be met at all levels, for both the Sterling, VA and Wallops Island, VA sounding sites for 0000, 1200, and 0000 UTC the following day to ensure that the entire 24-hour period is synoptically-weak.

3.2 Satellite Imagery for Cloud Identification

3.2.1 \textit{GOES Satellite Imagery Data Collection}

Geospatial Operational Environmental Satellite (GOES I-M Imager) imagery data are obtained by the Comprehensive Large Array-data Stewardship System (CLASS) and will be used to identify areas of convection through the detection of cloud cover (NOAASIS, 2010). The GOES I-M Imager is a five channel imaging radiometer used to sense radiant and solar reflected energy from Earth (NOAASIS, 2010). The GOES I-M Imager satellite, channel number 1 (visible), operates on a wavelength range of 0.55 to 0.75 µm and performs within 5% of maximum scene irradiance with an instantaneous geographic field of view (IGFOV) at nadir of 1 km resolution (NOAASIS, 2010). The time delay on the GOES I-M Imager is less than three minutes and can be held to high accuracy (NOAASIS, 2010). The data collected are provided in raw count form; these data are relativized (relative to space) and normalized (destriped) but no calibration is applied (NOAASIS, 2010). Scene radiances are converted into an electrical signal that represents 0.1-100% albedo after callibration.
To maintain a consistent set of satellite images for all synoptically-weak days, three hour satellite imagery are used. The following daylight hours are investigated: 1500, 1800, and 2100 UTC for all synoptically-weak days in the study period. Other times are omitted because they occur at night. GOES visible satellite imagery are collected for the entire domain spanning from 74ºW to 78ºW and 36ºN to 40ºN at 1500, 1800, and 2100 UTC for each synoptically-weak day.

3.2.2 Cloud/Non-Cloud Criteria

Geospatial Operational Environmental Satellite (GOES-10 Imager) imagery data are used to identify cloud cover. Criteria are made for cloud/non-cloud based on these raw count values. These raw count values can be converted into percent albedos; however, histograms are used to display the distribution of these raw data to formulate a cloud/non-cloud criteria for 1500, 1800, and 2100 UTC (Figure 6).

This histogram shows a higher frequency among the lower reflectance values (0-5,999). These lower reflectance values are indicative of the Earth’s surface rather than clouds because the Earth’s surface has a lower albedo than do clouds. The decrease in frequency for reflectance values ≥ 6,000 is likely representative of the apparent change in albedo between the Earth’s surface and a cloud. The value 6,000 serves as a baseline in determining what is considered a cloud and what is not considered a cloud. Furthermore, visual inspection of each image for all three time periods lead to the following cloud/non-cloud criteria: 1500 UTC: ≥ 5500 = cloud, < 5500 = non-cloud, 1800 UTC: ≥ 6000 =
cloud, \( < 6000 = \) non-cloud, 2100 UTC: \( \geq 5000 = \) cloud, \( < 5000 = \) non-cloud. Figures 7-12 give examples of select GOES visible satellite images and the associated maps generated using the binary cloud criteria.

Figure 6: Distribution of reflectance values for GOES satellite imagery for all days that meet synoptic criteria in the study period
Figure 7: May 1, 2001 GOES satellite image (column two) compared to binary images (column one) based on cloud criteria at 1500, 1800, and 2100 UTC.
Figure 8: May 11, 2004 GOES satellite image (column two) compared to binary images (column one) based on cloud criteria at 1500, 1800, and 2100 UTC.
Figure 9: June 25, 2004 GOES satellite image (column two) compared to binary images (column one) based on cloud criteria at 1500, 1800, and 2100 UTC.
Figure 10: August 3, 2005 GOES satellite image (column two) compared to binary images (column one) based on cloud criteria at 1500, 1800, and 2100 UTC
Figure 11: October 24, 1998 GOES satellite image (column two) compared to binary images (column one) based on cloud criteria at 1500, 1800, and 2100 UTC.
Figure 12: October 24, 2000 GOES satellite image (column two) compared to binary images (column one) based on cloud criteria at 1500, 1800, and 2100 UTC.
Different cloud/non-cloud thresholds are found for each time interval to account for sun angle change throughout the day. There is more attenuation (increased atmospheric absorption) of the solar beam given a lower sun angle; therefore, the reflectance of a given surface is less intense than it would be at times with a higher sun angle.

It is unlikely that all clouds be accounted for based on this criteria due to variability in cloud thickness, cloud height, cloud shadowing from other clouds (affecting its albedo resulting in a lower reflectance value), and changes in sun angle throughout the season. However, visual inspection of all synoptically-weak days ensures that there is more error in under detecting clouds rather than over detecting clouds. Images where a grayscale is applied, compared to binary cloud images, capture the same spatial patterns of cloud cover. While testing numerous threshold values for each 1500, 1800, and 2100 UTC, binary cloud images remain consistent in showing the spatial distribution of cloud cover, however, the extent to which the edges of the cloud extend varies. With reasonable error in cloud detection, cloud patterns still persist. Again, visual inspection of each image ensures that cloud detection be underachieved than overachieved to be certain that what is coined as a cloud is indeed a cloud. It is unlikely that the exact cloud cut off be found for each image but rather represent the spatial orientation and distribution of clouds for each image.
3.3 Determining Cloud Cover Frequencies

3.3.1 Frequency Plots of Cloud Cover

Once reflectance values are decided based on the cloud/non-cloud criteria, all reflectance values within the domain that meet the cloud criteria are assigned a value of one while those reflectance values that meet non-cloud criteria are assigned a value of zero. This allows binary cloud databases to be constructed for 1500, 1800, and 2100 UTC. The number of times a number one (cloud) occurs is summed for each grid point across the domain and divided by the number of possible times a cloud could have existed at that particular grid point (all of the synoptically-weak days). This provides the percentage of days a cloud occurred at each grid point out of all synoptically-weak days within the study period. This allows for frequency plots to be created based on cloud frequency (percentage of synoptically-weak days that clouds exist at a given grid point) over the domain. Frequency plots are constructed for each time interval in the study period (1500, 1800, and 2100 UTC) to quantify the spatiotemporal distribution of cloud cover on synoptically-weak days.

3.3.2 Bootstrap Cloud Frequency Plots

To understand the spatial distribution and orientation of where cloud frequencies are highest, the bootstrap mean method is applied to all grid points across the domain. A bootstrap is used to estimate confidence intervals around a set of observed values (Wilks D.S., 2006). This set of observed values (i.e. cloud frequencies at each grid point) serve
as a sample from some larger population. The observed values are sampled with replacement (1,000 times) to generate bootstrap replicates representative of a mean population. To determine the significance of cloud frequencies across the study region, the bootstrap mean method is used to bootstrap the cloud frequencies at each grid point to generate bootstrap replicates of the average cloud frequency at each grid point. This allows 95% confidence intervals to be placed around the median bootstrap replicate. This is done for all grid points at 1500, 1800, and 2100 UTC to determine if distinct areas significantly (p < 0.05) differ among cloud frequency on synoptically-weak days. If the upper and lower 95% confidence limit for a particular grid points bootstrap replicates does not include the median of another grid points bootstrap replicates, those two grid cells are significantly (p < 0.05) different. Due to a large number of grid points across the domain, natural neighbor interpolation is applied to all grid point values across the domain in order to visually display the median, upper, and lower confidence limits. This allows for general regions in the study area to significantly (p < 0.05) differ from one another.

3.4 Regional Differences among Total Cloud Cover and Precipitation Received

3.4.1 Multi-sensor Precipitation Estimate Data

Multi-sensor precipitation estimates, derived from hourly WSR-88D data (Weather Surveillance Radar – 1988 Doppler) are used for precipitation analysis (Fulton et al., 1998; U.S. Department of Commerce, 2006b). Radar-based precipitation estimates
are useful while researching small-scale or intense precipitation variability because of their high spatial and temporal resolution. Despite the well known disadvantages of radar precipitation estimates (i.e. beam blockage, false return signal, truncation error) multi-sensor data are produced by combining hourly radar precipitation estimates (i.e., Stage I data), in the form of a digital precipitation array (DPA), with hourly surface-based observations from the hydrometeorological automated data system (HADS) network. The HADS network includes a number of different surface observations including the NWS ASOS/AWAS sites, to calculate a corrective mean field gauge-radar bias using a Kalman filtering approach, which is a local adjustment to the radar-derived precipitation field (Smith and Krajewski, 1991). These local adjustments, done for each individual radar coverage site, are used to correct radar-based precipitation estimates, called Stage II data. Finally a mosaic of Stage II data are used to create a continuous field of multisensory precipitation estimates named Stage III data by using the average or maximum of all available radar fields over a point chosen manually during quality control procedures done by the NWS river forecasters (Briedenbach et al., 1998; NOAA/NWS, 2007).

It should be noted that in recent years, the Office of Hydrologic Development (OHD) of the NWS has made a transition from the Stage III processing algorithms to the updated Multisensor Precipitation Estimator (MPE) algorithm. One notable difference between the Stage III and MPE algorithms is the ability to incorporate satellite-based precipitation estimation products (Kondragunta and Seo, 2004). Despite the inability of
having precipitation estimates based solely off of one algorithm, it should be noted that
the spatial variation in total rainfall remains the primary interest for this project rather
than the exact amount of precipitation; therefore, overall precipitation depth biases are
acceptable.

Stage III and multi-sensor precipitation estimates are provided by the NWS in
XMRG format, and are projected in the Hydrologic Rainfall Analysis Project (HRAP)
coordinate system. The HRAP coordinate system is a polar stereographic projection
centered at 60°N/105°W, with a nominal 4 × 4 km grid resolution. For the purposes of
this study, the multi-sensor precipitation estimates were decoded such that the latitude
and longitude of the respective HRAP grid cell center was associated with the
corresponding precipitation value.

3.4.2 Determining Regional Differences of Average Total Cloud Cover Received

To determine if the average total cloud cover differs among areas over land
(Maryland and the Delmarva Peninsula) or over the Chesapeake Bay, a bootstrap mean
method is applied to each of these areas separately. The bootstrap replicates represent the
average number of times a cloud occurs for all time intervals in the study (1500, 1800,
and 2100 UTC) at each grid point across a given area. Bootstrap replicates are simulated
for areas over land and again for areas over the Chesapeake Bay. The number of grid
points over the Chesapeake Bay differs from the number of grid points over land;
however, the bootstrap mean method yields 1,000 bootstrap replicates of the average
amount of cloud cover received over a given area per grid point; therefore, these data are normalized when using the bootstrap mean method. Once bootstrap replicates have been simulated for the land and again for the Chesapeake Bay, 95% confidence limits can be placed around the median of the bootstrap replicates. The bootstrap mean method is applied to both of these areas separately to determine if the two regions significantly (p < 0.05) differ in the average total cloud cover received (for each grid point). If the upper and lower 95% confidence interval placed around the median, of one areas bootstrap replicates, does not contain the median of another areas bootstrap replicates, those areas are significantly (p < 0.05) different from one another. Furthermore, the same method is applied to each state across the study region to determine if Maryland, Delaware, Virginia, or the Chesapeake Bay receives significantly (p < 0.05) different total cloud cover than any other(s).

3.4.3 Determining Regional Differences in Average Total Precipitation Received

To determine if the same areas receiving significantly (p < 0.05) different average total cloud cover, receive significantly (p < 0.05) different average total precipitation, hourly multi-sensor precipitation estimate data derived from hourly NEXRAD are used in applying a bootstrap mean method. Days when no precipitation data are recorded over the study area are not considered in further analysis. The bootstrap replicates represent the average total precipitation recorded for all time intervals in the study (1500, 1800, and 2100 UTC) at each grid point across all of the land in the study.
region and again for areas over the Chesapeake Bay. Upper and lower 95% confidence limits are placed around the median of the bootstrap replicates for those over the land and again over the Chesapeake Bay to determine if the land or the Chesapeake Bay receives significantly ($p < 0.05$) different average total rainfall amounts (aerial total precipitation differences).

The number of grid points over the Chesapeake Bay differs from the number of grid points over land, however the bootstrap mean method yields 1,000 bootstrap replicates of the average amount of total precipitation received over a given area per grid point; therefore, these data are normalized when using the bootstrap mean method. Furthermore, the same method is applied to each state across the study region to determine if Maryland, Delaware, Virginia, or the Chesapeake Bay receives significantly ($p < 0.05$) different average total precipitation than any other(s). This allows quantitative conclusions to be drawn based on the amount of precipitation that these regions receive on synoptically-weak days.
CHAPTER IV
RESULTS

4.1 Synoptically-weak Days Used for Cloud Cover and Precipitation Analysis
(1998-2006)

Data are available and meet synoptic criteria for 57 days within the study period, all of which are used in determining cloud frequencies across the domain. Twenty three of the 57 synoptically-weak days have recorded precipitation and are used in the precipitation analysis (Table 1).

Table 1: Number of synoptically-weak days and those with recorded precipitation within the study period

<table>
<thead>
<tr>
<th>Month</th>
<th>Number of Days that meet Synoptic Criteria</th>
<th>Number of Days with Recorded Precipitation</th>
</tr>
</thead>
<tbody>
<tr>
<td>May – June</td>
<td>23</td>
<td>8</td>
</tr>
<tr>
<td>July - August</td>
<td>20</td>
<td>10</td>
</tr>
<tr>
<td>September - October</td>
<td>14</td>
<td>5</td>
</tr>
</tbody>
</table>
4.2 Frequency Plot Analysis of Cloud Cover on Synoptically-weak Days

Frequency plots are made for each 1500, 1800, and 2100 UTC based on cloud/non-cloud criteria (Figure 13). To help in the identification of pointing out areas across the study region that received noticeably different amounts of cloud cover generalized areas have been circled that are of particular interest at 1500 UTC (Figure 14).

The specific values (each individual grid point) associated with each region are not exact but rather a general representation of the overall characteristics of that region. The middle of the Delmarva Peninsula (region C) has the highest percentage ($\approx 31.6 - 33.7\%$) of cloud frequencies across the region at 1500 UTC on synoptically-weak days. While areas in north-western shore of Maryland (region A) have a few areas that receive higher frequencies, the general area receives approximately $24.9 - 27.0\%$ of cloud cover on synoptically-weak days. South of region A, just north of the District of Columbia (region B) receives a lower ($\approx 13.7 - 15.8\%$) percentage of cloudy days. The lowest frequencies across the study domain ($9.2 - 11.4\%$) are found over the southern portions of the Chesapeake Bay (region D).
Figure 13: Frequency plots of cloud cover across Maryland and Delmarva Peninsula for all (57) synoptically-weak days at 1500, 1800, 2100 UTC, respectively
Figure 14: Particular regions of interest across the study area at 1500 UTC to help identify areas where clouds differ in frequency.

Furthermore, the frequency plot at 1800 UTC shows an even lower frequency (≈ 4.8 – 7.0 %) for clouds to exist over the southern portions of the Chesapeake Bay (region D) (Figure 15). The highest frequencies (≈ 31.6 – 33.7 %) are found just north of Baltimore, MD (region B). When compared to the southern portions of the Chesapeake Bay (region D), the area along the Atlantic Ocean (region C) continues to receive higher (≈ 22.6 – 24.8%) frequencies for clouds cover. This could be related to an increase in the thermal gradient between the Delmarva Peninsula and the Atlantic Ocean as daytime.
heating has likely contributed to a higher increase in temperature over the land. Region B (north of District of Columbia) at 1500 UTC is similar to region A (north of District of Columbia) at 1800 UTC, while both regions receive clouds approximately 13.7 – 15.8% of the time on synoptically-weak days.

![Map showing cloud cover percentages](image)

Figure 15: Particular regions of interest across the study area at 1800 UTC to help identify areas where clouds differ in frequency

By 2100 UTC the highest frequency for clouds to exist is over the western shore of Maryland (region A) which is approximately 38.3 – 40.0% of the time (Figure
16). Just south of region A, region B (southeast of the District of Columbia) has a much lower frequency (≈ 20.4 – 22.5%) for clouds to exist. There remains a relatively higher (≈ 31.6 – 33.7%) frequency for clouds to exist near the east coast of the Delmarva Peninsula (region C). Again, frequencies over the southern region of the Chesapeake Bay (region D) receive the lowest (≈ 11.5 – 13.6%) frequency of cloud cover across the study region.

Figure 16: Particular regions of interest across the study area at 2100 UTC to help identify areas where clouds differ in frequency
4.3 **Bootstrap Mean Frequency Analysis of Cloud Cover on Synoptically-weak Days**

To gain a better understanding of the significance of these cloud frequencies, a bootstrap mean method is applied to the cloud frequencies at each grid point across the domain. This series of maps provide a quantitative description of the frequency and spatiotemporal extent of these cloud patterns, adding insight into when and where they are more likely to develop.

4.3.1 **Cloud Frequencies at 1500 UTC**

The following frequency plots are made for 1500 UTC to display the upper and lower 95% confidence limits around the median bootstrap replicate of cloud frequency for each grid point (Figure 17).

At 1500 UTC cloud frequencies are significantly (p < 0.05) higher for region C (mid-Delmarva) than regions D (southern half of the Chesapeake Bay) and B (north of District of Columbia) (Table 2). Furthermore, region A (the northern half of the western shore of Maryland) has significantly (p < 0.05) higher frequencies than region D (southern half of the Chesapeake Bay) (Table 2).
Figure 17: Upper and lower 95% confidence limits placed around the median frequency for clouds to exist at 1500 UTC (percentage)
Table 2: General upper and lower 95% confidence limits placed around the median of mean frequencies for clouds to exist at regions depicted in Figure 17

<table>
<thead>
<tr>
<th>Region (1500 UTC)</th>
<th>Lower confidence limit</th>
<th>Median</th>
<th>Upper confidence limit</th>
</tr>
</thead>
<tbody>
<tr>
<td>A (N. western shore)</td>
<td>17.0 – 19.7 %</td>
<td>27.9 – 30.6 %</td>
<td>41.6 – 44.2 %</td>
</tr>
<tr>
<td>B (N. of D.C.)</td>
<td>8.9 – 11.5 %</td>
<td>17.0 – 19.7 %</td>
<td>27.9 – 30.6 %</td>
</tr>
<tr>
<td>C (Mid-Delmarva)</td>
<td>19.8 – 22.4 %</td>
<td>27.9 – 30.6 %</td>
<td>41.6 – 44.4 %</td>
</tr>
<tr>
<td>D (S. Chesapeake Bay)</td>
<td>3.4 – 6.0 %</td>
<td>14.3 – 16.9 %</td>
<td>19.8 – 22.4 %</td>
</tr>
</tbody>
</table>

4.3.2 Cloud Frequencies at 1800 UTC

The following frequency plots are made for 1800 UTC to display the upper and lower 95% confidence limits around the median of mean cloud frequencies at each grid point (Figure 18).
Figure 18: Upper and lower 95% confidence limits placed around the median frequency for clouds to exist at 1800 UTC (percentage)
Table 3: General upper and lower 95% confidence limits placed around the median of mean frequencies for clouds to exist at regions depicted in Figure 18

<table>
<thead>
<tr>
<th>Region (1800 UTC)</th>
<th>Lower confidence limit</th>
<th>Median</th>
<th>Upper confidence limit</th>
</tr>
</thead>
<tbody>
<tr>
<td>A (N. of D.C.)</td>
<td>6.1 – 8.8 %</td>
<td>17.0 – 19.7 %</td>
<td>25.2 – 27.8 %</td>
</tr>
<tr>
<td>B (N. of Baltimore)</td>
<td>19.8 – 22.4 %</td>
<td>27.9 – 30.6 %</td>
<td>41.6 – 33.2 %</td>
</tr>
<tr>
<td>C (east coast Delmarva)</td>
<td>19.8 – 22.4 %</td>
<td>27.9 – 30.6 %</td>
<td>41.6 – 44.2 %</td>
</tr>
<tr>
<td>D (S. Chesapeake Bay)</td>
<td>0.6 – 3.3 %</td>
<td>3.4 – 6.0 %</td>
<td>11.6 – 14.2 %</td>
</tr>
</tbody>
</table>

Cloud frequencies are significantly (p < 0.05) higher for regions B (north of Baltimore, Maryland) and C (east coast of the Delmarva Peninsula) than for regions A (north of the District of Columbia) and D (southern half of the Chesapeake Bay) (Table 3). Furthermore, region A (north of the District of Columbia) has a significantly (p < 0.05) higher frequency range than does region D (southern half of the Chesapeake Bay) (Table 3).

### 4.3.3 Cloud Frequencies at 2100 UTC

The following frequency plots are made for 2100 UTC to display the upper and lower 95% confidence limits around the median of mean cloud frequencies at each grid point (Figure 19).
Again region D (southern half of the Chesapeake Bay) has a significantly ($p < 0.05$) lower frequency than do regions A (northern half of the western shore of Maryland) and C (east coast of the Delmarva Peninsula) (Table 4). Furthermore, region A (northern half of the western shore of Maryland) has a significantly ($p < 0.05$) lower frequency than does region B (southeast of the District of Columbia) (Table 4).

Regions where clouds are most likely to exist undoubtedly vary by time of day. Despite the inability to determine the underlying causes of these preferred cloud locations, primarily due to the complexity in land characteristics over the study region, results indicate that localized convection follows definite spatial patterns during synoptically-weak days. Results of the bootstrap mean frequencies show similar spatial patterns in the distribution for cloud existence as the frequency plots reveal over the study region. A few single images captured at 2100 UTC verify this spatial pattern (Figure 20, 21).
Figure 19: Upper and lower confidence limit of the 95% confidence interval placed around the median frequency for clouds to exist at 2100 UTC (given in percentage)
Table 4: General upper and lower 95% confidence limits placed around the median of mean frequencies for clouds to exist at regions depicted in Figure 19

<table>
<thead>
<tr>
<th>Region (2100 UTC)</th>
<th>Lower confidence limit</th>
<th>Median</th>
<th>Upper confidence limit</th>
</tr>
</thead>
<tbody>
<tr>
<td>A (N. western shore)</td>
<td>27.9 – 30.6 %</td>
<td>38.8 – 41.5 %</td>
<td>52.5 – 55.1 %</td>
</tr>
<tr>
<td>B (SE of District of Columbia)</td>
<td>11.6 - 14.2 %</td>
<td>19.8 – 22.4 %</td>
<td>30.7 – 33.3 %</td>
</tr>
<tr>
<td>C (east coast Delmarva)</td>
<td>17.0 – 19.7 %</td>
<td>27.9 – 30.6 %</td>
<td>41.6 – 44.2 %</td>
</tr>
<tr>
<td>D (S. Chesapeake Bay)</td>
<td>3.4 – 6.0 %</td>
<td>6.1 – 8.8 %</td>
<td>19.8 – 22.4 %</td>
</tr>
</tbody>
</table>
Figure 20: GOES satellite image (top), binary cloud image (bottom, cloud ≥5000) on May 30, 1999 at 2100 UTC
Figure 21: GOES satellite image (top), binary cloud image (bottom, cloud \( \geq 5000 \)) on June 05, 2005 at 2100 UTC
4.4 Regional Differences in Total Cloud Cover and Total Precipitation Received

4.4.1 Aerial Bootstrap Mean of Total Amount of Cloud Cover

Based on the 95% confidence limits placed around the median of the average total number of times a cloud occurs at either 1500, 1800, or 2100 UTC, the land receives significantly (p < 0.05) higher total cloud cover than does the Chesapeake Bay (Figure 22).

Furthermore, Maryland, Delaware, Virginia, and the Chesapeake Bay all receive significantly (p < 0.05) different average total cloud cover (Figure 23). Delaware receives significantly (p < 0.05) higher average total cloud cover than does any other region (43.2 – 43.6 times out of 171). Maryland receives the next to highest average total cloud cover (40.2 - 40.6 times out of 171 (57 days times 3 time intervals)) and Virginia receives between 23.7 and 24.4 times out of 171 possible. The Chesapeake Bay significantly (p < 0.05) receives the least amount of average cloud cover (22.0 – 22.5 times out of 171).
Figure 22: Upper and lower 95% confidence intervals placed around the median of aerial means of total cloud cover over the Chesapeake Bay and over all of the land in the study area.
Figure 23: Upper and lower 95% confidence intervals placed around the median of aerial means of total cloud cover over the Chesapeake Bay, Maryland, Delaware, and Virginia.
4.4.2 Aerial Bootstrap Mean of Total Amount of Precipitation

From the 57 synoptically-weak days, 25 days had no recorded precipitation while 23 days had recorded precipitation. The remaining 9 days had incomplete precipitation datasets and therefore are not used in this study. Results reveal that the Chesapeake Bay receives significantly less average total precipitation for all time intervals in the study than does the land (Figure 24).

The same method is applied to the different locations across the study region including, the Chesapeake Bay, Maryland, Delaware, and Virginia to determine if any one of these regions receive significantly (p < 0.05) different amounts of precipitation than any other region or regions (Figure 25).
Figure 24: Upper and lower 95% confidence intervals placed around the median of aerial means of total precipitation over the Chesapeake Bay and over all of the land in the study area.
The Chesapeake Bay region receives significantly (p < 0.05) less total precipitation on synoptically-weak days than does Maryland or Delaware. Furthermore, Delaware receives significantly (p < 0.05) more rainfall than both the Chesapeake Bay and Maryland. Virginia does not receive a significantly (p < 0.05) different amount of rainfall than do surrounding areas. Comparatively, total average cloud cover follows the same pattern as total average precipitation when comparing the amounts received among
Maryland, Delaware, and the Chesapeake Bay. The only region that does not follow this same pattern is Virginia, which is mostly due to the variations in intensity and total rainfall that this small region receives. This allows quantitative conclusions to be drawn based on the average amount of cloud cover and precipitation that these regions receive on synoptically-weak days.
Overall, cloud cover is more frequent over the land versus the Chesapeake Bay. This is not surprising as cumulus convection is more likely to initiate over a warmer surface (i.e. land). However, preferred locations for clouds to exist reveal unique spatial clustering. Pielke (1974) suggest that preferred locations of cumulus clouds are strongly influenced by some mesoscale boundary. This presents a challenge in determining whether or not these cloud patterns are the result of cumulus convection alone or cumulus convection enhanced by mesoscale convergence.

Strong consideration should be given to the convex nature of the coastlines on both the eastern and western sides of the Delmarva Peninsula. Convex coastline curvature support stronger convergence, (Baker et al., 2000; McPherson, 1970) and may provide evidence for cumulus convection enhanced by mesoscale convergence and support the significant cloud frequencies over this area at 1800 UTC (Figure 26).

The higher cloud frequencies found on the eastern side of the Delmarva Peninsula as opposed to the western side could be explained by what Pielke and Baker et al. (1974, 2000) found which suggests that stronger convergence occurs when low level prevailing winds are in opposition to the winds produced by a sea breeze. In this case, synoptically-weak flow, calm and from the west, opposes the sea breeze flow pattern (from the east)
causing stronger convergence at the surface creating an increase in upward vertical velocities which affect the dynamic environment.

Other consideration should be given to the influence of the sea-breeze induced by the Atlantic Ocean. Findings proposed by Pielke (1974) suggest that preferred locations of cumulus clouds over south Florida are strongly controlled by sea-breeze circulations. Due to changes in the thermodynamic field of the boundary layer, the dynamics and thermodynamics of any cumulus clouds that form are significantly influenced by these changes (Pielke, 1974). Therefore, the increase in cloud frequency along the east coast of the Delmarva Peninsula at 1800 UTC, as well as Delaware having the highest average total cloud cover, is likely supported by stronger convergence caused by the sea-breeze over this area (Figure 27, 28).
Figure 26: GOES satellite image (top), binary cloud image (bottom, cloud ≥5000) on June 05, 2005 of possible influence from convex coastline
Figure 27: GOES satellite image (top), binary cloud image (bottom, cloud ≥5000) on June 08, 2004 at 2100 UTC showing a possible sea breeze convective boundary
Figure 28: GOES satellite image (top), binary cloud image (bottom, cloud ≥5000) on July 22, 2002 at 2100 UTC showing a possible sea breeze convective boundary

Cumulus convection proves to be significantly (p <0.05) more frequent over the northern half of the western shore of Maryland while areas just south receive
significantly lower frequencies. These differences in cloud frequencies are likely due to differences in the sensible rather than latent heat flux. The northern half of the western shore is characterized by hay pastures which receive little to no irrigation while areas south are characterized by mixed forests that also receive little or no irrigation during the warm season. Reductions in vegetation density (which can be found across the northern half of the western shore of Maryland characterized by hay/pasture land cover), decrease evapotranspiration rates and increase the effects of the sensible heat fluxes (Segal et al. 1998). This increase in the sensible heat flux likely contributes to the higher cumulus convection found over this area. While areas just south are characterized by mixed forests suggesting denser vegetation, higher evapotranspiration rates and lower sensible latent heat fluxes. The decrease in the sensible heat flux found over areas south of the District of Columbia, may contribute to the lower frequencies in cloud cover.

Precipitation analysis provides significant (p < 0.05) evidence for higher average total precipitation amounts over land when compared to areas over the Chesapeake Bay with the highest average precipitation totals found over Delaware. Baker et al. (2000) uses computer simulations to show the most intense convergence and upward motion caused by the sea breeze convergence zone would also be a preferred location for convective rainfall. If we assume stronger convergence on the west coast of the Delmarva Peninsula to be caused by a combination of opposing low-level prevailing winds, convex curvature, and the sea-breeze, it is not surprising then that the highest average precipitation totals exist over Delaware. Baker et al. (2000) supports coastline curvature
as being a primary factor in determining rainfall intensity. The convex coastline on the eastern side of the Delmarva Peninsula supports stronger surface convergence which has been shown to determine the total rainfall amount (Figure 29) (Baker et al. 2000). Furthermore, Baker et al. (2000) confirms that the heaviest precipitation occurs over wet soil. As noted earlier, land cover over the Delmarva Peninsula consists mainly of cultivated crops and is heavily irrigated during the warm season. Evaporation (latent heat flux) from the wet soil contributes to an increase in boundary layer moisture which increases the convective available potential energy (CAPE) (Baker et al. 2000). In increasing the saturation mixing ratio, due to the evaporation, the lifted condensation layer (LCL) becomes lower. These findings by Baker et al. (2000) may provide insight as to why the highest average precipitation totals are found over Delaware.

While coastline curvature, particularly convex coastlines, provide a focal point for the strongest convergence to exist towards the center of the peninsula, days influenced by a typical sea breeze phenomena likely adds to the higher recorded precipitation over this area as well (Figure 30).
Figure 29: Total precipitation for 1500, 1800, and 2100 UTC on June 10, 2005 possibly caused by stronger convergence over the Delmarva Peninsula.
There is more variability among rainfall totals over Virginia when compared to those areas over Delaware. Delaware is a larger land mass which heats faster than the smaller land mass to the south (southern tip of the Delmarva Peninsula/Virginia). Therefore, stronger convection and thermals act in a more predictable fashion while compared to areas that support weaker convection (to the south) that are surrounded by
larger bodies of water, and have a more variable chance for precipitation as depicted by this example from a day within the study period (Figure 32).

Figure 31: Total precipitation for 1500, 1800, and 2100 UTC on September 01, 2000 possibly caused by a double sea breeze which would support stronger convergence
The land heats faster than the surrounding water on synoptically-weak days during the warm season creating relative low pressure over the Delmarva Peninsula. Due to rising air over land, the air at the surface must be replaced by surrounding areas (areas that are over a moist environment; Chesapeake Bay and Atlantic Ocean). This replacement of moist air on both sides of the Delmarva Peninsula may also explain higher total precipitation rates over Delaware (Figure 33).

In opposition to these areas that see a high frequency in cloud cover and precipitation on synoptically-weak days, large bodies of water such as the Chesapeake Bay heat up slower than the surrounding land (given that all synoptically-weak days in the study period occur in the warm season). The lack of cloud cover over the Chesapeake Bay is likely due these thermal differences and lack of surface convection/convergence. Even those areas where rivers extend inland see relatively less cloud cover then adjacent land areas.

Undoubtedly there are many reoccurring themes of cloud cover as well as precipitation across the study region. There are seemingly multiple explanations as to why these boundaries set up; however, the recognition of such patterns will allow forecasters to gain insight into weather phenomena caused by local effects. These localized areas of cloud cover and precipitation are unlikely to be identified by everyday meteorological model output data such as the North American Mesoscale (NAM) model of the Global Forecast System (GFS) model due to limitations in model resolution, and therefore require individual diagnosis from the research community.
Figure 32: Total precipitation for 1500, 1800, and 2100 UTC on June 09, 2005 possibly caused by a double sea breeze which would support stronger convergence.
CHAPTER VI

CONCLUSIONS

Maryland and the Delmarva Peninsula region present a unique set of surface characteristics that may influence convective weather patterns, specifically cloud cover and precipitation, on synoptically-weak days. This region contains five physiographic provinces and can be identified by many contrasting surface characteristics of land cover, land use, coastline curvature, and soil type (USGS, 2010). Surface heterogeneities are recognized to cause differential heating that can generate mesoscale convective boundaries, sometimes leading to cloud development and enhanced localized precipitation. In order to improve the quality of mesoscale convective cloud and precipitation forecasting, it is important to identify the spatial distribution of known weather patterns.

This research suggests that certain geographic locations are more susceptible to cloud cover than others. Furthermore, precipitation patterns follow this same regional distribution. The direct cause of this preferred pattern is unknown; however is supported by ideas found in current literature. Locations along the eastern sea board of the Delmarva Peninsula and on the western shore of Maryland, receive significantly more frequent cloud cover than locations over the Chesapeake Bay and even southern half of the Delmarva Peninsula on synoptically-weak days.
Exploratory research across this domain was necessary in providing a starting point for understanding the underline cause of the preferred cloud pattern associated with synoptically-weak days over Maryland and the Delmarva Peninsula. While the influence of the Chesapeake Bay on weather phenomenon is greatly supported by local communities throughout the area, the research community has not provided significant evidence.

Future research is needed to determine if underlying surface characteristics, if any, influence the thermodynamic environment of this area. Computer simulations could be used to analyze thermodynamic variables such as surface wind speed and direction, temperature, dewpoint, environmental lapse rates, and instability over the domain on synoptically-weak days. Soil moisture, land cover, and land use could also be investigated using numerical weather prediction models. Local effects from the Chesapeake Bay, coastline curvature, irrigation systems, and major metropolis areas provide a number of variables to be analyzed to better understanding the unique nature of weather phenomena, on synoptically-weak days, over this study region.
REFERENCES


