The Pennsylvania State University

The Graduate School

Department of Educational Psychology, Counseling, and Special Education

SEASONAL AFFECTIVE DISORDER: ILLUMINATING THE LATITUDE HYPOTHESIS

A Dissertation in

Counseling Psychology

by

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Submitted in Partial Fulfillment
of the Requirements
for the Degree of

Doctor of Philosophy

December, 2015

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ABSTRACT

The present study investigated the relationship between meteorological variables and depressive symptoms. More specifically, we explored the effects of time of year (hours of daylight, or photoperiod, will serve as a proxy measure for time of year) and cloud cover (irradiance measures from surface radiation budget sites across the United States) on depression scores in both treatment and non-treatment seeking samples of college students. Previous research into the latitude gradient has neglected important environmental factors that can influence the level of light a person experiences day-to-day. We hypothesized that time of year and cloud cover would be inversely related to depression scores. The results failed to support the hypotheses, which is later discussed in greater detail.

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Acknowledgments

A heartfelt thank you my family, friends and graduate school mentors. A special thanks to Larry Page, Sergey Brin, Chad Hurley, Steve Chen, and Jawed Karim. And finally, not a single thank you goes to the "I love lamp" fantasy football league – to be clear, this dissertation was, *in no way*, made possible by any of my fellow lamp-leaguers.

Chapter 1

Seasonal Affective Disorder (SAD) was originally defined in 1984 as “recurrent depressions that occur annually at the same time each year” (Rosenthal et al., 1984). Some SAD scholars suggest that, since 1984, SAD has “become virtually synonymous with winter depression as the vast majority of seasonal depressions occur in the fall/winter period” (Danilenko & Levitan, 2012, p. 279). Neither the *Diagnostic and Statistical Manual of Mental Disorders*, 5th edition, (DSM-V; American Psychiatric Association, 2013), nor the *International Statistical Classification of Diseases and Related Health Problems*, 10th revision (ICD-10; World Health Organization, 2008) classify SAD as a distinct diagnostic entity. Rather, a seasonal pattern specifier can be used in conjunction with major depressive disorder and bipolar I or II in the DSM-V (APA, 2013). The ICD-10 also offers provisional diagnostic criteria for both seasonal depression and bipolar disorders (WHO, 2008).

The behavioral symptoms of SAD include hypersomnia, increased appetite, and weight gain. These symptoms are often labeled “atypical” because they are the reverse of the neurovegetative symptoms observed in non-seasonal depression (Rosenthal et al., 1984). Depressed moods in SAD tend to be mild to moderate, and more severe depressive episodes following a seasonal pattern are sometimes indicative of the depressive component observed in a bipolar cycle (Goel et al., 2002). Danilenko and Levitan (2012) note that early studies found a high rate of bipolar diagnoses with a seasonal pattern, but attribute this phenomenon to the “lenient criteria for hypomania present at that time” (p. 279), and conclude that a minority of individuals with seasonal depression would be considered truly bipolar, today.

Early studies found the prevalence of SAD to range from 4% to 9% in United States samples (e.g., Kasper, Wehr, Bartko, Gaist, & Rosenthal, 1989; Rosen et al., 1990). These early prevalence studies, however, used the Seasonal Pattern Assessment Questionnaire (SPAQ; Magnusson, 1996) as a diagnostic instrument. Since then, researchers have cautioned against using the SPAQ to diagnose SAD, as it provides misleadingly high estimates of prevalence (Thompson & Cowan, 2001). More conservative, and likely more accurate, estimates ranging from 1% to 2.5% were reported in studies that utilize structured interviews based on relevant *seasonal pattern* criteria (e.g., APA [DSM-III-R], 1987; APA [DSM-IV], 2000; e.g., Blazer, Kessler, & Swartz, 1990; Michalak, Wilkinson, Dowrick, & Wilkinson, 2001; Murray, Allen, & Trinder, 2001).

In their review, Magnusson and Boikin (2003) reported that a majority of studies found SAD to be more common among females than males. Although some studies reported the opposite within their respective samples, the average female to male ratio across studies was shown to be 1.8:1 (Magnusson & Axelsson, 2003). Thus, from a global perspective, females and males are differentially susceptible to SAD, and the evidence suggests females incur the highest risk.

The incidence of SAD varies across developmental periods. Although seasonal depression can present in children and older adults (e.g., Carskadon & Acebo; Eagles et al., 1999), the highest incidence is repeatedly found in persons 20 to 30 years of age (e.g., Imai, Kayukawa, Ohta, Li, & Nakagawa, 2003; Low & Feissner, 1998; Magnusson, 1998; Sourander, Koskelaineu, & Helenius, 1999). As such, there exists a general consensus that individuals between 20 and 30 years of age are most susceptible to the affective dysregulation that follows a seasonal pattern (Magnusson & Boivin, 2003).

In summary, the most conservative estimates of prevalence range from 1% to 2.5% across studies using diagnostic interviews, as opposed to the 4% to 9% across studies using the SPAQ as a diagnostic instrument. The estimates derived from structured interviews likely represent more accurate estimates given the questionable psychometrics of the SPAQ (Mersch, 2001). Further, females are more likely to receive a mood disorder diagnosis with the *seasonal pattern* specifier than their male counterparts (female: male = 1.8:1; Magnusson & Boikin, 2003). Finally, the onset of seasonal depression can occur during childhood, adolescence, or adulthood, with individuals twenty to thirty years of age shown to be most susceptible to the deleterious effects of seasonality (Magnusson & Boivin, 2003). Taken cumulatively, an estimated 1% to 2.5% of the general population suffers from a subtype of depression following a seasonal pattern, and females between 20 and 30 years of age incur the greatest risk.

Although the biological substrates of SAD are currently unknown, potential pathophysiological explanations include, broadly, circadian rhythm disruptions (e.g., Lam & Levitan, 2000), atypical neurotransmitter activity (e.g., Herbert, Beattie, Tam, Yathan, & Lam, 2004), and genetic predispositions (e.g., Sher, Goldman, Ozaki, & Rosenthal, 1999). Many scholars have attempted to uncover the biological substrates of SAD, but there are no universally agreed upon pathophysiological explanations. There is, however, a general consensus that decreased winter light can trigger a biological response that is phenotypically expressed as psychological depression. Stated another way, decreased light in winter is the common context under which each proposed mechanism operates. Because daylight hours (photoperiod) decrease with increases in northern latitude, it stands to reason that the prevalence of seasonal depression should increase with increases in northern latitude. This notion is commonly referred to as "the latitude hypothesis," but evidence to support the theory is mixed.

Some researchers have found a clear and distinct latitude gradient across which seasonal depression is more prevalent at higher northern latitudes (e.g., Carskadon & Acebo, 1993; Magnusson & Axelsson, 1993; Rosen et al., 1990). In contrast, other researchers who have examined the latitude hypothesis have found no difference in depressive symptoms across latitudes (e.g., Blazer, Kessler, & Swartz, 1998; Levitt & Boyle, 2002; Murray & Hay, 1997). The inconsistent findings have prompted some to describe the latitude gradient as "an important wanting in the validity of SAD" (Magnusson & Boikin, 2003, p. 197), whereas others have turned strong and harsh criticism on the SAD construct itself (e.g., Hansen, Skre, & Lund, 2008). A more moderate position to explain the discrepant findings is that latitude only serves as an indirect measure of light (Magnusson & Partonen, 2005).

While latitude and photoperiod are the dominant factors in establishing a risk to seasonal depression, other local factors, such as cloudiness, air pollution, and shading by buildings all contribute to the amount of sunlight to which an individual is exposed (Danilenko & Levitan, 2012). The present study investigated the local environmental factor of cloud cover as it relates to depressive symptoms in a college student population.

The college student population is understudied in the SAD literature (Agumadu et al., 2004; Low & Feissner, 1998). The scarcity of college student representation is especially curious considering they primarily attend school during the time of year when sunlight is at a minimum in the Northern Hemisphere. Further, considering the finding that prevalence seems to be especially high among young adults, seasonal changes in mood could negatively impact academic performance (e.g., lack of motivation), as well as other important aspects of college students' lives (e.g., social interaction).

The present study will investigate the effects of time of year (hours of daylight, or photoperiod, will serve as a proxy measure for time of year) and cloud cover (irradiance measures from SURFRAD sites) on depression scores in both treatment and non-treatment seeking samples of college students. Previous research into the latitude gradient has neglected important environmental factors that can influence the level of light a person experiences day-to-day. This study will add to the current body of literature by measuring the environmental factor of cloud cover. We hypothesize that time of year and cloud cover will account for variation in depression scores. More specifically, time of year and cloud cover will be inversely related to depression scores.

Chapter 2

Seasonal Affective Disorder: Illuminating the Latitude Hypothesis

Seasonal Mood Variation: A Historical Perspective

Relatively recently, researchers at the National Institute of Mental Health (NIMH) coined the term Seasonal Affective Disorder (SAD) to describe fluctuations in mood and behavior that varied with the changing seasons (Rosenthal et al., 1984). Rosenthal and colleagues (1984) were the first to systematically describe the seasonality phenomenon and subsequently offered an empirically grounded clinical constellation of the construct. Further, their work was instrumental in generating widespread interest in the topic within the scientific community. The Rosenthal group can be considered pioneers in the systematic study of SAD, but the notion that a depressed mood might follow a seasonal pattern is neither new nor novel. For the purpose of perspective, the following discussion begins with those who came before the Rosenthal group. The time-period is vast and the disciplines are diverse, but the evidence converges to construct a compelling case that seasonal mood variation (seasonality) has been a topic of interest throughout human history. The modern science on this frontier, prompted by Rosenthal and colleagues (1984), appears to be confirming what ancient philosophers, physicists, physiologists, and psychologists have proposed across the centuries. The nature of such propositions ranges from anecdotal to empirical, but, taken cumulatively, they are representative of humanities' long-standing interest in seasonal mood variation.

Pre-SAD Seasonality: An Anecdotal Account

Early observations to describe concomitantly changing seasons and moods are strewn throughout classical texts dating back thousands of years. Hippocrates is credited with being the first to observe a relationship between depression and time of year. Over two thousand years ago, he noted: “It is chiefly the changes of the seasons which produce diseases” (Rosenthal, 1998, p. 276). In other words, the father of modern medicine attributed the etiology of all disease to the changing seasons (Wehr & Rosenthal, 1989). In the second century A.D., Aretaeus suggested that “lethargics” cure their disease of gloom by laying in the rays of the sun (Rosenthal, 1998).

Whereas Hippocrates described an all-inclusive relationship between seasonality and illness (i.e., physical and/or mental), Aristotle and Posidonius confined their observations to the emotional realm. For example, Posidonius observed that melancholy occurred in autumn, while mania was normally seen in the summer months. Aristotle postulated a causal relationship between extreme cold and groundless despondency, followed by the behavioral consequence of suicide by hanging. The writings of Esquirol, an eighteenth century psychiatrist, echo the sentiments of Posidonius. In some individuals, he observed a state of prostration or agitation during the summer months, and the opposite condition during the winter months (Wehr & Rosenthal, 1989). It was not, however, solely ancient thinkers (e.g., Hippocrates, Aretaeus, Aristotle, Posidonius) or early psychiatrists (e.g., Esquirol) who observed seasonal mood change. Rosenthal (1998) provides three clinical cases, ranging from the late seventeenth to the mid-twentieth centuries that exemplify a convergence of observations by mental health professionals.

Two physicians, Taylor and Wittie (1670), documented their patients’ mood states longitudinally. Anne Greenville, their patient, oscillated between seasonally based bouts of mania and depression. The course of Mrs. Greenville’s symptoms were well documented, particularly her propensity for mania during the summer months (Rosenthal, 1998).

In the second example, Rosenthal (1998) describes a case from the work of an eighteenth/nineteenth century psychiatrist, Esquirol. The patient, known only as "M," reported a tendency toward sadness and gloom at the beginning of autumn, and that his "affections revive" (Rosenthal, 1998, p. 280) as spring approached. Particularly interesting is Esquirol's chosen treatment approach and the consequent success of the atypical method. In lieu of hospitalization, the French psychiatrist recommended "M" travel from September until May in order to escape the cold. The patient diligently followed Esquirol's prescription. After the nine-month hiatus, "M" returned to Paris in May "in the enjoyment of excellent health" (Rosenthal, 1998, p. 280).

The third, and most recent (i.e., 1946), case illustration comes from a psychoanalyst working in the United States. Though Rosenthal dismisses Dr. Frumko's analytic case conceptualization and approach to treatment as "convoluted psychoanalytic interpretation" (p. 283), the patient's reported symptoms bear striking resemblance to what has come to be known as SAD. The patient, for example, reported seasonally based symptoms of depression that onset in the autumn and winter months, and spontaneously remitted each spring and summer. At the time of the report, the patient had endured this seasonal cycle for ten years (Rosenthal, 1998).

Though the preceding case examples carry both intrigue and historical import, they function only anecdotally. They are simply case illustrations, not empirical inquiries. As such, each is devoid of systematic control and any conclusion must be constructed with a judicious degree of restraint. For example, the above cases simply illustrate that, across three centuries (i.e., 1670, 1825, and 1946), patients' seasonally based depressive symptoms (and manic episodes; i.e., the case of Mrs. Greenville) resemble certain aspects of the contemporary construct called SAD. In sum, these cases do not incrementally influence, nor improve, the construct validity of SAD; rather, they simply serve as historical evidence to suggest that although SAD was not formally described until 1984 (Rosenthal et al.), a seemingly similar phenomenon was observed, albeit informally, by mental health professionals many centuries prior. The empirical study of seasonal mood variation yields another class of information altogether. The following section turns to the empirical study of seasonally based mood fluctuations.

Pre-SAD Seasonality: An Empirical History

It was not until the twentieth century that researchers began to empirically investigate the speculations of ancient thinkers. Huntington (1938) reported a series of European studies that tended to support observations of the past. Approximately twenty years later, Kraines (1957) identified a significant peak in hospital admissions for depression during the month of September. Although these studies showed associations between the changing seasons and shifts in mood, they were criticized for their use of small samples and imprecise terminology (e.g., Eastwood & Stiasny, 1978).

In 1978, Eastwood and Stiasny aimed to improve upon these methodological shortcomings. Their study investigated a six-year period (1969-1974), utilized admissions data from Ontario psychiatric hospitals (42° N - 55° N latitude), grouped admissions frequencies by season (defined by solstices and equinoxes), and subdivided the sample by age (16-25, 26-35, 36-45, 46-55, 56-65, and 66^{+}). These researchers found that 'neurotic depressions' were higher in the fall and lower in the summer than expected.

Generally, the results demonstrated that hospital admissions for neurotic depression showed significant seasonal variation over a six-year period. This study represents the first methodologically rigorous research resulting in empirical evidence to support the existence of a relationship between season and depression.

Shortly thereafter, Frangos (1980) investigated the relationship between seasonality and affective psychosis. The results revealed an increase in depressive episodes from May through August, with the fewest episodes observed in November. Manic episodes peaked in May. As with depressive episodes, the fewest instances of mania occurred in November. The descriptive studies to document seasonal fluctuations in manic and depressive episodes (i.e., Eastwood & Stiansy, 1978; Frangos, 1980) were among the very few empirical efforts focused on the relationship between weather and mood. Some research, also falling under the umbrella of seasonal mood change, sought to extend the knowledge base by asking a more analytic question: What specific climactic variables account for the seasonality phenomenon?

Persinger (1975) investigated the utility of several climactic variables to explain seasonal mood fluctuations. The variables of interest included temperature, barometric pressure, relative humidity, sunshine hours, wind speed, and global geomagnetic activity. He found that lower moods were associated with fewer sunshine hours, higher relative humidity, and smaller humidity variations. However, the sample comprised only ten participants, and generalizations based solely on these results are indefensible.

Sanders and Brizzolara (1982) then conducted a study in response to Persinger (1975). These researchers criticized the small sample size in Persinger (1975), yet only increased their own sample by twenty participants ($n = 30$). Therefore, their findings that relative humidity was strongly inversely correlated with vigor, social affection, and elation must be interpreted with caution.

In each of the above-mentioned studies there exist methodological shortcomings that function as threats to external validity. In some cases, sample sizes were too small to make generalizations with any degree of confidence (e.g., Persinger, 1978; Sanders & Brizzolara, 1982). In others, the samples were larger, but comprised solely of psychiatric inpatient populations (e.g., Eastwood & Stiansy, 1978; Frangos et al., 1980). Shortcomings aside, these authors were among the first to provide empirical evidence to suggest that the changing seasons may account for changes in mood. In sum, a proposed relationship between the seasons and mood has been documented for thousands of years, and only a handful of researchers systematically pursued seasonal mood shifts prior to the advent of SAD in 1984 (e.g., Eastwood & Stiansy, 1978; Frangos et al., 1980; Huntington, 1938; Kraines, 1957; Persinger, 1978; Sanders & Brizzolara, 1982).

Taken cumulatively, the anecdotal nature of the ancients' observations, the scarcity of seasonality as a scientific pursuit, and the methodological shortcomings found in the scant research conducted prior to 1984 preclude the formulation of valid conclusions concerning the relationship between the weather and mood. As Wehr and Rosenthal (1989) note, however, the observations of the ancient thinkers map onto the contemporary clinical constellation of SAD surprisingly well.

SAD: The Clinical Constellation and Diagnostic Criteria

The Rosenthal group (1984) published the original research describing the clinical constellation of Seasonal Affective Disorder and preliminary findings using bright light therapy. The researchers described winter-SAD as a syndrome in which depression develops during the autumn or winter months and remits the following spring or summer, occurring for at least two successive years. These authors reported that depressive symptoms tend to remit with exposure to daylight or bright light therapy (Rosenthal et al., 1984). The most prevalent symptoms of SAD were reported to be lower mood, decreased energy despite increased sleep, decreased social activities, and the "atypical" symptoms of hypersomnia, carbohydrate craving, and weight gain (Rosenthal et al., 1984). The latter symptoms are deemed *atypical* because they are in opposition to the normative vegetative symptoms of non-seasonal depression. As such, Rosenthal, Bradt, and Wehr (1984) developed and published the Seasonal Pattern Assessment Questionnaire to assess for the atypical symptoms observed in the original sample (Rosenthal et al., 1984).

At present, neither international classification system (ICD-10, DSM-V) lists SAD as a distinct diagnostic entity; rather, a *seasonal pattern* specifier that can be used to describe the course of particular mood disorders is found in both the DSM-V and ICD-10 (American Psychiatric Association [DSM-V], 2013; World Health Organization [ICD-10], 2008). The seasonal episodes may take the form of major depressive or bipolar disorders (Lurie, Gawinski, Pierce, & Rousseau, 2006). The DSM-V lists the following four criteria for the seasonal pattern specifier: A) There has been a regular temporal relationship between the onset of Major Depressive Episodes in Bipolar I or Bipolar II or Major Depressive Disorder, Recurrent, and a particular time of year (e.g., regular appearance of the Major Depressive Episode in the fall or winter. *NOTE*: Do not include cases in which there is an obvious effect of seasonal-related psychosocial stressors (e.g., regularly being unemployed every winter); B) Full remissions (or a change from depression to mania or hypomania) also occur at a characteristic time of the year (e.g., depression disappears in the spring); C) In the last 2 years, two Major Depressive Episodes have occurred that demonstrate the temporal seasonal relationships, and no non-seasonal Major Depressive Episodes have occurred during that same period; D) Seasonal Major Depressive Episodes (as described above) substantially outnumber the non-seasonal Major Depressive Episodes that may have occurred over the individual's lifetime (APA [DSM-V], 2013).

In summary, 1984 marked the year that the clinical picture of SAD emerged, promising preliminary evidence supporting bright light therapy appeared, and a self-report designed to assess for SAD was developed (SPAQ; Rosenthal et al., 1984; Rosenthal, Bradt, & Wehr, 1984). In turn, the original conceptualization of SAD was transformed into the course specifying criteria for a *seasonal pattern*, first published in DSM-III-R (APA [DSM-III-R], 1987). Neither the clinical constellation of SAD nor the seasonal course criteria in the DSM have undergone changes since their respective inceptions (i.e., APA [DSM-III-R], 1987; Rosenthal et al., 1984); however, the epidemiological and etiological studies that followed have contributed to increased understanding within each domain.

Epidemiology

Early studies found the prevalence of SAD to range from 4% to 9% in United States samples (e.g., Kasper, Wehr, Bartko, Gaist, & Rosenthal, 1989; Rosen et al., 1990). These early prevalence studies, however, used the Seasonal Pattern Assessment Questionnaire (SPAQ; Magnusson, 1996) as a diagnostic instrument. Since that time period, researchers have cautioned against using the SPAQ to diagnose SAD, as it provides misleadingly high estimates of prevalence (Thompson & Cowan, 2001). More conservative, and likely more accurate, estimates ranging from 1% to 2.5% are reported in studies that utilize structured interviews based on relevant *seasonal pattern* criteria (e.g., APA [DSM-III-R], 1987; APA [DSM-IV], 2000; e.g., Blazer, Kessler, & Swartz, 1998; Michalak, Wilkinson, Dowrick, & Wilkinson, 2001; Murray, Allen, & Trinder, 2001).

In their review, Magnusson and Boikin (2003) reported that a majority of studies found SAD to be more common among females than males. Although some studies reported the opposite within their respective samples, the average female to male ratio across studies was found to be 1.8:1 (Magnusson & Boikin, 2003). Thus, from a global perspective, females and males are differentially susceptible to SAD, and the evidence suggests females incur the highest risk.

The incidence of SAD varies across developmental periods. Although seasonal depression can present in children and older adults (e.g., Carskadon & Acebo, 1993; Eagles et al., 1999), the highest incidence is repeatedly found in persons 20 to 30 years of age (e.g., Imai, Kayukawa, Ohta, Li, & Nakagawa, 2003; Low & Feisner, 1998; Magnusson, 1998; Sourander, Koskelaineu, & Helenius, 1999). As such, there exists a general consensus that individuals between twenty and thirty years old are most susceptible to the affective dysregulation that follows a seasonal pattern (Magnusson & Boivin, 2003).

In summary, the most conservative estimates of prevalence range from 1% to 2.5% across studies using diagnostic interviews, as opposed to the 4% to 9% across studies using the SPAQ as a diagnostic instrument. The estimates derived from structured interviews likely represent more accurate estimates given the questionable psychometrics of the SPAQ (Mersch, 2001). For example, Hansen, Skre, and Lund (2008) reanalyzed the data from 45 SAD studies that used the SPAQ and were able to formulate an equally compelling case for the existence of Seasonal *Anxiety* Disorder. In other words, the SPAQ is not specific to seasonal depression; rather, it assesses seasonality (not necessarily seasonal depression), which resulted in the misleadingly high prevalence estimates in early studies. Further, females are more likely to receive a mood disorder diagnosis with the *seasonal pattern* specifier than their male counterparts (female: male = 1.8:1; Magnusson & Boikin, 2003). Finally, the onset of seasonal depression can occur during childhood, adolescence, or adulthood, with individuals twenty to thirty years of age shown to be most susceptible to the deleterious effects of seasonality (Magnusson & Boivin, 2003). Taken cumulatively, an estimated 1% to 2.5% of the general population suffers from a subtype of depression following a seasonal pattern, and females between twenty and thirty years of age incur the greatest risk.

Etiology

The biological mechanism of action implicated in seasonal mood change is currently unknown, but the various hypotheses fall under three general headings: 1) circadian rhythm disruptions, 2) atypical neurotransmitter activity, and 3) genotypes (Sohn & Lam, 2005). A detailed review of the proposed biological substrates is outside the scope of this discussion. As such, Table 1 lists the specific hypotheses, briefly summarizes the theories subsumed under each heading, and indicates the extent to which the available empirical evidence supports each theory. Although the respective mechanistic hypotheses in Table 1 may appear disparate, they all operate under a shared broader context. The trans-theoretical assumption, common to each specific hypothesis, is that decreased winter light can trigger a biological response that is phenotypically expressed as psychological depression. Stated another way, decreased light in winter is the common-context under which each proposed mechanism operates. Independent of the precise biological substrates, or proximal explanations, is the general consensus that reduced light in winter is the overarching, or distal, cause of seasonal depression (e.g., Magnusson & Partonen, 2005; Westrin & Lam, 2007). Thus, because daylight hours decrease with increases in northern latitude, it stands to reason that the prevalence of seasonal depression should increase with increases in northern latitude. However, evidence to support this assertion is mixed.

Table 1
Proposed Biological Substrates for Seasonal Mood Change (Proximal Causes)

Theory	Brief Summary	Evidence
Circadian Rhythms		
Melatonin	Decreases in melatonin disrupt circadian rhythmicity	Mixed and inconclusive[1]
Phase-Shift	Internal circadian rhythms are phase-delayed relative to the external clock	Robust supporting evidence Equally robust conflicting evidence[2]
Neurotransmitters		
Serotonin (5-HT)	5-HT turnover and 5-HT hypothalamic transporter sights lower in winter	Supporting evidence[3] Lacks SAD-specificity Correlational data, no causality Interpretations difficult
Dopamine (DA)	DA mediates retinal light/dark adapted states, thus deficient retinal DA activity results in atypical light/dark adaptation	Preliminary support[4] Replication needed
Genetic Hypotheses		
Heritability	Atypical responses to light and dark are inherited	Robust findings Family history studies yield consistent support[5] Replicated support in twin studies[6]
Molecular Genetics	Variant alleles in the 5-HT system affect the serotonergic	Mixed and inconclusive[7]

response to light (dec. activity)

[1] (e.g., Lam & Levitan, 2000; Lee et al., 1997; Levitt & Boyle, 2002; Michalak & Lam, 2002; Terman et al., 1989); [2] (e.g., Lewy et al., 1998; Lewy, Sack, Singer, White, & Hoban, 1988; Terman, Terman, Lo, & Cooper, 2001; Wirz-Justice et al., 1993); [3] (e.g., Neumeister et al., 2000; Neumeister, Konstantinidis, & Praschak-Rieder, 2001); [4] (e.g., Hebert, Beattie, Tam, Yathan, & Lam, 2004); [5] (for review see Sher, Goldman, Ozaki, & Rosenthal; 1999); [6] (e.g., Jang et al., 1997; Madden et al., 1996); [7] (e.g., Johansson et al., 2001; Willeit et al., 2003).

The Latitude Hypothesis

The idea that the prevalence of SAD varies directly with latitude, due to an inverse relationship between winter ambient light and latitude, is typically described as *the latitude hypothesis* (Axelsson, DPhil, Stefansson, Magnusson, & Sigvaldason, 2002). The common vernacular is, indeed, a convenient shorthand description (Axelsson et al., 2002), but the theory itself is composed of two separable, and complex, elements: 1) a descriptive component and 2) an etiological component. The descriptive portion attends to the direct variance in prevalence with latitude, and the etiological element implicates light deprivation as the principle causal factor (Axelsson et al., 2002). The accumulated findings, from both the descriptive and etiological realms, do not conveniently coalesce to create compelling, nor consensual, conclusions to elucidate the nature of the relationship between weather and mood. Some researchers have found a clear and distinct latitude gradient across which seasonal depression is more prevalent at higher northern latitudes (e.g., Carskadon & Acebo, 1993; Magnusson & Axelsson, 1993; Rosen et al., 1990). In contrast, other researchers who set out to explore this gradient have not found similar success (Blazer, Kessler, & Swartz, 1998; Levitt & Boyle, 2002; Murray & Hay, 1997). The inconsistent findings have prompted some to describe the latitude gradient as “an important wanting in the validity of SAD” (Magnusson & Axelsson, 2003, p. 197), whereas others have turned strong and harsh criticism on the assembled findings due to these disparate results (e.g., Hansen, Skre, & Lund, 2008). A more moderate position to account for the discrepant findings is that latitude is only an indirect measure of the amount of light individuals receive in the winter (Magnusson & Partonen, 2005). Even at similar latitudes (e.g., State College, PA and Boulder, CO are both located at approximately 40° N latitude) the amount of daily sunlight can vary due to local environmental factors (e.g., cloud cover).

Seasonal Mood Variation in College Students

The college student population is understudied in the SAD literature (Agumadu et al., 2004; Low & Feissner, 1998). The scarcity of college student representation is especially curious considering they primarily attend school during the time of year when sunlight is at a minimum in the Northern Hemisphere. Seasonal changes in mood could negatively impact academic performance (e.g., lack of motivation), as well as other important aspects of college students' lives (e.g., social interaction). Because the college student population is an underrepresented group in the SAD literature, we conducted a pilot study investigating a potential latitude gradient across multiple colleges and universities. We hypothesized that depressive symptoms would be significantly greater at higher northern latitudes across the United States.

The Pilot Study

The pilot study was exploratory in nature, with its sole aim to investigate the relationship between specific geographic variables and mood within a traditionally understudied population - college students. A leading hypothesis in the etiology of this phenomenon involves fluctuation in sunlight (Kasof, 2009). This study investigated the relationship between depressive symptoms, latitude, and time of year within and across geographic locations. We hypothesized that latitude and time-of-year would predict fluctuations in the Counseling Center Assessment of Psychological Symptoms-62 (CCAPS-62; Locke et al., 2011) depression subscale, in general. Based on the latitude hypothesis, we predicted a direct relationship between depressive symptoms and latitude. Within a specific latitude (i.e., 40° N), we predicted depressive severity would vary as a function of time of year.

The pilot study used the Center for Collegiate Mental Health (CCMH; 2010, March) database containing the CCAPS-62 (Locke et al., 2011) depression subscale data from August 2008 to December 2008 including 66 colleges and universities, ranging in latitude from 25° – 46° N to investigate depressive symptoms across latitudes. The sample was composed of 19,243 treatment-seeking students who completed the CCAPS-62 at intake. We used the CCAPS-62 depression subscale data from August 2008 through February 2010 at 40° N latitude to investigate seasonal changes in depression within a specific latitude. The sample was composed of 5,323 treatment-seeking students who completed the CCAPS-62 at intake. We used an ANOVA to investigate seasonal differences in mean depression at 40°N, and multiple regression to investigate the relationship between Depression (Y), latitude (X_1), time-of-year (X_2), and their interaction (X_3) across latitudes ranging from 25° – 46° N.

The hypothesis that the severity of depressive symptoms would vary as a function of time of year at a specific latitude was not supported. The omnibus ANOVA did not result in significant differences between mean depression scores across seasons $F(3, 5323) = 2.7$, $p > .01$. A significant model emerged in the regression analysis $F(3, 19243) = 18.83$, $p < .001$ that accounted for 0.3% of the variance in CCAPS-62 depression scores. None of the predictors, however, were significant and the model significance was likely due to the large sample size.

The pilot study used seasons (defined by equinoxes and solstices) and latitudes as indirect measures of light. This ignores the *quality of light* that any location received on any given day. The lack of any compelling evidence to support seasonal mood fluctuations could be a result of the crude manner in which we indirectly measured light. The present study will take light into account with more precision. Cloud cover and photoperiod will be calculated as a means of assessing both the quality (e.g., dark clouds or blue skies) and amount (photoperiod) of light a location receives. This will increase the precision with which we take light into account, and go beyond the overly simplistic latitude hypothesis.

Beyond the Latitude Hypothesis

Although the pathophysiology of SAD remains unknown, it is generally believed that the reduction in sunlight exposure during the winter is the main trigger for SAD in vulnerable individuals (e.g., Eastman, 1990; Magnusson & Partonen, 2005; Westrin & Lam, 2007). Proposed mechanisms of action include disruptions in circadian rhythms, abnormal neurotransmitter activity, and genetic hypotheses (Table 1). Indisputable, however, are the systematic changes in the natural environment that are responsible for reductions in sunlight exposure in the winter at different locations. For example, the number of daylight hours from sunrise to sunset (photoperiod) decreases as winter approaches, and the maximum intensity of sunlight is reduced due to the earth's rotation and proximity to the sun (Eastman, 1990). There is also evidence to suggest that variability in lifestyle factors across seasons reduces exposure to sunlight during the winter months (Eastman, 1990). Such factors include reductions in outdoor activities due to the cold and less opportunity for exposure because of the combined effects of a shorter photoperiod and work interference (Eastman, 1990). In sum, humans experience reduction in winter sunlight exposure due to systematic changes in the natural environment and lifestyle factors that accompany modernity. As mentioned above, latitude is only an indirect (and rudimentary) measure of light. While latitude and photoperiod are the dominant factors in establishing a risk to SAD, other local factors, such as cloudiness, air pollution, and shading by buildings, all contribute in this regard (Danilenko & Levitan, 2012). The present study will investigate the contribution of the local environmental factor of cloud cover.

The Present Study

The present study investigated the effects of time of year and cloud cover, within and across locations that are similar in latitude but exposed to different amounts of sunlight, on depressive symptoms in both treatment-seeking and non-treatment seeking populations of college students. Time of year was indirectly measured through daily hours of sunlight from sunrise to sunset (photoperiod). Where available, total irradiance was attained through the surface radiation (SURFRAD) network measurements of solar energy lost due to cloudiness (i.e., direct beam energy lost, diffuse field energy lost, and total energy lost due to clouds). Total irradiance provides an idea of what the week actually looked like in terms of dark clouds or blue skies. These measures of total irradiance are available from 7 SURFRAD sites throughout the United States. The SURFRAD sites provide direct measures of total irradiance within a 10-kilometer range. Thus, the colleges/universities contributing data to the CCMH practice-research network that are within an approximate 10-kilometer range of the respective SURFRAD sites will be included in the analysis. This study will examine depression scores of clinical and nonclinical populations of college students.

Within a single location at 40° N latitude, we hypothesize that time of year, cloud cover, and their interaction will significantly predict depressive symptoms. The sample included non-treatment seeking students from the Psychology 100 participant pool from 2010 – 2012. The choice to investigate a non-clinical sample was made because students in treatment generally experience decreases in depressive symptoms, which are arguably a function of being in treatment. As such, the results of a within-subjects repeated measures design with a clinical sample could be conflated by virtue of the students being in treatment. For example, a student could be making gains in individual therapy due to the positive impact therapy has on depression despite concurrent decreases in sunlight.

At different locations we hypothesize that time of year (photoperiod will serve as a proxy measure for time of year) and total irradiance (i.e., cloud cover) will account for differences in depressive symptoms.

Chapter 3

Method

Participants

The present study utilized mental health data collected through the Center for Collegiate Mental Health (CSCMH, 2009; CCMH, 2010; CCMH, 2012; CCMH, 2013) from a nationally representative sample of students from 2010 – 2012. The data came from three distinct sources: 1) The 2010-2011 clinical dataset, 2) the 2011-2012 clinical dataset, and 3) the students enrolled in Psychology 100 at Penn State between 2010 and 2012 who completed the Counseling Center Assessment of Psychological Symptoms-62 (CCAPS-62; McAleavey, Nordberg, Hayes, Castonguay, Locke, & Lockard, 2012).

Of approximately 28,000 students who participated in the 2008 CSCMH Pilot Study, almost 26,000 provided usable data. Of those who provided usable data, 9,141 identified as male (35.4%) and 16,615 as female (64.3%). 1,911 (7.7%) identified as African American/Black, 109 as American Indian or Alaskan native (0.4%), 113 Arab American (0.5%), 1,558 Asian American/Asian (6.2%), 156 East Indian (0.6%), 17,589 European American/Caucasian/White (70.4%), 77 Hawaiian or Pacific Islander (0.3%), 1,444 Hispanic/Latino/a (5.8%), 799 multi-racial (3.2%), 607 preferred not to answer (2.4%), and 623 identified as other (2.5%). Of approximately 60,000 students in the CCMH 2010-2011 dataset, 22,714 identified as male (37.0%), and 38,360 identified as female (63.0%). Of the exact 58,349 students in the sample, 7.9% identified as African American/Black, .5% American Indian or Alaskan Native, 5.9% Asian American/Asian, 71.9% Caucasian/White, 6.9% Hispanic/Latino/a, .2% Native Hawaiian or Pacific Islander, 3.5% multi-racial, 1.6% preferred not to answer, and 1.7% other. Of approximately 70,000 students in the CCMH 2011-2012 dataset, 27,984 identified as male (35.8%), and 49,695 identified as female (63.5%). Of the exact 73,997 students who participated, 8.6% identified as African American/Black, .5% American Indian or Alaskan native, 6.0% Asian American/Asian, 70.6% Caucasian/White, 7.1% Hispanic/Latino/a, 0.3% Native Hawaiian or Pacific Islander, 3.6% multi-racial, 1.6% preferred not to answer, and 1.7% other.

The present study utilized the CCMH data (i.e., SDS and CCAPS) from the Penn State Psychology 100 participant pool across four semesters, ranging from 2010 to 2012 academic years. The students completed the SDS and CCAPS during the first week of their Psychology 100 level class, and subsequently completed the CCAPS each week for the remainder of the semester (14 measurement occasions in total). The majority of these students were non-treatment seeking and represented the general college student population. Those who endorsed current participation in therapy, and/or endorsed current use of psychotropic medication, were eliminated from the analysis. This resulted in 102 participants in the Spring 2011 semester (n = 31 male, n = 71 female), 212 participants in the Fall 2011 semester (n = 55 male, n = 157 female), 101 participants in the Spring 2012 semester (n = 35 male, n = 66 female), and 219 in the Fall 2012 semester (n = 54 male, n = 165 female).

Materials

The Counseling Center Assessment of Psychological Symptoms is a 62-item self-report questionnaire specifically designed to assess the mental health concerns of college students (CCAPS-62; Locke et al., 2011). Students are asked to rate each item on a 5 point scale where *0 = Not at all like me* and *4 = Extremely like me*. The CCAPS-62 contains eight subscales, but the only scale germane to this study was the Depression subscale. This subscale contains 13 items including questions such as: *I feel isolated and alone, I feel worthless,* and *I am enthusiastic about life*. The internal consistency coefficient of the Depression subscale has been shown to be very good, with a Cronbach's α of .913 (Locke et al., 2011). Evidence of convergent validity was initially shown through the significant Pearson product-moment correlation between the Depression subscale and the Beck Depression Inventory, r (496) = .721, p < .001 (BDI; Beck, Ward, Mendelsohn, Mock, & Erbaugh, 1961; Locke et al., 2011), and subsequent studies have produced strong evidence of construct validity (e.g., McAleavey, Nordberg, Hayes, Castonguay, & Locke, 2012).

The Standardized Data Set (SDS) was developed with input from more than 100 counseling centers and represents a standardized set of questions typically asked of students seeking services (CSCMH, 2009). In the case of the repeated measures portion of this study, however, the SDS was administered to non-treatment seeking students. As such, we used the SDS to eliminate those students who were currently seeking psychological services and/or taking psychotropic medication for a mental health concern for the longitudinal portion of the study (i.e., repeated measures within Penn State location). The questions that were used to filter out treatment seeking students read, "Are you currently receiving counseling or other therapeutic services on campus" and "Are you currently receiving counseling or other therapeutic services off campus." The response options are *Yes* or *No*. The SDS also asks students to "indicate if and when you have had the following experiences: Taken a prescribed medication for mental health concerns." The response options are: *Never, Prior to college, After starting college,* or *Both.* Those who endorsed *Never* were included in the analyses.

The present study utilized surface radiation budget measurements from The National Oceanic and Atmospheric Administration's (NOAA's) Surface Radiation budget network (SURFRAD). The network began in 1995 with the mission "to provide the climate research, weather forecasting, satellite, and educational communities with continuous, accurate, high quality surface radiation budget measurements for different climates of the United States" (Augustine, DeLuisi, & Long, 2000, p. 2341). In addition to providing direct measurement of key variables (e.g., upwelling and downwelling components of broadband solar and thermal infrared irradiance, direct and diffuse components of downwelling solar irradiance, and other radiometers to measure wavebands of special interest; e.g., broadband ultraviolet radiometers), the SURFRAD data provides researchers with supplemental measurements and calculated quantities that "aid in the interpretation of the measurements and help improve the understanding of the effects of clouds, aerosols, and water vapor on the surface radiation budget" (Augustine et al., 2000, p. 2341). The present study utilized SURFRAD measures of cloud cover, temperature, and photoperiod. It is important to note, SURFRAD makes these data available down to the minute level of analysis, but the author of the present study requested the data at the daily average level and subsequently calculated weekly averages to be used in the statistical analyses.

In using the SURFRAD data, cloud cover is calculated through a combination of observationally estimated and directly measured irradiance values that show how much solar energy was lost due to cloudiness, measured in Joules per meter squared (J/m^2).

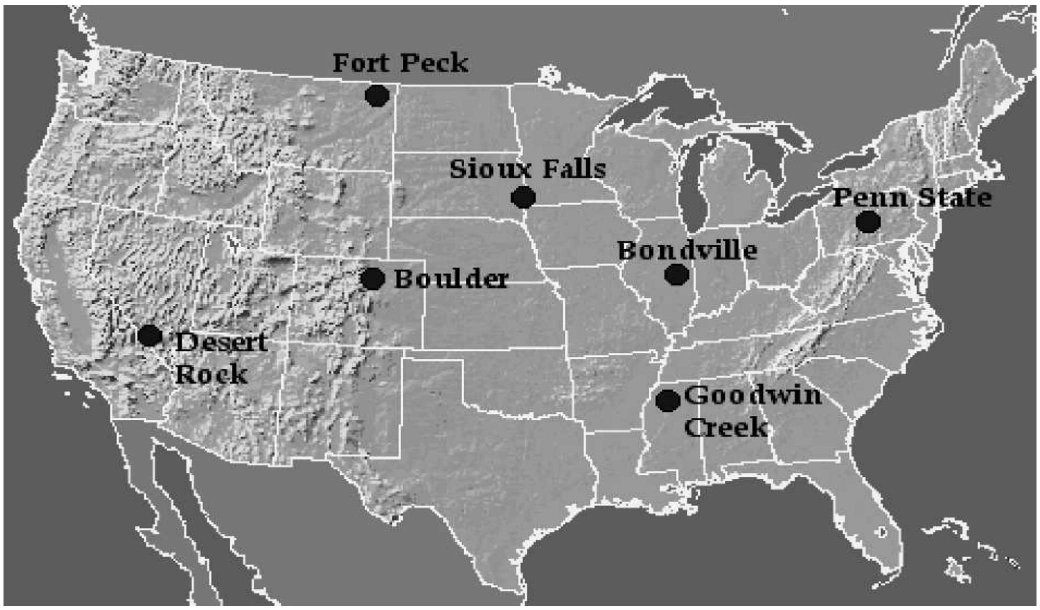
The solar energy (J/m^2) that could potentially reach the Earth's surface, as if it were a cloud free day, is observationally estimated, and the actual energy to reach the earth's surface is measured by the SURFRAD instruments. In subtracting the latter (i.e., actual solar energy that reaches the surface) from the former (i.e., total energy available if it were a cloud free day), the difference shows how much solar energy was lost due to cloudiness. Put simply, the higher the losses, the cloudier the day. The total energy lost due to cloudiness can be further divided into losses of direct beam energy and diffuse field energy. Direct beam solar irradiance is a measure of the rate of solar energy arriving at the Earth's surface from the sun's direct beam, on a plane perpendicular to the beam. Diffuse field solar irradiance is the component of incoming solar irradiance on a horizontal plane at the Earth's surface resulting from the scattering of the Sun's beam due to atmospheric constituents (e.g., molecules, aerosols, clouds). This study calculated each of the three types of cloud cover measurements (loss of total, direct, and diffuse solar energy due to cloudiness).

Photoperiod is the number of daylight minutes from sunrise to sunset, and is calculated within the SURFRAD data as the number of minutes per day that the sun is 11.5° above the horizon. Daily average temperature is measured in degrees Celsius.

There are seven SURFRAD sites across the United States. These sites include Bondville, Illinois (BDN; 40.05° N latitude), Table Mountain, Boulder, Colorado (TBL; 40.13° N latitude), Desert Rock, Nevada (DRA; 36.63° N latitude), Fort Peck, Montana (FPK; 48.31° N latitude), Goodwin Creek, Mississippi (GCM; 34.25° N latitude), Penn State University (PSU; 40.72° N latitude), Sioux Falls, South Dakota (SXF, 43.73°N latitude), and the Atmospheric Radiation Measurement (ARM) Southern Great Plains

Facility, Oklahoma (SGP; 36.80° N latitude). The present study utilized SURFRAD data from Boulder, CO, Bondville, IL, and State College, PA (i.e., Penn State) ranging from January 1, 2010 through December 31, 2012.

Figure 1
Locations of surface radiation (SURFrad)sites



Procedure

The present study utilized data previously collected through the efforts of the CCMH research team and the SURFRAD network. The majority of the participants in the study were treatment seeking college students. A minority of participants included 4 cohorts of non-treatment seeking students from the Penn State Psychology 100 participant pool who completed the CCAPS-34 on a weekly basis during one of four semesters (i.e., Spring 2011, n = 102; Fall 2011, n = 212; Spring 2012, n = 101; Fall 2012, n = 220). The treatment seeking college students' depression scores, from their initial consultation (i.e., one measurement period), were used in the between-locations analyses (i.e., Champaign-Urbana, Colorado, Penn State), and the non-treatment seeking students' depression scores, collected on a weekly repeated-measure basis (i.e., 14 measurement periods per student), were used in the within-subjects analyses.

The CCMH schools that are within 10-kilometers of a SURFRAD site include Penn State (University Park), The University of Colorado at Boulder, and The University of Illinois at Champaign – Urbana. In order to avoid identification of specific colleges and universities, an honest broker approach was implemented wherein institutions were only identifiable in terms of their latitude, and not their institution's name. For example, Penn State University is located at approximately 40° N latitude (longitude excluded), but the authors of the present study were only aware of the institution's latitude (not name), longitude was excluded, and thereby had no way of identifying this institution as Penn State. In order to zero in on the specific institution, the reader would also have to know the longitude of the university. The honest broker converted institutional codes to latitude coordinates, provided the coordinates to the authors, and had no further involvement in the project. The purpose of this approach was to ensure the protection of institution identification.

One of the seven SURFRAD sites with the ability to measure cloud cover is located at Penn State University. Also at Penn State, the CCMH research team has collected data from repeated administrations of the CCAPS-34 and SDS responses from the Psychology 100 participant pool from 2010 to 2012. This provides the unique opportunity to examine any differences in mean depression data at 40° N latitude as a function of time of year and cloud cover. Meteorology variables (e.g., cloud cover, photoperiod and temperature) at the Penn State SURFRAD site were converted from daily into weekly averages to investigate the relationship between these variables and depression scores, as assessed by the CCAPS-34 Depression subscale (Locke et al., 2011). The purpose of this portion of the research was to investigate the relationship between sunlight (or lack thereof) and depressive symptoms across seasons, within the same latitude, and for a non-treatment seeking sample of college students.

The next phase of the present study investigated the relationship between total irradiance, diffuse field irradiance, photoperiod (i.e., a proxy measure for time of year), and depression scores at three different locations.

Analysis

During the dissertation proposal meeting, the committee recommended consulting with those who have expertise in advanced statistical analysis, given the complexity of the data. After consultation with the Penn State Statistics Consulting Center, and a personal contact with a graduate degree in statistics, the optimal analytic choice became clear for both the cross sectional (i.e., one point in time) and longitudinal data (i.e., repeated measures). Hierarchical linear modeling (HLM) was recommended to analyze both types of data. The hierarchical linear models are delineated in greater detail in the respective subsections below (i.e., *Cross Sectional Data Analysis* and *Longitudinal Data Analysis*). Prior to running these analyses, the CCMH and SURFRAD data had to be requested, recoded, and merged into usable datasets.

Cross Sectional Data Analysis

There is an obvious hierarchical structure for the cross sectional data in which the participants (Level 1) were nested within locations (Level 2; i.e., Champaign-Urbana, Boulder, Penn State). Failure to account for nested structures can obscure the results of a study, as was shown, in dramatic fashion, by Roberts (2004), who analyzed data with and without taking the nested structure into account. Without accounting for nesting, Roberts' (2004) results revealed a .77 correlation coefficient between the substantive variables of interest. By accounting for the nested nature of the data in a second analysis, Roberts' (2004) results revealed a -.81 correlation between the same variables of interest. Again, this is an atypically dramatic example (i.e., the reversal of the observed effect), but it "serves as a good reminder for why accounting for nesting is so important" (Anderson, 2012, p. 4). As such, the present study began by building a hierarchical linear model to account for the nesting of participants within location.

A first step in HLM is to calculate the intraclass correlation (ICC), which ranges from 0 to 1.0 and describes the proportion of total variance that depends on group membership (e.g., the degree to which variance at level 1 depends upon group membership at level 2). In building the model for the present study, the ICC was less than .01 (i.e., .0078), meaning that less than 1 percent of the variability in depression scores was due to the nested structure of the data. As such, continuing with HLM was not warranted (Lee, 2000), and the present study used a single level regression equation to analyze the cross sectional data. This was an appropriate technique because the low ICC indicates that there is only a small amount of dependence on higher-level groupings (i.e., less than 1%), and the assumption of the independence of observations within the single-level regression was not violated.

Prior to running the analysis, the SURFRAD meteorology data needed to be transformed from daily averages into weekly averages and required subsequent calculations of irradiance lost due to cloud cover (J/m^2; see Materials section). These calculations resulted in three cloud cover measures: 1) total energy lost due to cloudiness,

2) direct beam energy lost, and 3) diffuse field energy lost. These became three of the multiple predictors used in examining the relationship between meteorological variables (i.e., photoperiod, cloud cover), gender, and depressive symptoms amongst 9,719 treatment-seeking students (i.e., n = 4,496 for site 1; n = 2,368 for site 2; n = 2,855 for site 3). The (x) predictors that were regressed on the (y) depression scores included different combinations of gender, location, photoperiod, cloud cover and photoperiod by cloud cover interaction terms. For the meteorology variables, 1-week trailing averages were calculated, in that, the depression scores were examined as a function of the previous week's weather. For example, depression scores on December 8 were modeled as a function of weather variables averaged across December 1 – 7.

Longitudinal Data Analysis

Though less obvious, the concept of nesting (i.e., students nested within location – Champaign-Urbana, Boulder, or Penn State), can be readily applied to the study of change over time, or longitudinal data (Anderson, 2012) by viewing measurement occasions of such data as nested within the individual. HLM for repeated-measures designs results in more statistical control by calculating a slope for each individual, as opposed to the traditional method of a single average slope across participants. In addition to increased statistical control, repeated-measures HLM offers several distinct advantages over traditional longitudinal analyses (e.g., ANOVA). The advantages are a function of very few assumptions about the structure of the data, which makes the application of HLM more appropriate in more cases, or more flexibly applied. Stated another way, it is less likely that a statistical assumption is violated to the point that the results are spurious. For example, the appropriate application of HLM for longitudinal data does not require equal intervals between administrations, missing data can be handled flexibly unlike a repeated-measures ANOVA or single-level regression (e.g., must discard all of a participant's data for missing a measurement period in such analyses), and HLM does not require uniform measurement occasions (i.e., the same points in time) for all participants. These advantages were important for the present study because of the unequal intervals between administrations given the academic calendar (e.g., Thanksgiving Break, Spring Break), the fact that many students missed one or more measurement occasions, and the lack of uniformity in measurement occasions for each cohort across the four semesters.

As mentioned above, the purpose of the ICC estimation is to determine what percent of the variance is caused by the groupings, and what percent of the variance is the result of random error. Subsequent steps to reduce the amount of random error include later adding intercepts and factors, but again, the ICC initially indicates the necessity of HLM. In this case, the ICC was .782, meaning that 78.2 of the variability seen in depression scores is simply a function of being a different person. Thus, we proceeded with a hierarchical linear model.

Chapter 4

Results

Preliminary Analyses

The purpose of the following section is to familiarize the reader with the data by way of descriptive statistics and correlations between variables used in conducting the primary and additional analyses. The descriptive statistics, for both the cross sectional (i.e., between locations) and longitudinal (i.e., Penn State repeated measures) data are found in Tables 2 and 3, below.

Table 2
Descriptive statistics for cross-sectional data

	Mean	Standard Deviation	Range
Location 1 (n = 4496)			
Total Energy (E) Lost†	6.80×10^6	5.80×10^6	$-1.14 \times 10^6 – 27.90 \times 10^6$
Direct Beam E Lost†	9.30×10^6	6.50×10^6	$-2.30 \times 10^6 – 27.80 \times 10^6$
Diffuse Field E Lost†	-2.45×10^6	2.25×10^6	$-9.77 \times 10^6 – 2.10 \times 10^6$
Photoperiod††	555.44	102.88	389 – 760
Temperature (°C)	10.27	9.38	-10.25 – 34.62
Depression Score	1.58	.95	0 – 4
Location 2 (n = 2368)			
Total Energy (E) Lost†	5.91×10^6	5.78×10^6	$-3.54 \times 10^6 – 25.30 \times 10^6$
Direct Beam E Lost†	8.34×10^6	6.81×10^6	$-1.83 \times 10^6 – 26.76 \times 10^6$
Diffuse Field E Lost†	-2.48×10^6	2.41×10^6	$-1.11 \times 10^6 – 1.55 \times 10^6$
Photoperiod††	555.44	102.88	389 – 760
Temperature (°C)	11.04	9.94	-17.08 – 32.87
Depression Score	1.79	.93	0 – 4
Location 3 (n = 2855)			
Total Energy (E) Lost†	4.00×10^6	4.84×10^6	$-.66 \times 10^6 – 27.38 \times 10^6$
Direct Beam E Lost†	6.58×10^6	6.43×10^6	$-.21 \times 10^6 – 29.02 \times 10^6$
Diffuse Field E Lost†	-2.40×10^6	2.30×10^6	$-11.48 \times 10^6 – 3.24 \times 10^6$
Photoperiod††	560.04	98.79	395 - 757
Temperature (°C)	12.65	9.80	-20.08 – 33.75
Depression Score	1.68	.90	0 – 4

† Measured in Joules per meter squared
†† Measured in minutes per day that the sun is 11.5 degrees above the horizon.

Table 3
Descriptive statistics for longitudinal data for each measurement occasion

Spring 2011 Semester
(*n* =102)

Measurement Occasion	Depression Mean	SD	Total E lost†	Direct†	Diffuse†	Temperature	Photoperiod††
1	.69	.64	2.48×10^6	4.56×10^6	-2.17×10^6	-3.36	401.00
2	.56	.60	3.70×10^6	5.65×10^6	-2.11×10^6	-4.64	412.71
3	.51	.63	4.59×10^6	6.29×10^6	-1.81×10^6	-5.51	427.71
4	.56	.74	7.28×10^6	9.04×10^6	-2.00×10^6	-3.21	445.00
5	.54	.73	5.60×10^6	7.50×10^6	-2.01×10^6	-2.19	464.14
6	.44	.61	4.83×10^6	1.18×10^6	6.28×10^6	-2.53	484.29
7	.40	.61	5.32×10^6	8.47×10^6	-1.84×10^6	5.91	505.29
8	.43	.66	7.08×10^6	8.93×10^6	-2.06×10^6	0.20	526.29
9	.42	.63	7.78×10^6	9.33×10^6	-1.84×10^6	4.42	547.43
10	.40	.65	7.39×10^6	1.07×10^6	-3.55×10^6	8.74	588.29
11	.32	.54	8.55×10^6	1.08×10^6	-2.61×10^6	3.11	608.14
12	.35	.57	1.01×10^6	1.30×10^6	-3.41×10^6	3.41	626.86
13	.31	.51	1.75×10^6	1.83×10^6	-1.92×10^6	7.51	645.00
14	.31	.56	1.40×10^6	1.42×10^6	-1.15×10^6	11.70	662.71
15	.28	.47	1.63×10^6	1.78×10^6	-2.47×10^6	11.95	679.43

Fall 2011 Semester
(*n* =212)

Measurement Occasion	Depression Mean	SD	Total E lost†	Direct†	Diffuse†	Temperature	Photoperiod††
1	.67	.60	7.50×10^6	1.13×10^6	-3.34×10^6	23.04	687.00
2	.54	.65	9.05×10^6	1.44×10^6	-5.30×10^6	22.04	671.29
3	.49	.59	6.59×10^6	1.20×10^6	-5.22×10^6	22.78	654.14
4	.49	.64	15.70×10^6	17.60×10^6	-1.80×10^6	18.91	637.00
5	.44	.63	6.40×10^6	9.28×10^6	-2.82×10^6	17.48	618.29
6	.48	.71	10.01×10^6	15.10×10^6	-5.00×10^6	19.80	599.43
7	.42	.68	12.90×10^6	15.00×10^6	-2.08×10^6	15.67	579.71
8	.42	.67	3.31×10^6	4.35×10^6	-1.03×10^6	16.17	559.43
9	.41	.69	9.00×10^6	11.90×10^6	-2.72×10^6	15.58	539.14
10	.42	.66	6.48×10^6	8.71×10^6	-1.69×10^6	12.33	518.29
11	.36	.61	6.85×10^6	9.07×10^6	-1.83×10^6	8.13	497.43
12	.39	.68	1.20×10^6	2.60×10^6	-1.29×10^6	8.82	477.14
13	.40	.68	2.58×10^6	3.83×10^6	-1.09×10^6	11.27	457.29
14	.39	.65	4.67×10^6	6.03×10^6	-1.14×10^6	9.43	422.49
15	.34	.57	3.08×10^6	4.26×10^6	-9.91×10^6	8.03	408.43

Spring 2012 Semester
(*n* =101)

Measurement Occasion	Depression Mean	SD	Total E lost†	Direct†	Diffuse†	Temperature	Photoperiod††
1	.85	.84	3.13×10^6	5.33×10^6	-2.07×10^6	1.31	399.29
2	.74	.90	3.60×10^6	5.26×10^6	-1.51×10^6	-0.40	410.43
3	.73	.94	4.54×10^6	7.07×10^6	-2.27×10^6	-2.58	424.71
4	.60	.86	6.98×10^6	8.91×10^6	-1.63×10^6	3.08	441.71
5	.47	.76	5.31×10^6	7.49×10^6	-1.92×10^6	4.80	460.71
6	.50	.74	5.92×10^6	8.45×10^6	-2.14×10^6	-0.01	481.00

7	.52	.82	6.23×10^6	8.46×10^6	-1.94×10^6	2.72	501.57
8	.50	.82	6.96×10^6	9.67×10^6	-2.37×10^6	3.68	522.57
9	.48	.78	7.88×10^6	10.00×10^6	-1.92×10^6	5.10	543.43
10	.54	.80	4.54×10^6	7.60×10^6	-3.15×10^6	18.27	584.71
11	.53	.85	9.51×10^6	12.60×10^6	-3.25×10^6	17.32	604.43
12	.54	.84	8.31×10^6	10.02×10^6	-1.81×10^6	8.63	623.71
13	.48	.80	1.37×10^6	2.30×10^6	-0.92×10^6	11.76	642.00
14	.46	.84	10.03×10^6	10.52×10^6	-4.95×10^6	11.28	659.71
15	.51	.84	9.62×10^6	10.34×10^6	-3.99×10^6	15.68	676.86

Fall 2012 Semester
(*n* =220)

Measurement Occasion	Depression Mean	SD	Total E lost†	Direct†	Diffuse†	Temperature	Photoperiod††
1	.68	.67	5.52×10^6	9.10×10^6	-3.69×10^6	22.10	674.14
2	.54	.70	4.12×10^6	7.08×10^6	-3.20×10^6	24.09	657.43
3	.50	.70	8.92×10^6	12.60×10^6	-3.70×10^6	22.71	640.00
4	.51	.73	1.85×10^6	4.22×10^6	-2.45×10^6	19.21	621.29
5	.42	.69	6.89×10^6	9.54×10^6	-2.76×10^6	17.18	602.43
6	.39	.64	9.22×10^6	13.30×10^6	-4.23×10^6	15.13	583.43
7	.39	.65	7.94×10^6	11.30×10^6	-3.43×10^6	16.61	563.00
8	.45	.73	4.63×10^6	7.35×10^6	-2.77×10^6	10.89	542.57
9	.42	.72	5.98×10^6	8.50×10^6	-2.60×10^6	13.05	522.00
10	.41	.70	5.42×10^6	6.85×10^6	-1.45×10^6	16.38	501.14
11	.40	.69	9.83×10^6	10.50×10^6	-7.41×10^6	4.86	480.57
12	.39	.68	3.36×10^6	5.36×10^6	-2.05×10^6	5.98	460.86
13	.44	.76	2.09×10^6	3.57×10^6	-1.47×10^6	6.11	442.29
14	.43	.70	3.20×10^6	4.99×10^6	-1.74×10^6	3.84	410.71
15	.44	.74	3.81×10^6	5.00×10^6	-1.07×10^6	8.03	408.43

Note: There are no means and/or standard deviations reported for the meteorology variables because there is only one value for each of these variables per measurement occasion, and it is the same for each participant. Put simply, the temperature is the same for everyone when measured at the same time.
† Measured in Joules per meter squared
†† Measured in minutes per day that the sun is 11.5 degrees above the horizon

Prior to running the regression analysis for the cross-sectional data, correlations between the variables were calculated. Some meteorology variables were highly correlated (e.g., total energy lost due to cloudiness and direct beam energy lost, and also photoperiod and temperature), which introduces the statistical problem of multicollinearity in regression analysis. Multicollinearity can create high noise in the model, and subsequently increase the likelihood of Type II error (i.e., the null hypothesis is false, but erroneously fails to be rejected). The correlations between variables are found in Table 4, and to reduce the risk of Type II error resulting from highly correlated predictor variables, the direct beam energy measures (r = .94 with total energy lost) and total energy losses were not used in the same regression analyses. Further, temperature and photoperiod (r = .64) were not entered simultaneously in the additional analyses. Taken cumulatively, the primary analysis ultimately included gender, photoperiod, total energy lost due to cloudiness, diffuse field energy lost due to cloudiness, and location as predictors for variability in depression scores. In the additional analyses section, the predictive abilities of different combinations of variables were investigated.

Table 4
Associations between variables

	1	2	3	4	5	6	7
1.Gender	1						
2.Total E	-.01	1					
3. Direct	-.01	.94†	1				
4. Diff. E	.01	-.33†	-.60†	1			
5. Photo.	-.01	.30†	.38†	-.41†	1		
6. Temp.	.01	-.02	.04†	-.22†	.66†	1	
7. Dep.	.06†	-.01	-.01	.01	-.01	-.01	1

† $p < .01$

Primary Analyses

A single-level regression analysis was used to test the first hypothesis that variability in cloud cover (i.e., total energy lost due to cloudiness, diffuse field energy lost due to cloudiness), photoperiod (i.e., minutes of sunlight per day), gender, location, and a cloudiness by photoperiod interaction terms would predict variation in depression scores. Put simply, the first hypothesis investigated the degree to which meteorological and demographic variables predicted depression scores. It is important to remember that the exact locations (i.e., Boulder, Champaign-Urbana, and Penn State) were de-identified prior to running the analyses, per the rules/regulations of using CCMH data, and are anonymously referred to as location 1, location 2, and location 3 moving forward (non-respectively).

The primary regression analysis resulted in a significant model in which cloud cover, photoperiod, gender, location and cloudiness by photoperiod explained a small amount of the variance in depression scores ($F(7, 9633) = 16.41$, $p < .01$, $R^2 = .01$, $R^2_{\text{Adjusted}} = .01$). In other words, the predictor variables accounted for one-percent of the variance in depression scores. Neither the meteorology variables nor the interaction terms accounted for a statistically significant proportion of the variance in depression scores. Gender and location were, however, significant predictors ($t_{\text{gender}}(1, 9633) = 5.7$, Beta = .01, $p < .01$; $t_{\text{Location1contrast}}(1, 9633) = -4.27$, Beta = -.10, $p < .01$; $t_{\text{Location2contrast}}(1, 9633) = 4.05$, Beta = .11, $p < .01$) and the relationship between gender, location, and depression scores was more closely examined in an additional analysis (see Additional Analyses, below).

A repeated-measures hierarchical linear model was used to analyze the longitudinal data (i.e., Penn State Psych. 100 participant pool) examining the predictive power of meteorology variables (i.e., total energy lost due to cloudiness, direct beam energy lost, diffuse field energy lost, photoperiod, temperature, and season) and gender in accounting for changes in individual's depression scores over time. As mentioned in the Analysis subsection, a first step in building a hierarchical linear model is to calculate an intraclass correlation (ICC). The purpose of the ICC is to determine both the proportion of variance caused by the nested structure of the data (i.e., nested within the individual, in this case) and the proportion of variance resulting from random error. The actual ICC value is also a means of assessing the appropriateness of continuing to build the hierarchical model. It is defined as:

$\rho = \frac{\tau_{00}}{\sigma^2 + \tau_{00}}$ where,

ρ = the ICC,

τ_{00} = variance at level 2 (i.e., nested within the individual), and

σ^2 = variance at level 1 (i.e., repeated measures variable).

In constructing the model, the ICC was calculated with above general equation, and when replacing the symbols with numerical values, it becomes ICC = .400/(.400 + .111) = .782. This means that 78.2% of the variability in depression scores comes from differences in simply being a different person, which made proceeding with HLM quite necessary.

In constructing the baseline model, only the repeated measures variable (i.e., time point, or level one) was used to predict depression scores, and the other predictors (i.e., total energy lost due to cloudiness, diffuse field energy lost, photoperiod, and temperature) were added in subsequent steps. Multiple iterations of the model were run, and each predictor variable was added to the next version, but ultimately the models did not converge. The steps in constructing the longitudinal hierarchical model are outlined in the following paragraphs.

To begin, a baseline model that includes only the repeated measures variable was constructed. This model used compound symmetry as the covariance type, which assumes the variability in dependent variable (i.e., depression scores) is uniform over time. However, the results revealed a significant relationship between the repeated measures variable and depression scores, F (14, 4479.45) = 33.56, $p < .01$, in which depression scores significantly decreased with progressions through measurement occasions. This suggests using a different covariance type that assumes the relationship between time points and the dependent variable changes across measurement occasions. The heterogeneous autoregressive covariance (ARH1) type fits this description, and is often used in health related studies in which medicines have trailing-off effects. In running the same baseline model (repeated effects only), and adjusting the covariance type to ARH1, there was a considerable drop in the fit statistic (e.g., -2 Log Likelihood dropped from 7545.43 to 6360.35), which indicated a better fit using this covariance structure. From here, we moved through the model progressions using the ARH1 covariance structure.

It is common practice to enter categorical variables separately to test for fixed effects (Anderson, 2012). Fixed effects, by definition, are those that on average should demonstrate a consistent increase or decrease on the dependent variable as a function of categorical variable levels (i.e., male or female, in this case). We added gender as a fixed effect to the model, and there was no lift in the fit statistics (e.g., -2 Log Likelihood of 6360.35 changed to 6360.32), and gender was not a significant predictor of depression scores, F (1, 858.88) = .02, p = .89. Then, gender was dropped from the model and time point was entered to see if it is a variable best treated as fixed. The only differences between this model and the baseline model were the ARH1 covariance structure (as opposed to compound symmetry) and treating time point as a fixed (as opposed to random) effect. There was considerable improvement in the fit statistics (-2 Log Likelihood went from 6360.32 to 5526.52) and time point significantly predicted depression scores, F (14, 2007.56) = 21.90, p < .01. However, time point was only a significant predictor for the first seven measurement occasions, and then the association between time points and depression scores was not significant (i.e., trailing off effects; Table 5).

Table 5
Time point as a predictor of depression scores

Time Point	Mean	SD	Std. Error	df	*t*	Significance
1	.71	.67	.02	1230.69	15.25	$p < .001$
2	.58	.70	.02	1290.19	8.57	$p < .001$
3	.53	.71	.02	1065.22	6.60	$p < .001$
4	.52	.73	.02	1010.45	6.49	$p < .001$
5	.45	.69	.02	922.03	3.32	$p = .001$
6	.45	.68	.02	870.47	3.07	$p = .002$
7	.42	.68	.02	868.76	2.45	$p = .01$
8	.44	.72	.02	800.17	1.90	$p = .06$
9	.43	.71	.02	891.03	2.06	$p = .04$
10	.43	.70	.02	983.42	2.52	$p = .012$
11	.40	.67	.02	912.88	.47	$p = .64$
12	.41	.70	.02	964.31	1.07	$p = .28$
13	.41	.71	.02	920.57	1.11	$p = .26$
14	.40	.70	.01	898.08	1.23	$p = .22$

The next step involved entering different combinations of predictor variables into the model that assumed the ARH1 covariance structure and treated time point as a fixed effect, given the results of the above-mentioned steps in constructing the model. Again, due to some predictors being highly correlated (e.g., total energy loss due to cloudiness and direct energy loss due to cloudiness, and the association between photoperiod and temperature), they were not simultaneously entered into the same regression model to begin with. None of the continuous predictors, in the longitudinal analysis (i.e., total energy, diffuse energy, and photoperiod), which were entered in several combinations to account for multicollinearity, significantly predicted changes in individuals' depression scores over time. In other words, the models did not converge as meteorology variables were added to the model that treated time point as fixed and used the ARH1 covariance structure. Table 6 below is included simply for demonstration purposes, and includes all of the potential predictor variables. This is not the optimal model to use based on fit statistics and the fact that including non-significant predictors can only hurt a model. Again, it is simply to demonstrate that the only significant predictor was time point, which was also true when separate models that accounted for multicollinearity were run. In sum, the substantive finding is that none of the continuous variables were significant predictors in depression scores, in any combination, with the exception of the original repeated-measures variable (i.e., time point).

Table 6
Predictor variables entered into model simultaneously for demonstration purposes

Predictor Variable	*t* statistic	Significance
Gender	.07	$p = .94$
Total energy lost due to cloudiness	1.31	$p = .20$
Direct beam energy lost	.91	$p = .22$
Diffuse field energy lost	.89	$p = .19$
Temperature	1.08	$p = .28$
Time point	12.87	$p < .001$

In moving through several iterations of the hierarchical model, entering different combinations of variables based on collinearity concerns, and adjusting the covariance type for the best fit statistic, the time point itself was the only significant predictor of depression scores over time, for each of the four cohorts of students. As time went on, there was a very clear trend that participants' depression scores significantly decreased until the eighth measurement occasion when they leveled off (i.e., non-significant differences; Table 5). The results, however, provided no evidence to suggest that the changes were due to meteorological variables themselves.

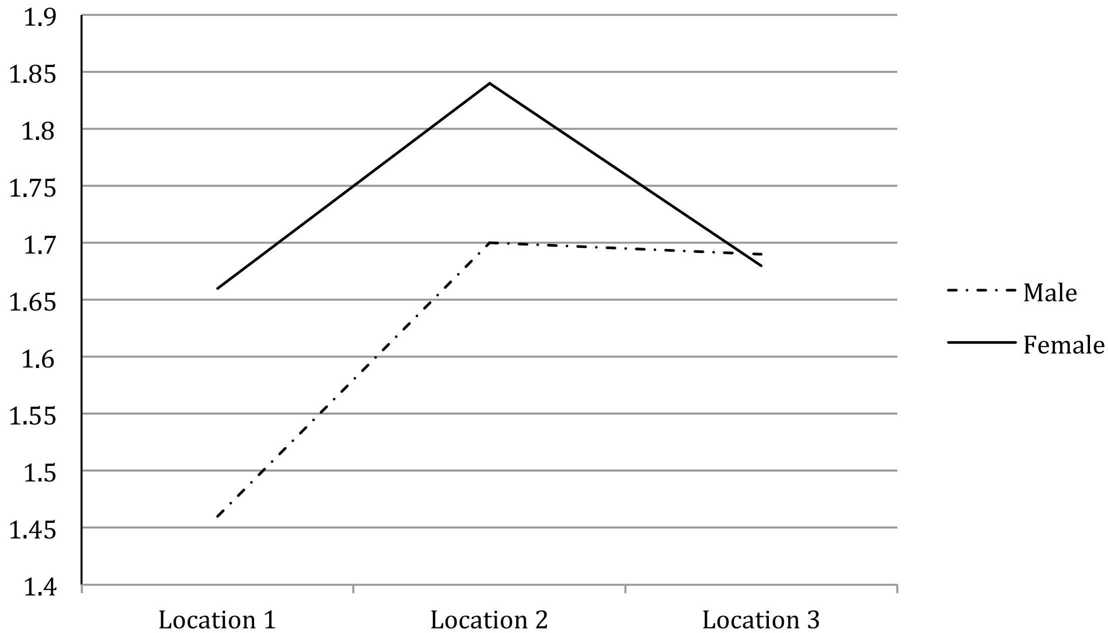
Additional Analysis

In the primary analysis of the between locations data, the regression equation revealed no significant predictors of depression scores outside of gender and location. As such, a post-hoc ANOVA was run to investigate any interaction between gender and location. The results of the post-hoc ANOVA revealed significant differences between male and female depression scores at locations one and two ($F(1,4476) = 49.80$, $p < .001$; $F(1,2351) = 12.43$, $p < .001$)), but no differences by gender within the third location, $F(1, 2813) = .10$, $p = .76$. The descriptive statistics for this analysis are shown in Table 7 below, and a graphic representation of the result is found in Figure 1, below.

Table 7
Gender by location post-hoc analysis: Depression Scores, Means, Standard Deviations, F statistics and significance

Location 1	Mean	SD	*F*	Significance
Male (*n* = 1926)	1.47	.96		
Female (*n* = 2550)	1.66	.93	49.80	$p < .001$
Location 2				
Male (*n* = 1000)	1.71	.93		
Female (*n* = 1351)	1.84	.93	12.43	$p < .001$
Location 3				
Male (*n* = 1148)	1.69	.90		
Female (*n* = 1665)	1.68	.90	.01	$p = .76$

Figure 2
Mean depression scores: Gender by location



In sum, the meteorology variables did not significantly predict variation in depression scores at any of the three locations, but there were differences in mean depression scores between male and female participants within two of the three locations. It was only within the third location that female depression scores were reduced and equitable with male depression scores.

In addition to the post-hoc ANOVA, we ran several regression analyses in different combinations as long as multicollinearity was not a concern (i.e., correlation coefficients were less than .60 between variables). The variables that could not be entered simultaneously due to multicollinearity were: A) Total energy lost and direct energy lost (r = .94), B) Direct energy lost and diffuse energy lost (r = -.60), and C) Photoperiod and temperature (r = .66). The additional regression equations included separate models with the following combinations of predictors: 1) Gender, location, direct energy lost due to cloudiness, photoperiod, and a photoperiod by direct energy loss interaction, in which a significant model emerged, F (6, 9685) = 23.51, $p < .01$) , R^2 = .01, R^2_{Adjusted} = .01, but gender and location were, again, the only significant predictors of depression scores; 2) Gender, location, total energy lost, diffuse energy lost and temperature, in which a significant model emerged, (F (6, 9685) = 18.75, $p < .01$) , R^2 = .01, R^2_{Adjusted} = .01, but gender and location were, again, the only significant predictors of depression scores; 3) Gender, location, direct energy lost, and temperature, in which a significant model emerged, F (5, 9686) = 22.44, $p < .01$, R^2 = .01, R^2_{Adjusted} = .01, but gender and location were, again, the only significant predictors of depression scores. As is obvious, gender and location were the only significant predictors of depression scores in any of the cross sectional (i.e., between locations) analyses.

In terms of the longitudinal analysis (i.e., within one location – Penn State), there was no need to run multiple additional analyses because insignificant predictors are dropped from the model in progressing through the steps of hierarchical modeling, and multicollinearity was not a concern because none of the meteorology variables were significant. Because it was available, we looked at the effect of temperature on depression scores in the longitudinal design. As it turned out, temperature did significantly predict changes in depression scores at $p < .05$, but not at the $p < .01$ level, F (1, 2481.20) = 3.94, $p = .047$. The beta weight for temperature was -.0016, and although it is significant at $p < .05$, the magnitude itself is very small.

Chapter 5

Discussion

The present study utilized modern technologies and contemporary analyses to further examine the centuries-old observation of a systematic relationship between the weather and mood. The primary purpose of this study was to further explore the relationship between meteorology variables (e.g., photoperiod, cloud cover) and mood variation (i.e., depression scores), which was done through a cross sectional comparison (i.e., Boulder, Champaign-Urbana, and Penn State) and a longitudinal design (i.e., repeated measures within a single location). Across locations, we hypothesized that gender, time of year, and measures of solar irradiance would account for the variance in depressive symptoms. Within a single location at 40° N latitude, we hypothesized that photoperiod, cloud cover, and their interaction would account for changes in individual's depressive symptoms over time. The results failed to support the primary hypotheses, but some unexpected findings did emerge. For example, at one location (but not the other two), there was no difference in depression scores amongst men and women, which is unexpected in the context of previous CCMH annual reports (CCMH, 2014; CCMH, 2013, CCMH, 2012; CCMH, 2011; CCMH, 2010; CCMH, 2009) showing women's depression scores to be higher than men's when aggregated across all participating colleges and universities (n = 140 institutions, at present; CCMH, 2014). The following subsections will separately discuss the findings that failed to support the primary hypotheses for the cross sectional and longitudinal designs, and then discuss the unexpected results in more detail. The limitations of the present study are unavoidably strewn throughout the discussion. A brief conclusion and recommendations for future directions are offered in the final subsection.

Depressive Symptoms Between Locations

The primary hypothesis that variability in cloud cover (i.e., total energy lost due to cloudiness and diffuse energy lost due to cloudiness), photoperiod (i.e., minutes of sunlight per day), gender, and location would predict depression scores was not supported. There are several potential explanations for failure to detect an association that fall under one of two broad categories: 1) There truly is no relationship between the weather and mood, 2) A relationship exists, but went undetected due to methodological restrictions precluding the inclusion of important contributing factors in the seasonal depression construct. Each of these potential explanations is discussed in greater detail below.

The explanation that there is no relationship between the weather and mood is consistent with numerous articles that have failed to detect an association between the two (e.g., Boyce & Parker, 1988; Hansen et al., 2008; Magnusson et al., 2000; Mersch, Middendorp, Bouhoys, & Van den Hoofdakker, 1995; Molin, Mellerup, Bolwig & Scheike, 1996; Nillni, Rohan, Rettew, & Achenbach, 2009; Young, Meaden, Fogg, Cherin, & Eastman, 1997). There is, however, equally robust evidence to suggest an association between weather and mood (e.g., Agumadu et al., 2004; Einat, Kronfeld-Schor, & Eilam, 2006; Carskadon & Acebo, 1993; Magnusson & Axelsson, 1993; Rosen et al., 1990), and thus, neither side possesses a clear preponderance of evidence. The results of the present study are simply in line with one of two equally compelling categories of findings. Previous researchers have interpreted their respective results as evidence supporting the existence or nonexistence of weather related fluctuations in mood (e.g., Hansen et al., 2008; Magnusson et al., 2000). Though their conclusions are certainly grounded in the results of their respective studies, they become less compelling when viewed in a cumulative context that considers equally robust divergent findings. For this reason, it is invalid to interpret the present study's failure to find an association between weather and mood as evidence that the relationship does not exist. There are several plausible alternative explanations. One such conceivable explanation is that there is an important subjective component to seasonal depression that this study could not take into account.

The present study relied on the objective measurement of meteorological variables recorded and made available by the National Oceanic and Atmospheric Administration, but individuals' subjective interpretations of the weather, and how it impacts them, were absent from the study given the use of preexisting databases. An individual's subjective interpretation of the weather's impact on his or her psychological functioning could prove to be more important than any objective measure of the natural environment. An analogy that springs to mind to highlight the importance of subjectivity is found within the realm of research on pain tolerance. In a 2010 review, Coghill stated that "in experimental studies using carefully controlled noxious stimuli, tremendous individual differences [in subjective ratings of pain] are consistently observed" (p. 1532). For example, the author cites one study in which participants were exposed to the same objective degree of thermal stimulation (i.e., burning of the skin), yet their respective ratings of pain spanned the entire *1* (mild pain) to *10* (the most severe pain imaginable) scale (Coghill & McHaffie, 2003). In other words, the objective amount of thermal stimulation seemed less important than persons' subjective experience, and a similar phenomenon may be at work regarding the relationship between weather and mood. Again, however, we had no way of including the potentially important subjective component given the use of archival data.

Relatedly, the majority of research on the seasonal affective disorder either focuses on the impact of the changing seasons or latitude coordinates on mood, but there are very few efforts that focus on person-specific variables that may moderate the relationship between weather and mood. A notable exception to the scant research on person-specific variables is a study that found personality traits strongly influenced the likelihood of one receiving a diagnosis of seasonal affective disorder (Bagby, Schuller, Levitt, & Joffe, 1996). More specifically, participants who scored higher on the Openness to Experience factor of the Neuroticism-Extraversion-Openness to Experience Personality Inventory (NEO-PI; Costa & McCrae, 1992) were more likely to be diagnosed with seasonal depression. The authors of the article made the argument that those who are more open to experience are more open to unconventional explanations for their depressive symptoms, such as changes in the weather. In turn, the openness to the nontraditional explanation becomes a self-fulfilling prophecy of sorts, and these individuals are more susceptible to cycles of depression that coincide with their phenomenological perception of changes in the weather, which may not align with the objective changes in the weather. Again, their psychological struggles may have less to do with the objective weather itself, and more to do with personality traits (i.e., the Openness to Experience factor on the NEO-PI; McCrae & John, 1992) that influence their subjective experience. A more parsimonious explanation of these findings could be that people who are more open to experience are simply more open to the environment, including weather, and thus may be more influenced by fluctuations in the weather. Independent of parsimony, however, is the fact that both explanations require an intermediary step in the association between weather and mood (i.e., personality traits, in this case), or person-specific variables, that could not be captured in the present study. In addition to personality traits, there are other plausible person-specific characteristics that could moderate the relationship between weather and mood. Other potentially important characteristics include an internal or external locus of control, and levels of acclimatization.

Rotter (1966) was the first to describe the concepts of internal and external loci of control. Stated simply, persons with a high internal locus of control generally believe they control their own lives, and tend to make internal attributions for life's happenings (e.g., I failed the test because I am not smart enough to understand the material); whereas, persons with a high external locus of control believe their lives are generally controlled by environmental factors they cannot influence, and tend to make external attributions for life's happenings (i.e., I failed the test because the professor doesn't know how to teach). It stands to reason that locus of control could be an important moderating variable in the relationship between weather and mood. For example, those with a high internal locus of control may make more internally based attributions for their depressive symptoms and be less sensitive/reactive to changes in the external environment as a function of their tendency to search within themselves for explanations. Those with a high external locus of control, however, could be more sensitive/reactive to the external environment as a function of their tendency to search outside themselves for explanations.

Another important person-specific variable that could influence the relationship between weather and mood is the degree to which a person has acclimated to colder/harsher environments. Magnusson et al. (2000) suggested that those raised in climates with long and harsh winters might acclimate to the deleterious effects of weather on psychological functioning. The present study had no way of knowing where participants were raised, and/or how many developed the protective factor of acclimatization. Further, the demographic information that was available did not provide thorough family histories and/or complete psychiatric histories, which are important in making accurate mental health diagnosis, or in assessing a person's predisposed vulnerability to any mental health concern.

Beyond the inability to account for any subjective component of seasonal depression, there were other methodological problems that could have impacted the association between weather and mood going undetected. Specific to the cross sectional component of this study was the fact that the data itself was cross sectional. Rosenthal et al. (1984) highlighted the importance of longitudinal assessment of depressive symptoms in their original conceptualization of SAD, and this idea is also found within the diagnostic criteria for the seasonal pattern specifier in DSM-V (i.e., criterion C) In the last 2 years, two Major Depressive Episodes have occurred during that same period; APA, [DSM-V], 2013). Future studies could improve on this methodological shortcoming by tracking individual's moods longitudinally (ideally, over a two year period). Relatedly, the present study aggregated the meteorology variables across a one-week period, but this choice was not grounded in previous research simply because there is no research-based consensus about the optimal way to aggregate weather variables in relation to mood. Perhaps the data needs to be aggregated in a different way (e.g., daily, hourly) to detect an association.

In sum, it is difficult to formulate valid conclusions based on the cross sectional results of the present study, and more questions may have been raised than were answered due to methodological shortcomings. The most conservative conclusion that can be validly formulated is that the objective measures of length of day, total energy lost due to cloudiness, and diffuse energy lost due to cloudiness did not explain a significant amount of the variability in CCAPS depressions scores at three different locations among college students. Though the meteorology variables did not predict depression scores, both gender and location did predict depressive symptoms. As such, an additional analysis was conducted to further investigate this relationship, and these results are discussed below.

The additional analysis revealed a significant gender by location interaction, in which females reported higher depression scores at locations one and two, but were reduced and equitable with males' depression scores at location three (Figure 1). There are at least two problems in explaining this result: 1) The locations were de-identified prior to running the analyses, and 2) The CCMH data collected from 2010 – 2012 have demonstrated that females report significantly higher depression scores than their male counterparts when aggregated across the nationwide sample. This was consistent with the finding from the present study that treatment seeking males are significantly less depressed than treatment seeking females at locations one and two, but report equal depression scores at location three. Also depicted in Figure 1, the men at location one are far less depressed than the men (and women) at locations two and three, and the women at location two are far more depressed than the women (and men) at locations one and three. The locations were, in fact, de-identified prior to running the analyses, but even if we knew the locations it would remain difficult to formulate any valid conclusions to explain the results because we did not (and could not given the use of preexisting databases) include other potential variables in the study beyond the weather (e.g., personality factors, locus of control, acclimatization).

Depressive Symptoms Over Time, Within-Subjects at One Location

Similar to the cross sectional component of the present study, the primary hypothesis for the longitudinal component was that in a non-treatment seeking sample of college students, their individual depression scores would predictably vary as a function of gender, photoperiod, and solar energy lost due to cloudiness. Again, however, this hypothesis was not supported. In the primary longitudinal analysis, the measurement occasion, or time point, was the only significant predictor of individuals' depression scores. In an additional analysis, temperature was added as a predictor and found to be significant at the $p < .05$ level. The following paragraphs discuss these findings in more detail.

The weather variables likely failed to predict depression scores for reasons similar to those already mentioned (i.e., could not account for any subjective impact of the weather), and for the unique reason that the longitudinal aspect of the study utilized a non-treatment seeking sample. Generally speaking, people are differentially susceptible to experiencing a depressive episode, and there is some research to support the notion that some people are more susceptible to bouts of seasonal depression, specifically. The research is certainly limited, and the respective samples were relatively small (i.e., $n = 27$

and n = 80), but one article found a negative attribution style to be more predictive of seasonally based depression than non-seasonal depression (e.g., Enggasser & Young, 2007), and as mentioned above, another study found that those who scored higher on the Openness to Experience factor of the Neuroticism-Extraversion-Openness to Experience Personality Inventory (NEO-PI; McCrae & John, 1992) were more likely to be diagnosed with seasonal depression (Bagby et al., 1996). The participants in the present study could have simply been less susceptible to any type of depression, including the type following a seasonal pattern. It is admittedly unlikely that the entire sample was depression-resistant, but the fact that they were not seeking psychotherapy and/or pharmacotherapy makes it a possibility, however improbable.

The only significant predictor of depression scores over time was the actual time point variable itself. In Table 5 of the Results section, the association between time point and depression becomes, and remains, insignificant on the eighth measurement occasion. Prior to the eighth measurement occasion, depression scores significantly decreased from week to week. Again, it is difficult to make valid inferences without more information, but it is interesting to note that the week following week eight coincided with Spring Break for both of the Spring semester cohorts, and Thanksgiving Break was within a two week span for the Fall semester cohorts.

Because it was available, combined with the fact that no one has conducted a study of this nature before, temperature was included in a final additional analysis. As mentioned in the results section, temperature was a significant predictor of depression scores at $p < .05$, with a beta weight of -.0016. This means that for every 1°C increase in temperature, depression scores decrease by .0016 units. The relationship is, indeed, significant; however, it does not have much real world utility. Based on this finding, and by applying some simple arithmetic, it can be calculated that for a depression score to decrease from say 1.5 to 1.4 (a decrease of .10) based solely on temperature requires an increase of 62.5°C (or 144.5°F). Thus, the observed effect of temperature in this study is irrelevant in the real world.

Conclusions and Future Directions

Again, the limitations of the present study were strewn throughout the previous subsections, and recommendations for future research involve improving upon the aforementioned methodological shortcomings. It is important to remember that the shortcomings could not be improved upon within this study itself, simply due to the use of archival data, but this was an initial attempt to bring more precision to the study of weather and mood, and lessons for improving future designs were learned. The primary recommendation is building in a measure of participants' subjective experience of the weather, which could moderate the relationship between depressive symptoms and meteorological variables.

The second recommendation for future designs is to assess for participants' differential susceptibilities to depressive episodes (i.e., past depressive episodes, family history, etc.), and to build this information into the study either as a means of screening or as a variable to be controlled for, experimentally or statistically. Further, the locations of the surface radiation budget sites used in the between locations portion of this study were all very similar in latitude (40.05° N, 40.13° N, and 40.72° N). In other words, this study held latitude constant and instead focused on the amount (i.e., weekly hours of sunlight) and the quality (i.e., cloud cover) of light available at different locations to investigate their impact on depressive symptoms. Future research utilizing the surface radiation data should make use of all seven locations, which would add variability in latitude (i.e., 34.25° N, 36.63° N, 36.80° N, and 43.73° N).

This study was conducted from a broad perspective, and the relationship between weather and mood may be more granular than a study of this nature could accommodate. For example, several person-specific variables that were not taken into account within this study should be taken into account in future studies. Such variables include personality characteristics, locus of control, and levels of acclimatization. Further, this study only investigated the amount and quality of light *available*, and did not incorporate any measure of the amount and quality of light individuals were actually *exposed* to. Though time consuming, expensive, and complicated, future studies could improve upon this by assessing for actual exposure to sunlight. Ideally, this would be done through a wearable ultraviolet sensor for the sake of precision.

The relationship between the natural environment and mood was initially observed by ancient thinkers, and later confirmed through scientific inquiry, but this study failed to detect the centuries-old observation. The divergent results are likely due to methodological shortcomings that have already been discussed, and are unlikely due to the nonexistence of seasonally based mood fluctuation. Further, there are certainly critics of Seasonal Affective Disorder (e.g., Hansen et al., 2008), but the criticism may be a result of past research, including this research, having largely overlooked critically important granular components of the seasonal depression phenomenon.

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