NIH Public Access
Author Manuscript
Int J Child Health Hum Dev. Author manuscript; available in PMC 2009 March 4.

Published in final edited form as:
Int J Child Health Hum Dev. 2008 ; 1(2): 181–203.

Mood Oscillations and Coupling Between Mood and Weather in Patients with Rapid Cycling Bipolar Disorder

Steven M. Boker, PhD[1,*], **Ellen Leibenluft, MD**[2], **Pascal R. Deboeck, PhD**[3], **Gagan Virk, MD**[4,5], and **Teodor T. Postolache, MD**[5]

[1]Department of Psychology, The University of Virginia, Charlottesville, Virginia, USA

[2]Chief, Section on Bipolar Spectrum Disorders, Emotion and Development Branch, Mood and Anxiety Disorders Program, National Institute of Mental Health, Bethesda, MD

[3]Department of Psychology, The University of Notre Dame, Notre Dame, Indiana, USA

[4]St. Elizabeths Hospital, Residency Training Program, Washington DC

[5]Mood and Anxiety Program, University of Maryland School of Medicine, Baltimore, MD

Abstract

Rapid Cycling Bipolar Disorder (RCBD) outpatients completed twice-daily mood self-ratings for 3 consecutive months. These ratings were matched with local measurements of atmospheric pressure, cloud cover, and temperature. Several alternative second order differential equation models were fit to the data in which mood oscillations in RCBD were allowed to be linearly coupled with daily weather patterns. The modeling results were consistent with an account of mood regulation that included intrinsic homeostatic regulation as well as coupling between weather and mood. Models were tested first in a nomothetic method where models were fit over all individuals and fit statistics of each model compared to one another. Since substantial individual differences in intrinsic dynamics were observed, the models were next fit using an ideographic method where each individual's data were fit separately and best-fitting models identified. The best-fitting within-individual model for the largest number of individuals was also the best-fitting nomothetic model: temperature and the first derivative of temperature coupled to mood and no effect of barometric pressure or cloud cover. But this model was not the best-fitting model for all individuals, suggesting that there may be substantial individual differences in the dynamic association between weather and mood in RCBD patients. Heterogeneity in the parameters of the differential equation model of homeostatic equilibrium as well as the coupling of mood to an inherently unpredictable (i.e., nonstationary) process such as weather provide an alternative account for reported broadband frequency spectra of daily mood in RCBD.

Keywords

Rapid Cycling Bipolar Disorder; Dynamical Systems; Differential Equations; Linear Oscillator; Mood Regulation

*Correspondence: Steven M. Boker PhD, Associate Professor, Department of Psychology, The University of Virginia, PO Box 400400, Charlottesville, VA 22904, USA, E-mail E-mail: boker@virginia.edu.

NIH-PA Author Manuscript

NIH-PA Author Manuscript

INTRODUCTION

Since admissions for mania may be related to weather [1,2] and exposure to light may have mood-altering effects in bipolar disorder patients [3], the present study examines the relationship between weather and mood in patients with rapid cycling bipolar disorder (RCBD). Patients with RCBD, who by definition, experience four or more major affective episodes per year [4], represent an important population for studying a potential relationship between mood and weather because significant mood changes occur over a relatively short interval of time. From a theoretical standpoint, the evaluation of a possible relationship between weather and mood would contribute to our knowledge of mood regulation and dysregulation. Clinically, the severity of RCBD and its challenging management warrant the effort to define the environmental factors that might contribute to the frequent shifts observed in the mood of these patients. This would allow the estimation of short term prognosis, the anticipation of situations of increased vulnerability, and the design of secondary and tertiary prophylactic measures [5].

The present study examines the relationship between daily self-reported mood ratings from a sample of RCBD patients and three weather variables: temperature, sky cover, and atmospheric pressure. A relationship between affective states and temperature has been suggested in multiple studies, although the relationship has not been replicated consistently [6,5]. Sky cover was chosen because of the antidepressant effect of light and its potential for stabilizing or destabilizing RCBD patients depending on the timing of the exposure [7]. Evidence that atmospheric pressure is involved in mood regulation is less direct, but there are indications that atmospheric pressure affects neurotransmitters implicated in mood regulation.

Temperature

Neurotransmitters involved in mood regulation are also involved in thermoregulation. It has been shown that injection of either dopamine or 5-HT in a small dose causes a fall in core in rats at about 17 degrees Celsius [8]. During cold exposure, the levels of NE increase many-fold [9]; NE is released from peripheral nerve endings and exerts thermoregulatory response through alpha adrenergic receptors on smooth muscles and beta adrenergic receptors on skeletal muscles.

Malberg et al. [10] showed a different core temperature and 5-HT neurotoxicity profiles after administration of fenuramine at different ambient temperatures. They demonstrated that FEN treated rats at hypo- or hyperthermic temperatures showed a large depletion in 5-HT and 5HIAA, the metabolite of serotonin. Ghosh et al. [11] showed higher environmental temperature-induced increases in body temperature involving serotonin in the GABA-mediated interaction of the opioidergic system. Blanc et al. [12] showed variation of dopamine and noradrenaline levels in response to stress. According to them, there was an increase in NE or DA in response to the cold wind stress and these two affect the level of other amine levels. O’Shea et al. [13] studied the effect of MDMA on dopamine and serotonin levels at various ambient temperatures in rats. They noticed a difference in the response to the same dose of MDMA at different temperatures. It was seen that MDMA produced a greater increase in dopamine levels at higher temperatures than at lower temperatures. Also, MDMA produced a greater thermogenic response at higher ambient temperatures as compared to lower ambient temperatures.

Finally, there is some recent neuroimaging evidence of the effect of temperature on affect. Sung et al. [14], using brain fMRI reported that warm stimulation results in increased activation of regions related to affective/emotional awareness and processing. The study concluded that appropriate thermal stimulation induces mood states and activates emotion/affect related regions of the brain.

Sky Cover

One reason to suspect sky cover as a potential predictor of mood regulation is the evidence from seasonality. Changes in photoperiod are followed by changes in temperature, sunlight, humidity, etc. Winter depression and photoperiodism [15] are phenomena of which many people are aware. However, it is less widely known that the majority of incidents of depression are during spring, and successful suicides are more frequent in spring than in other seasons. In fact, one of the most highly replicated findings in psychiatric epidemiologic research is the seasonal spring peak in suicide [16], an ultimate and tragic result of mental illness. A peak in spring was reported for depression exacerbation, admissions for depression, and ECT use [17,18,19,20,21,22]. Admissions for bipolar depression also peak in April [23,24]. Photoperiod, changes in photoperiod, and light intensity have been proposed as possible driving forces for peaks of suicide and depression [25]. However, upon careful scrutiny, the peak times of suicide occurrence (April and May, reviewed by Altamura et al. [26]) do not match the peak of photoperiod (centered on the Summer Solstice in late June) or the time when photoperiodic changes are at their greatest (centered on the Spring equinox in March) [27,28,29,30,31].

Atmospheric Pressure

There are several indirect reasons why atmospheric pressure may play a role in mood regulation. Several studies report that atmospheric pressure may influence serotonin metabolism, a major neurotransmitter involved in mood regulation and dysregulation. For instance, atmospheric pressure has been reported to explain a portion of the variance in platelet [3H]Paroxetine binding in normal volunteers [32], and in the ratio between the serotonin precursor L-tryptophan and the sum of the amino acids known to compete for the same cerebral uptake mechanism [5]. Furthermore, a negative correlation was shown between air pressure and CSF 5-HIAA [33], but this finding was not replicated at a second location with different climatic conditions [34].

DYNAMICAL SYSTEMS AND MOOD

Gottschalk et al. [35] studied daily mood ratings from a group of 7 bipolar patients and reported that mood in patients with bipolar disorder was not cyclic for extended periods of time based on evidence from power spectrum analysis. While Gottschalk et al. [35] concluded that this was evidence of deterministic chaos, Krystal and Greenside [36] noted that many processes other than deterministic chaos can lead to the broadband spectra and low correlation dimensions reported by Gottschalk and colleagues. In fact, many nonstationary processes including linear processes coupled to exogenous nonstationary processes can masquerade as low dimensional chaos, as measured by methods such as spectral analysis and correlation dimension [37,38]. If mood and weather were coupled, and given the demonstrated nonstationarity of weather [39, 38], one plausible explanation for the reported broadband spectra of daily mood ratings would be a linear homeostatic emotion regulation process with coupling to exogenous inuences such as weather. We compare the fit of several models of this form to daily mood rating and weather data.

Modern state space techniques [40,41,42,43] can estimate the parameters of models that are linear in their differential form, but exhibit phase resetting either due to intrinsic dynamics or coupling to exogenous influences. The method we chose uses differential equation models estimated through state space techniques to represent continuous patterns of change within systems (intrinsic dynamics) and between systems (coupling) [44,45,46]. Differential equation models allow the expression of effects within the system in terms of the instantaneous rates of change of variables as well as in terms of the values of the variables themselves [47,48]. Suppose mood is a variable that has a homeostatic equilibrium value, a value around which daily mood fluctuates. We could then consider daily mood as a displacement from this equilibrium value. A differential equation model for mood might include a prediction about how the displacement of mood from its equilibrium is related to the derivative of the mood with respect to time, that is how rapidly the mood is changing at that same moment. A model for cyclic fluctuations in mood would include a relationship between the displacement of mood and the second derivative of mood with respect time, that is how rapidly mood was accelerating or decelerating in its change.

One of the simplest physical systems that exhibits cyclic behavior is a pendulum. A pendulum swings with a particular frequency that is related to the length of the pendulum and will come to rest over an interval of time that is related the friction inherent in the pendulum's pivot point. If we make a few simplifying assumptions that the friction is constant and that there are no other influences on the pendulum's trajectory, a linear differential equation can describe the pendulum with friction: the damped linear oscillator [49]. The equation for the damped linear oscillator can be expressed as a linear regression formula where the acceleration of the pendulum is the outcome variable and the position and velocity of the pendulum are the predictor variables. If x_t is the displacement of the pendulum from equilibrium, then

$$\ddot{x}=\eta x_t+\zeta \dot{x}+e_t, \quad (1)$$

where x_t is the value of the displacement from equilibrium at time t, $\dot{x}$ is the first derivative, and $\ddot{x}$ is the second derivative with respect to time. This results in two main parameters: η is related to the square of the frequency of the oscillation of the system and ζ is related to the amount of damping (friction) in the system. These two have appealing substantive interpretations. The frequency parameter from the linear oscillator equation represents the fundamental frequency with which a particular RCBD patient's mood would tend to cycle if she or he were isolated from external influences. The damping or friction parameter from the equation represents how rapidly a patient would return to a euthymic state if they were influenced by a single event and then isolated from external influences.

Mood Dynamics in the Context of Weather

One way to think of the dynamic relationships between variables in dynamical systems terms is as coupling between the variables. For instance, imagine a pendulum. Attached to the mass of this pendulum is a spring that can be used to push or pull the mass from its prescribed trajectory. The push or pull of the spring can affect the pendulum in many different ways. The spring can modulate either the frequency or damping of the pendulum, or both. Consequently, the trajectory of the pendulum could become quite intricate overtime, particularly if the push or pull on the spring changes with time. Differential equation models can formalize and test these ideas by comparing how well alternative models account for data from the pendulum (mood) and the spring (weather).

Due to the irregularity of weather patterns [39,50,51], the effects of weather on mood over extended periods of time may appear to be highly complex. This, however, does not preclude the use of local linear approximations of the derivatives of weather variables with respect to time to examine how they may act as an external influence on mood. These models need not account for patterns of weather, but in order to be useful, they should account for the degree to which changes in weather variables can account for changes in mood. In addition to the effect of the exogenous weather variables, we wish to understand how much of the variability in mood might be accounted for by an intrinsic dynamic – to what extent changes in mood can be accounted for by an intrinsic self-regulatory process.

Even if all external influences on mood were perfectly understood, the long term trajectory of daily mood may not be able to be predicted, that is to say, mood might exhibit sensitive dependence on initial conditions. However, even if the time-varying trajectory of daily mood turns out to be some deterministic nonlinear or stochastic nonstationary process, it is still possible to gain an understanding of the dynamics of daily mood over short intervals of a few days by using local linear approximations of the derivatives.

Furthermore, we are interested in how weather variables may be related to daily mood dynamics. We wonder whether coupling between weather and mood involves a direct effect of the displacement of weather from its mean on the displacement of mood from its mean. Or perhaps the displacement of a weather variable from its mean value or the rate of change in the weather variable modulates the frequency or damping parameters of mood. In the analyses below, we test hypotheses about the relationship between weather and the dynamics of fluctuations of daily mood in a sample of RCBD patients.

METHODS

A clinical sample of 15 RCBD patients rated their mood every morning and evening for 3 months. In addition, a variety of weather variables were recorded each day for the same period. Four variables were chosen to study the coupling between mood and weather: the twice-daily mood rating, the barometric pressure, the percentage of sky cover, and the mean temperature for each day on which a measurement was obtained. Three models were fit to these data in order to explore the potential for understanding the cycling of mood in RCBD as a dynamical system and to test the degree of coupling between such a system and the three indicators for weather. Three additional models tested the coupling of each of the weather variables one at a time with the mood of RCBD patients.

Subjects

Fifteen patients diagnosed with rapid cycling bipolar disorder (7 Bipolar I, 8 Bipolar II) participated in the experiment. The patients had all been on stable medication (see Table 1) for at least three consecutive months. Eleven patients were female and 4 were male and their mean age was 42.2. Fourteen patients were Caucasian while the remaining patient was Asian. The patients all lived in the Washington, DC area: 2 in the District of Columbia, 7 in Northern Virginia and 6 in Maryland.

All participants were outpatients followed at the outpatient research clinic for patients with rapid cycling bipolar disorder at the National Institute of Mental Health (NIMH). All patients met the criteria for bipolar illness as established by a Structural Clinical Interview for DSM-III-R [52,53]. In addition, patients reported having had at least four major affective episodes within the past year, including at least one each among major depression and hypomania (or mania). We excluded patients with substance abuse or dependence within the past year, and those that met criteria for borderline or antisocial personality disorder by the Structural Clinical Interview for DSM-III-R Personality Disorders (SCID-II) [54]. Patients signed informed consent.

Procedure

Patients completed daily mood self-ratings twice a day, once shortly after awakening and once just before bedtime. Patients rated their mood on a 100mm line with 0 representing “most depressed I’ve ever felt” and 100 representing “most manic I’ve ever felt”. Patients were able to view their previous responses. The region less than 35 was labeled “depressed”, from 35 to 65 was labeled “euthymic” and greater than 65 was labeled “hypomanic/manic”. In addition patients completed a sleep log with a 15 minutes resolution every day. During the clinic visits, the patients were rated using the Structured Interview Guide for the Hamilton Rating Scale for Depression: Seasonal Affective Disorder Version (SIGH-SAD) [55] to measure the typical and atypical depressive symptoms while the Hypomania Interview Guide (HIGH-SAD) [56] was used to measure hypomanic/manic symptoms.

Data were gathered during the spring, summer and fall of 1993 and 1994. Each patient was studied for three consecutive months beginning as early as April and as late as September. Weather variables for the Washington DC metropolitan area were obtained from the National Climatic Data Center as measured at Dulles Airport. Barometric pressure was collected as a daily average based on eight observations per day at 3 hour intervals. Barometric pressure was measured in units of .001 inches of Mercury and was rescaled to units of .1 inches of Mercury for purposes of the analysis. Sky cover was measured as the daily average cloud cover from midnight to midnight, with data values varying from 0.0 representing clear for the entire 24 hour period to 100.0 representing completely overcast. Daily mean temperature was collected as a daily average based on eight observations per day at 3 hour intervals, rounded to the nearest degree Fahrenheit.

Models

The process by which differential equation models were fit to these data involved four main steps. First optimal analysis intervals, (τ), were estimated individually for each subject. Second, local linear approximations to the first and second derivatives of each variable were estimated for each available triplet of occasions of measurement separated by the chosen analysis interval. Third, covariances between all the variables and their derivatives were calculated. Finally, seven competing structural equation models were fit to the covariance matrices and the results compared.

Since there may be important categorical differences between the patients in this population, we chose to estimate the derivatives in two different ways. First, we use a nomothetic approach in which the grand mean of all of the individual analysis intervals is calculated and used to estimate derivatives for all patients and occasions. The covariances between these derivatives are then used to fit the seven candidate models to the population. Second, we used an ideographic approach in which each patient's estimated optimal analysis interval was used to fit all seven models to that patient's repeated observation data. In this approach we do not aggregate over patients, but rather compare which models are best-fitting within patient.

We expand on each of these modeling steps below, starting with an explanation of local linear approximation (LLA) of derivatives. We then present the damped linear oscillator model and discuss the estimation of the analysis interval. Finally we discuss alternative models for coupling daily mood with weather variables.

Local Linear Approximation of Derivatives—In order to fit a differential equation model to data, the data must be in the form of approximations to the instantaneous first and second derivatives of the variable at each occasion of measurement. Local linear approximation can be used to estimate parameters of continuous time differential equations models [45].

Suppose the variable M is measured on three successive occasions separated by an interval of time Δt and resulting in the measurements M_1, M_2 and M_3. A local linear approximation for the first derivative of M at the second occasion of measurement is given by the average of the two slopes between M_1 and M_2 and between M_2 and M_3,

$$\dot{M}_{1+\tau} \approx \frac{M_{1+2\tau} - M_1}{2\tau\Delta t}, \qquad (2)$$

where in this case $\tau = 1$ because M_1, M_2 and M_3 are successive occasions of measurement and Δt is the interval of time between measurements. When many occasions of equal interval measurement exist, alternating measurements in a sequence (for instance M_1, M_3 and M_5) could also be used, in which case $\tau = 2$ would be used in the Equation 2.

Similarly, the local linear approximation for the second derivative of M at the second occasion of measurement can be calculated from the same triplet of scores M_1, M_2 and M_3 as the change in the slopes with respect to time,

$$\ddot{M}_{1+\tau} \approx \frac{M_{1+2\tau} - 2M_{1+\tau} + M_1}{\tau^2 \Delta t^2}. \tag{3}$$

For this analysis, we assumed that the within-subject mean value of the mood variable estimated the equilibrium value for each subject. We thus subtracted the within-subject mean values for each variable so as to express the mood variable as an estimated displacement from equilibrium. We did not standardize the mood or weather variables.

Damped Linear Oscillator Model of Daily Mood—A linear second order differential equation for a damped linear oscillator model of mood can be expressed as,

$$\ddot{M}_t = \zeta \dot{M}_t + \eta M_t + e_t \, , \tag{4}$$

where M_t represents the value of mood self-report mood at time t, η is related to the frequency of oscillation, ζ estimates the damping and e_t is the residual in estimating $\ddot{M}_t$. A plot of the trajectory resulting from this equation, given example parameter values for η and ζ and initial conditions at $t = 0$, is shown in Figure 1.

Although Equation 4 is a linear regression equation, the interpretation of its parameters is quite different. A normal linear regression model would estimate some expected growth line or expected growth curve. This differential equation regression model estimates an expected oscillation and damping given some set of initial conditions. In Figure 1 there are no exogenous influences on the variable M except at time $t = 0$. Of course, initial conditions may be change over time due to exogenous influences on mood. Thus, an individual's observed trajectory is some mixture of these exogenous influences and the intrinsic self-regulation in response to the exogenous input. When the model in Equation 4 is fit to repeated observations from an individual, it estimates how the individual self-regulates in response to exogenous input. Thus, this model does not describe a particular trajectory for a particular person, instead it describes a family of trajectories that would be expected in response to a distribution of possible exogenous influences.

In order to fit this model, the first and second derivatives for mood M were calculated using linear approximation as described above. Estimation bias in the damped linear oscillator model parameters has been shown to depend on the selection of the parameter τ, the interval of time between observations used to estimate the derivatives [45]. Therefore, individual values of τ were estimated for the mood data of each individual using the fixed-window surrogate R^2 technique [57,58]. This technique uses surrogate data analysis [59] to automate a plot-based method developed by Boker and Nesselroade [45] for low bias within-individual parameter estimation of damped linear oscillator models. Fixed-window analysis was used to estimate τ due to the possibility of relatively long frequencies relative to the time over which samples were collected; plots of results from the surrogate technique and the plots described by Boker and Nesselroade [45] were also examined for patterns uncharacteristic of damped linear oscillators. Values for τ were estimated for the morning and evening mood data separately and compared as a within-individual check of the data.

Analysis of data using the fixed-window surrogate technique begins by calculating the explained variance from fitting equation 4 to the observed time series of an individual, using LLA to estimate the first and second derivatives with a range of τ values. Boker and Nesselroade [45] have shown that plots of the explained variance versus τ tend to an approach asymptote as the ideal value for τ is approached. The black, wide line in Figure 2 shows a typical plot of the explained variance versus τ for an oscillating system.

A resampling technique called surrogate data analysis is then used to establish at what values of τ the observed explained variance is greater than would be expected by chance [59]. The original time series is randomly shuffled to create multiple *surrogate data sets*. Random shuffling of the original time series produces time series with the same distributional characteristics as the original data (e.g. mean, variance), but all meaningful relationships related to time are removed. Equation 4 is then fit to each surrogate data set in the same manner as the original data set. The results from the surrogate data analysis, depicted as thin, gray lines in Figure 2, can be used to estimate the explained variance that would be expected by chance if the observed time series had no time-based relationships.

At each value of τ the proportion of surrogate data sets that produced an explained variance smaller than the original data set can be calculated (range: 0 to 1). The proportion versus τ data is used to select the first value of τ that explains an unusual amount of variance. This is done by generating one-half square-waves (i.e. pulses) ranging from 0 to 1, with the first half of the pulse equal to 0. Pulses of varying lengths are then fit to the data, with the mean squared difference between each pulse and the proportion data calculated for each pulse length. The minimum mean squared difference is selected as the best indicator of the transition from low to high proportions, and is therefore related to the asymptote of the R^2 versus τ graph. The ideal values for τ, which have been shown to be nearly unbiased in the range of 15 to 95 observations per cycle, occurs at the first value equal to 1 of the pulse with the minimum mean squared difference.

After estimating an optimal time delay, τ for each subject, each triplet of values for which there were no missing data was used. Thus each subject, with twice daily measurement, might contribute as many as $2(N - 2\tau)$ observations, or fewer if some occasions were missing. The analysis used all possible within-subject triplets for which three values existed.

A path diagram representing the linear oscillator model from Equation 4 (Model A) is depicted in Figure 3. This diagram follows the conventions of RAM diagrams [60, 61] in which squares represent measured variables, circles represent unmeasured variables, single headed arrows represent regression coefficients and double headed arrows represent variance and covariance components. The box labeled M represents the mood variable, the box labeled dM represents the first derivative of mood and the box labeled $d2M$ represents the second derivative of the mood variable. The variances of M and dM are represented by the double headed arrows labeled V_M and V_{dM}, the regression coefficients ζ and η are represented by the corresponding single headed arrows, and the residual variance for $d2M$ is represented by V_e.

The weather variables in Model A (shown in Figure 3) are represented by the six boxes labeled B for barometric pressure, dB for change in barometric pressure, S for percentage of sky cover, dS for change in percentage of sky cover, T for mean temperature and dT for change in mean temperature. Note that in Model A there are no connections between the weather variables and the mood variables, thus Model A tests the hypothesis that the mood oscillator is not predicted by these weather variables. All weather variables were allowed freely covary, since we do not want to explicitly model the relationships between weather variables.

This structural model was then fit using the Mx software [62] to provide estimates of the coefficients that are closest to the observed covariances between the three variables of mood in the maximum likelihood sense. By comparing the differences in fit indices for each of these models we can test hypotheses that one model is preferred over another individually within each patients' data. It should be noted that there are no degrees of freedom in the linear oscillator portion of the model, so there is no potential contribution of misfit from the linear oscillator model of mood. However, there are two methods that can be used to help understand how well the linear oscillator portion of the model is accounting for the observed data. First, the explained variance R^2 for the $d2M$ can be calculated as the proportion of original variance of $d2M$ that does not appear as V_e. In addition, a index can be derived by multiplying the estimated η parameter by the squared delay value, $(\tau\Delta t)^2$, used for analysis. With oscillating systems $\eta(\tau\Delta t)^2$ tends to depart from the value −2, when $\tau\Delta t$ is not 1/4 or 3/4 the period (wavelength) of the oscillator [63]. In the case of the current data, measurements are one day apart, so $\Delta t = 1$. We will estimate the optimum delay value of τ given the data; this estimation procedure is described in a subsequent section.

We will refer to the three variables M, dM, and $d2M$ along with the single headed and double headed paths that connect them as the *mood oscillator*. We use this descriptive term since the algebraic form of these variables and their connections is equivalent to the damped linear oscillator from Equation 4. The remaining models test various hypotheses concerning the relationship between weather and mood.

Linear Oscillator Model of Mood Coupled to Weather—The covariances between the 9 variables (Mood and its first and second derivatives, and Barometric Pressure, Sky Cover and Mean Temperature and their respective first derivatives) are predicted by the six structural equation models represented by the path diagrams in Figure 4. Each model tests a different hypothesis concerning the observed covariances between the weather variables and the mood oscillator.

Models B, C, and D in Figure 4 test three hypotheses concerning the structure of the covariance between the weather variables and the mood oscillator. Model B tests the hypothesis that the weather variables act directly as part of the mood oscillator by predicting the second derivative of the mood ($d2M$) directly. Models C and D, respectively, test if there is a direct effect of weather variables on the displacement of mood from equilibrium (M) or the first derivative (dM) of mood.

Note that when the effects of weather on the second derivative are mediated through M or dM in Model C or D, the estimated parameter values for η and ζ will not change relative to those estimated in Model A. On the other hand when Model B is estimated, the estimates for the coefficients η and ζ will partially depend on the values estimated for the regression coefficients connecting the weather variables to $d2M$. Thus a preference for Model B over Models C and D would suggest that the parameters for the mood oscillator interacted with exogenous influences and might be considered to have state-like characteristics, whereas a preference for Model C over Model B would indicate that the estimated parameters for the mood oscillator were more stable, endogenous, trait-like parameters.

Models E, F, and G in Figure 4 test the hypothesis that only one weather variable dominates in its effect on the regulation of the mood oscillations. Models E, F, and G are in some sense complementary to Models B, C, and D in that Models E, F, and G test hypotheses about *what* does the regulation and Models B, C, and D test hypotheses about *how* the regulation happens. This model construction strategy may be useful in a wide variety of contexts where relevant theory posits coupling between variables. Note that all six of these models have the same number of degrees of freedom, but are not nested. Thus, direct likelihood ratio difference tests are inappropriate, but the AIC fit statistic may be used.

RESULTS

Descriptive statistics for the four variables used in the present analyses are displayed in Table 2. Most patients are missing only a few observations, however one patient is missing 36% of the total possible observations (patient 14). Recall that since a full non-missing triplet of data is needed to estimate the derivatives, there will be fewer observations actually included in the analysis. Due to the large proportion of missing observations, patient 14 was dropped from further analyses.

Data from three example patients are plotted in Figure 5. These examples were chosen to illustrate the individual differences shown in patterns in the mood trajectory. For instance, patient 6 shows strong and regular cycles in his/her mood trajectory, whereas the mood trajectory of patient 13 only hints at the possibility of a long frequency cycle, and any underlying cyclicity in patient 1 is not immediately apparent to the eye. It may also be useful to note that the Barometric Pressure and Temperature variables appear to have fewer high frequency components than the Sky Cover variable. The Temperature variable however shows clear trends over time, which are not as apparent in the Barometric Pressure and Sky Cover variables.

Within-Individual Estimation of τ

Previous simulations have indicated that the best estimates of the η and ζ parameters in damped linear oscillator models occur when the interval between the three measurements used to approximate the derivatives (τ) is an optimum value [45]. If the interval between the measurements is too small then error variance tends to be compounded in the approximation of the derivatives, whereas if the measurement interval is too long, the variance in the second derivative approaches zero and thus there is little or no residual variance that can be predicted with external variables.

Surrogate data analysis can be used to select values for τ which lead to low bias paramater estimates of the damped linear oscillator model [57,58]. This surrogate R^2 technique examines the variance explained by models using different τ values and selects the value for τ that occurs as the variance explained asymptotes. The asymptote in the explained variance has been identified as an optimal point for the selection of τ for oscillating systems with substantial error variance [45]. For the present analysis, the fixed-window surrogate R^2 technique was fit to the morning and evening data separately, for each individual. The estimated τ values are shown in Table 3.

Of the 14 patients, only three showed large differences between their morning and evening data: patients 5, 7, and 9. Thus, the estimated self-regulating dynamic for 11 of the 14 patients exhibited similar frequency properties in two interleaved samples. This suggests that it is unlikely that these estimates are due to random fluctuations. Furthermore, lower values of τ tend to be associated with time series with either a very weak signal and a large proportion of error variance, or even no signal at all. Based on a large scale simulation, Deboeck and Boker [58] suggest that when the estimated optimal analysis interval $\tau > 4$, data are unlikely to primarily consist of error variance. The grand mean of all patients' was $\mu(\tau) = 9.18$, providing converging evidence that variability in daily mood is unlikely to be attributable to random fluctuations.

For the nomothetic analysis below, derivatives were estimated using the integer value of the grand mean $\mu(\tau) = 9$. For the ideographic analyses, derivatives for each participant were estimated using the within-individual mean of the morning and evening τ values listed in Table 3. For both nomothetic and ideographic analyses, time between successive observations (Δt) was specified as 1/7, so that the estimated estimated parameters are scaled in terms of weeks. This scaling ensured that the variance of M and its derivatives spanned only few orders of magnitude. Variances spanning more than three orders of magnitude can be problematic for SEM estimation routines due to rounding precision.

The weather variables are not being explicitly modeled as outcomes and therefore did not require equivalent attention for the selection of τ. Derivatives for all three weather variables were calculated using a τ equivalent to one day. Time scaling of the weather derivatives, Δt was specified as 1/7 in order to maintain the time scaling used in the mood derivatives.

Nomothetic Modeling Results

We first fit the seven damped oscillator models to the covariance matrix calculated from data from all 14 patients. Since the data were largely complete for all included subjects, this approach allows us to provide estimates of mean values for the parameters of each model and to evaluate differences between models across all subjects. The results of fitting these models to the aggregated covariance matrix are presented in Table 4. The mean frequency parameter is essentially invariant across models, $\eta = -1.09$, resulting in a mean period of $\lambda = 2\pi\sqrt{-1/\eta + .25\zeta^2} = 6.01$ weeks. The mean damping parameter, $0.02 \le \zeta \le 0.05$, was small and positive, indicating that exogenous influences tended to be amplified into larger fluctuations as time elapsed.

Model A (AIC=41.74), in which weather is presumed to have no effect on mood fluctuations, and Model G (AIC=41.84), in which barometric pressure alone is couple to mood, are the two worst fitting models. The two best-fitting models are Model B (AIC=16.20), in which the weather variables predict the second derivative of mood, and Model F (AIC=6.02), in which temperature alone is used to predict all of the mood variables.

Discussion of Nomothetic Results—Given that the model hypothesizing no effect of weather on mood fluctuations fit substantially worse than all but one of the other models, it is concluded that it is unlikely for there to be no coupling between weather and mood fluctuations in these RCBD patients. However, the small number of subjects limits the generalizability of this conclusion to the population of all individuals diagnosed with RCBD.

The two best-fitting models, Model B and F come from two complementary categories of models. Model B tests a hypothesis about which type of regulation best accounts for the data. Model B allows regulation of the second derivative, and thus it is concluded that the regulation of mood coupled to weather is likely to be state-like in that there are likely to be time-dependent frequency and damping of an individual's observed trajectory over time. Model F excludes the effect of all weather variables but temperature. Thus, it is concluded that in relation to the other weather variables in these data, temperature better accounts for the observed mood fluctuations in these RCBD patients.

Each of the seven models accounted for approximately 62% of the variance in the second derivative of daily mood. While this R^2 might at first glance seem high, in previous simulations [45] when the true model was known to be a damped linear oscillator with invariant parameters, R^2 values exceeded 0.75 even when substantial noise (i.e., measurement error) was present. Thus, we conclude that either (a) there are substantial individual differences in the parameters of the model, (b) there are within-person time varying parameters to the model, (c) there are other exogenous influences to which mood is coupling, or (d) there exists a better dynamical systems model to account for self regulation within these data.

There is evidence from the τ estimation results in Table 3 that substantial individual differences exist in the period of oscillation for these patients. Thus, constraining the parameter values to a sample average in a nomothetic analysis may obscure reliable individual differences in the self-regulation of mood.

Ideographic Modeling Results

We next fit the seven models to each individual in order to estimate individual differences. Covariance matrices for each individual were calculated based on the individual τ values shown in Table 3. The number of complete data triplets (i.e. M, $\dot{M}$, $\ddot{M}$) range from 60 to 168, with the median person having 126 triplets.

The results from Model A are first considered. Individual values of $\eta(\tau\Delta t)^2$ range from −2.190 to −1.108, with a median value of −1.534. The departure of these values from −2 for many individuals suggests that underlying signal is behaving as would be expected for a damped linear oscillator [63].

Substantial individual differences in both the frequency (η) and damping (ζ) parameters for the damped linear oscillator model of mood were observed. Patients' frequency parameters range from a relatively rapid frequency of $\eta = -7.46$ (16.1 days) to slow frequencies of $\eta = -0.26$ (85.6 days). The median participant frequency was 34.8 days ($\eta = -1.59$). The individual differences in the damping parameter ζ range from $\zeta - 0.49$ to $\zeta = +0.42$, with a median ζ of −0.04. A negative damping parameter indicates that these individuals' oscillators are likely to reduce in amplitude over time.

All seven models were then fit to each individual's data. The AIC fit statistics for each of these models, for each individual, are summarized in Table 5. The last column in this table identifies the best-fitting model based on AIC, while the last two rows show mean and median AIC values within each model. The pattern of results for the mean AIC values are similar to those shown in the nomothetic results, with Models B and F displaying the best fit. However the median results seem to suggest that Models D and F are the best-fitting models.

Examination of results within individual suggest that substantial individual differences exist. The data of six individuals seems to be best fit by model F, the model that seemed to emerge as best from the nomothetic results, where temperature and its first derivative influences the damped linear oscillator model of mood. However model D, where weather variables affect the first derivative of mood, provides the best fit for three individuals. The data from two individuals are best fit by model E, where barometer and its first derivative affect the oscillator model. Data from one of each of the other three individuals are best fit by models A, B, and G. No single model provides the best fit for the majority of individuals in this sample.

In addition to examining which model fits best, one can also consider how weather variables may influence the mood oscillator. In models A, C, and D the estimated η and ζ parameters will be the same, but in the remaining four models the parameters of the mood oscillator will be affected by weather. We can compare the estimated values of η and ζ in models A and F, for instance, by calculating the change in parameter values within individual from one model to the other. The change in frequency ranges from −0.75 days to 3.04 days, with a median value of 0.10 days. These differences are relatively small compared to the range of frequency values estimated in Model A, which was 16.1 days to 85.6 days. The change in ζ ranges from −0.120 to 0.148, with a median value of −0.008. For some individuals these changes are of moderate magnitude compared to the range of ζ values estimate in Model A, which was −0.49 to 0.42. Similar results are observed for the change in η and ζ parameters for the other models where the mood oscillator was affected by weather variables.

Discussion of Ideographic Results—This analysis examined the within-subject variability in self-report mood measured at daily intervals over a span of 90 days. A set of models that interpret this intraindividual variability using a state space estimated second order differential equation were fit to these data and measures of goodness-of-fit were compared.

Individual results were not well characterized by a single model. While six of the individuals seemed to be best characterized by Model F, where temperature and its first derivative affect the mood oscillator, the remaining eight individuals were best characterized by a variety of models which included all models except model C. These differences could be due to a variety genetic and environmental influences, including possibly the effect of different medications or the existence of certain RCBD sub-types. Ideographic analyses with a larger sample of individuals would be required to address the sources of individual differences in best-fitting models. These results do suggest that averaging over all individuals may result in misleading conclusions for some individuals, as not all subgroups may be well represented; this seems to be the case with RCBD patients.

When self-report mood was modeled as a damped linear oscillator, there were marked individual differences in the values for the frequency and damping parameters of the mood oscillator. In addition to different frequencies of oscillation, substantial individual differences in the damping (or friction) parameter of the estimated mood oscillator were observed. Some subjects were estimated to have a relatively large negative value for this parameter and thus show damping in their mood oscillator, which could be interpreted as resiliency or a tendency to return to homeostasis after an exogenous influence. However other individuals were estimated to have positive values for their damping parameter and thus show amplification in their mood oscillator, a tendency to amplify small exogenous effects into large changes in mood – dysregulation to homeostasis. The individuals with positive damping parameters exhibit behavior that would also be consistent with a deterministic chaotic process.

Models B, E, F, and G all allowed for the possibility that weather, or certain components of weather, may affect the parameters of the hypothesized mood oscillator. Comparing changes in the frequency and damping parameters of these models to Model A, only small changes in the frequency of oscillation were observed for most individuals, relative to the range of observed frequencies. The damping parameter, however, showed the potential for moderately large changes for some individuals, relative to the range of observed damping estimates. This suggests that if and when weather variables do have an effect on the mood oscillator of RCBD patients, the greater effect is not on how quickly they transition from one affective state to the next but on how the regulation to homeostasis may change over time.

CONCLUSIONS

Two main conclusions emerge from analyses present in the current study. The first conclusion is that there appears to be substantial heterogeneity in this sample of RCBD patients. There were substantial individual differences in the parameters estimated by the mood oscillator model, differences that may have diagnostic value. One potential source of this heterogeneity could be overlap genes, such as proposed by Potash [64]. Further research is required to determine whether the techniques and models presented here will prove to differentiate RCBD patients into diagnostically useful categories, to anticipate periods of increased vulnerability to dysregulation, or to provide predictive power in short term prognosis. Taken together, the observed heterogeneity in dynamics indicates that averaging over individuals is likely to obscure rather than reveal the mood regulatory processes at work in these individuals. Such a view of adaptive heterogeneity in combination with deterministic dynamics is similar to the views proposed by Yeragani et al. [65].

The second main conclusion is that there is evidence that weather may be coupled to mood regulation in RCBD patients in several different ways. In the largest category of individuals, thermoregulation appears to be the primary source of coupling between mood and weather. A second type of coupling observed in these individuals is one in which one of the three weather variables tended to change the estimated damping parameter, the measure of homeostatic regulation. Thus it may be that weather, in particular heat, may both affect mood directly as well as affecting the way that mood is regulated. This indication of potential nonstationarity in the parameters of the model needs to be further explored. The model presented here has parameters that are fixed over time within subjects. Our analyses suggest that a better model would estimate the direct effect of weather on regulation using time-varying coefficients.

There are many possible explanations for an association between weather and regulation of mood. For instance, in better weather people may be more likely to spend time outdoors. This may result in increased activity and exercise. Increased outdoor time may also increase exposure to light as a positive consequence or to allergens as a negative consequence. Increased indoor time may increase exposure to viruses as well as reduce exercise and lower exposure to light. So, while weather and mood may be associated, this does not mean that there is necessarily a direct effect of weather on mood. The current analyses did not test any of these potential mediating or moderating influences.

Both frequency and damping are appealing ways to conceptualize aspects of mood regulation or dysregulation [66]. Frequency of oscillation of mood is an intuitive notion. But damping as a parameter of mood regulation has not received similar attention. Note that our model allows for exogenous inputs to the system that can drive it away from equilibrium. For instance, weather may be one exogenous influence that contributes to mood being pushed away from homeostasis. The effect of these exogenous influences mean that any one person’s modeled oscillations will likely never damp entirely to equilibrium. Exogenous variables other than weather, such as emotional stressors, challenges, threats, sleep loss, and other unpredictable outside influences on mood, may serve to push mood away from homeostatic equilibrium. Our modeling results are inconsistent with a hypothesis that the observed variability in mood is simply due to noise. If it were, then the most likely preferred model would have been Model A and the most likely estimated optimal τ would have been 1 or 2. In contrast, we only found one individual whose preferred model was Model A and only one other individual whose optimal τ was 2. An explanation consistent with our results is that exogenous random shocks, i.e, nonstationary effects are coupled to a homeostatic regulatory system. The effect of these nonstationary coupled influences would likely be a broadband spectrum of mood, such as reported by Gottschalk et al. [35], even if the regulatory mechanism were linear such as in the analyses reported here. Accounting for the physiological bases of these mechanisms of mood regulation and dysregulation remains an open and active field of inquiry. Clearly, new samples with more subjects and more observations per subject are called for in order to help determine the extent to which our findings in the current sample generalize to the population. In addition, seasonal effects and sleep may covary with mood – future studies should consider varying the time of year of sampling as well as collecting sleep data. We believe that the methods and results presented here offer an opportunity to refine the focus of psychopharmacological research into mood regulation and to test the outcomes of competing theoretical mechanisms.

Acknowledgments

This work was supported in part by the National Institute of Mental Health Intramural Research Program. This study was approved by the Institutional Review Board of the NIMH. Dr. Boker is supported by NIH Grant R29-AG14983 and NSF Grant BCS-0527485. Dr. Postolache is supported by two grants: R21 MH075891-01A1 and R01MH074891, both from the National Institute of Mental Health (PI: Teodor T. Postolache). Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the

National Science Foundation or National Institutes of Health. We would also gratefully acknowledge the help of Susana Feldman-Naim and Joseph Soriano, MS.

References

1. Mawson D, Smith A. Relative humidity and manic admissions in the London area. British Journal of Psychiatry 1981;138:134–138. [PubMed: 7260493]
2. Myers DH, Davies P. The seasonal incidence of mania and its relationship to climatic variables. Psychological Medicine 1978;8:433–440. [PubMed: 704710]
3. Leibenluft E, Turner E, Feldman-Naim S, Schwarts P, Wehr T, Rosenthal N. Light therapy in patients with rapid cycling bipolar disorder: Preliminary results. Psychopharmacology Bulletin 1995;31(4): 705–710. [PubMed: 8851643]
4. Dunner DL, Fieve RR. Clinical factors in lithium carbonate prophylaxis failure. Archives of General Psychiatry 1974;30:229–233. [PubMed: 4589148]
5. Maes M, Scharpe S, Verkerk R, D'Hondt P, Peeters D, Cosyns P, Thompson P, De Meyer F, Wauters A, Neels H. Seasonal variation in plasma L-Tryptophan availability in healthy volunteers. Archives of General Psychiatry 1995;52:937–946. [PubMed: 7487342]
6. Howarth E, Hoffman MS. A multidimensional approach to the relationship between mood and weather. British Journal of Psychology 1984;75:15–23. [PubMed: 6704634]
7. Leibenluft E, Albert PS, Rosenthal NE, Wehr TA. The relationship between sleep and mood in patients with rapid-cycling bipolar disorder. Psychiatry Research 1996;63:161–169. [PubMed: 8878312]
8. Cox B, Lee TF. Further evidence for a physiological role for hypothalamic dopamine in thermoregulation in the rat. Journal of Physiology 1980;300:7–17. [PubMed: 7381796]
9. Castellani JW, Young AJ, Kain JE, Sawk MN. Thermoregulatory responses to cold water at different times of day. Journal of Applied Physiology 1999;87:243–246. [PubMed: 10409581]
10. Malberg JE, Seiden LS. Administration of fenfluramine at different ambient temperatures produces different core temperature and 5- ht neurotoxicity profiles. Brain Research 1997;765:101–107. [PubMed: 9310399]
11. Ghosh S, Poddar M. Higher environmental temperature-induced increase in body temperature: Involvement of serotonin in gaba mediated interaction of opiodergic system. Neurochemical Research 1993;18(12):1287–1292. [PubMed: 7505891]
12. LeBlanc J, Ducharme MB. Plasma dopamine and noradrenaline variations in response to stress. Physiology and Behavior 2007;91:208–211. [PubMed: 17433386]
13. O'Shea E, Escobedo I, Orio L, Sanchez V, Navarro M, Green AR, M Isabel Colado MI. Elevation of ambient room temperature has differential effects on mdma- induced 5-ht and dopamine release in striatum and nucleus accumbens of rats. Neuropsychopharmacology 2005;30:1312–1323. [PubMed: 15688085]
14. Sung EJ, Yoo SS, Yoon HW, Oh SS, Han Y, Park HW. Brain activation related to affective dimension during thermal stimulation in humans: a functional magnetic resonance imaging study. International Journal of Neuroscience 2007;117(7):1011–1027. [PubMed: 17613111]
15. Wehr TA. Photoperiodism in human and other primates: Evidence and implications. Journal of Biological Rhythms 2001;16(4):348–364. [PubMed: 11506380]
16. Petridou E, Papadopoulos FC, Frangakis CE, Skalkidou A, Trichopoulos D. Exploring lag and duration effect of sunshine in triggering suicide. Epidemiology 2002;13(1):106–109. [PubMed: 11805594]
17. Eastwood MR, Stiasny S. Psychiatric disorder, hospital admission and season. Archives of General Psychiatry 1978;35(6):769–771. [PubMed: 655774]
18. Fossey E, Shapiro CM. Seasonality in psychiatry – a review. Canadian Journal of Psychiatry 1992;37 (5):299–308.
19. Frangos E, Athanassenas G, Tsitourides S, Psilolignos P, Robos A, Katsanou N, Bulgaris C. Seasonality of the episodes of recurrent affective psychoses. possible prophylactic interventions. Journal of Affective Disorders 1980;2(4):239–247. [PubMed: 6450783]
20. Kraines SH. The physiologic basis of the manic-depressive illness: a theory. American Journal of Psychiatry 1957;114(3):206–211. [PubMed: 13458478]

21. Maes M, Meltzer HY, Suy E, De Meyer F. Seasonality in severity of depression: relationships to suicide and homicide occurrence. Acta Psychiatrica Scandinavica 1993;88(3):156–161. [PubMed: 8249645]
22. Zung WW, Green RL Jr. Seasonal variation of suicide and depression. Archives of General Psychiatry 1974;30(1):89–91. [PubMed: 4808737]
23. Silverstone T, Romans S, Hunt N, McPherson H. Is there a seasonal pattern of relapse in bipolar affective disorders? a dual northern and southern hemisphere cohort study. British Journal of Psychiatry 1995;167(1):58–60. [PubMed: 7551610]
24. Morken G, Lilleeng S, Linaker OM. Seasonal variation in suicides and in admissions to hospital for mania and depression. Journal of Affective Disorders 1991;21(1):39–43. [PubMed: 1827475]
25. Goodwin, FK.; Jamison, KR. Manic-Depressive Illness. Vol. 1 ed.. Oxford: Oxford University Press; 1990.
26. Altamura C, VanGastel A, Pioli R, Mannu P, Maes M. Seasonal and circadian rhythms in suicide in cagliari, italy. Journal of Affective Disorders 1999;53(1):77–85. [PubMed: 10363669]
27. Tietjen GH, Kripke DF. Suicides in california (1968–1977): absence of seasonality in los angeles and sacramento counties. Psychiatry Research 1994;53(2):161–172. [PubMed: 7824676]
28. Barker A, Hawton K, Fagg J, Jennison C. Seasonal and weather factors in parasuicide. British Journal of Psychiatry 1994;165(3):375–380. [PubMed: 7994509]
29. Terao T, Soeda S, Yoshimura R, Nakamura J, Iwata N. Effect of latitude on suicide rates in japan. The Lancet 1994;360:1892.
30. Linkowski P, Martin F, De Maertelaer V. Effect of some climatic factors on violent and non-violent suicides in belgium. Journal of Affective Disorders 1992;25(3):161–166. [PubMed: 1527270]
31. Souetre E, Wehr TA, Douillet P, Darcourt G. Influence of environmental factors on suicidal behavior. Psychiatry Research 1990;32(3):253–263. [PubMed: 2388966]
32. D'Hondt P, Maes M, Leysen J, Gommeren R, Heylen L, DeMeyer F, Scharp S, Peeters D, Desnyder R. Seasonal variation in platelet [3H] paroxetine binding in healthy volunteers. Neuropsychopharmacology 1996;15:187–198. [PubMed: 8840355]
33. Nordin C, Sendin A, Zachau A. CSF 5-HIAA and atmospheric pressure. Biological Psychiatry 1992;31:644–645. [PubMed: 1374652]
34. Faustman W, Elliott P, Ringo D, Faull K. CSF 5-HIAA and atmospheric pressure: Failure to replicate. Biological Psychiatry 1993;33:58–63. [PubMed: 8420598]
35. Gottschalk, Allan; Bauer, Mark S.; Whybrow, Peter C. Evidence of chaotic mood variation in bipolar disorder. Archives of General Psychiatry 1995;52:947–959. [PubMed: 7487343]
36. Krystal AD, Greenside HS. Low-dimensional chaos in bipolar disorder? Archives of General Psychiatry 1998;55:275. [PubMed: 9510223]
37. Kantz, Holger; Schreiber, Thomas. Nonlinear Time Series Analysis. Cambridge: Cambridge University Press; 1997.
38. Ruelle D. Deterministic chaos: the science and the fiction. Proceedings of the Royal Society London A 1990;427:241–248.
39. Grassberger P. Do climate attractors exist? Nature 1986;323:609–612.
40. Chow SM, Ram N, Boker SM, Fujita F, Clore G. Capturing weekly fluctuation in emotion using a latent differential structural approach. Emotion 2005;5(2):208–225. [PubMed: 15982086]
41. Oud, Johan HL.; Jansen, Robert ARG. Continuous time state space modeling of panel data by means of SEM. Psychometrica 2000;65(2):199–215.
42. Oud, JHL. Continuous time modeling of reciprocal relationships in the cross-lagged panel design. In: Boker, SM.; Wenger, MJ., editors. Data Analytic Techniques for Dynamical Systems. Mahwah, NJ: Lawrence Erlbaum Associates; 2007. p. 87-130.
43. Wu, Wei; Gao, Yun; Bienenstock, Elie; Donoghue, John P.; Black, Michael J. Bayesian population decoding of motor cortical activity using a Kalman filter. Journal of the American Statistical Association 2006;18(1):80–118.
44. Boker SM, Graham John. A dynamical systems analysis of adolescent substance abuse. Multivariate Behavioral Research 1998;33(4):479–507.

45. Boker SM, Nesselroade JR. A method for modeling the intrinsic dynamics of intraindividual variability: Recovering the parameters of simulated oscillators in multi-wave panel data. Multivariate Behavioral Research 2002;37(1):127–160.

46. Boker SM. Consequences of continuity: The hunt for intrinsic properties within parameters of dynamics in psychological processes. Multivariate Behavioral Research 2002;37(3):405–422.

47. Hubbard, John H.; West, Beverly H. Differential Equations: A Dynamical Systems Approach. New York: Springer-Verlag; 1991.

48. Ray Wylie, C. Differential Equations. New York: McGraw-Hill; 1979.

49. Thompson, JMT.; Stewart, HB. Nonlinear Dynamics and Chaos. New York: John Wiley and Sons; 1986.

50. Nicolis C, Nicolis G. Is there evidence for a climate attractor? Nature 1984;311:529–532.

51. Tsonis AA, Elsner JB. The weather attractor on very short time scales. Nature 1988;33:545–547.

52. Spitzer, RL.; Williams, JBW.; Gibbon, M. Structural Clinical Interview for the DSM-III-R, Patient Version. New York, NY: New York State Psychiatric Institute; 1987.

53. Diagnostic and Statistical Manual of Mental Disorders – Third Edition, Revised. Washington, DC: American Psychiatric Association; 1987.

54. Spitzer, RL.; Williams, JBW.; Gibbon, M. Structural Clinical Interview for the DSM-III-R Personality Disorders. New York, NY: New York State Psychiatric Institute; 1987.

55. Williams, JB.; Link, MJ.; Rosenthal, NE.; Terman, ME. Structured Interview Guide for the Hamilton Depression Rating Scale, Seasonal Affective Disorder Version (SIGH-SAD). New York, NY: New York Psychiatric Institute; 1988.

56. Kasper, S.; Rogers, SLB.; Yancey, A.; Skwerer, RG.; Schulz, PM.; Rosenthal, NE. Psychological effects of light therapy in normals. In: Rosenthal, NE.; Blehar, MC., editors. Seasonal Affective Disorder and Phototherapy. New York, NY: Guilford Press; 1989. p. 260-270.

57. Deboeck, PR. Master's thesis, University of Notre Dame. 2005. Using surrogate data analysis to estimate τ for local linear approximation of damped linear oscillators.

58. Deboeck PR, Boker SM, Bergeman CS. Estimation of individual damped linear oscillator models. Multivariate Behavioral Research. submitted

59. Prichard, Dean; Theiler, James. Generating surrogate data for time series with several simultaneously measured variables. Physical Review Letters 1994;73(7):951–954. [PubMed: 10057582]

60. Boker, SM.; McArdle, JJ. Path analysis and path diagrams. In: Everitt, B.; Howell, D., editors. Encyclopedia of Statistics in Behavioral Science. Vol. Vol. 3. New York: John Wiley & Sons; 2005. p. 1529-1531.

61. McArdle, JJ.; Boker, SM. RAMpath. Hillsdale, NJ: Lawrence Erlbaum; 1990.

62. Neale, Michael C.; Boker, SM.; Xie, G.; Maes, Hermine H. Mx: Statistical modeling; Richmond, VA 23298. Department of Psychiatry; 2003. VCU Box 900126

63. Boker, SM.; Covey, ES. Two recent advances in estimating and testing differential equations models; Paper presented to the Annual Meeting of the Society of Multivariate Experimental Psychology; 2002.

64. Potash JB. Carving chaos: genetics and the classification of mood and psychotic syndromes. Harvard Review of Psychiatry 2006;14(2):47–63. [PubMed: 16603472]

65. Yeragani VK, Sree Hari Rao V. Patterns of oscillatory behavior in different human systems: a special reference to psychiatry and techniques to quantify such patterns. Bipolar Disorders 2006;8:421–422. [PubMed: 17042878]

66. Sprott JC. Dynamical models of happiness. Nonlinear Dynamics, Psychology, and Life Sciences 2006;9(1):23–36.

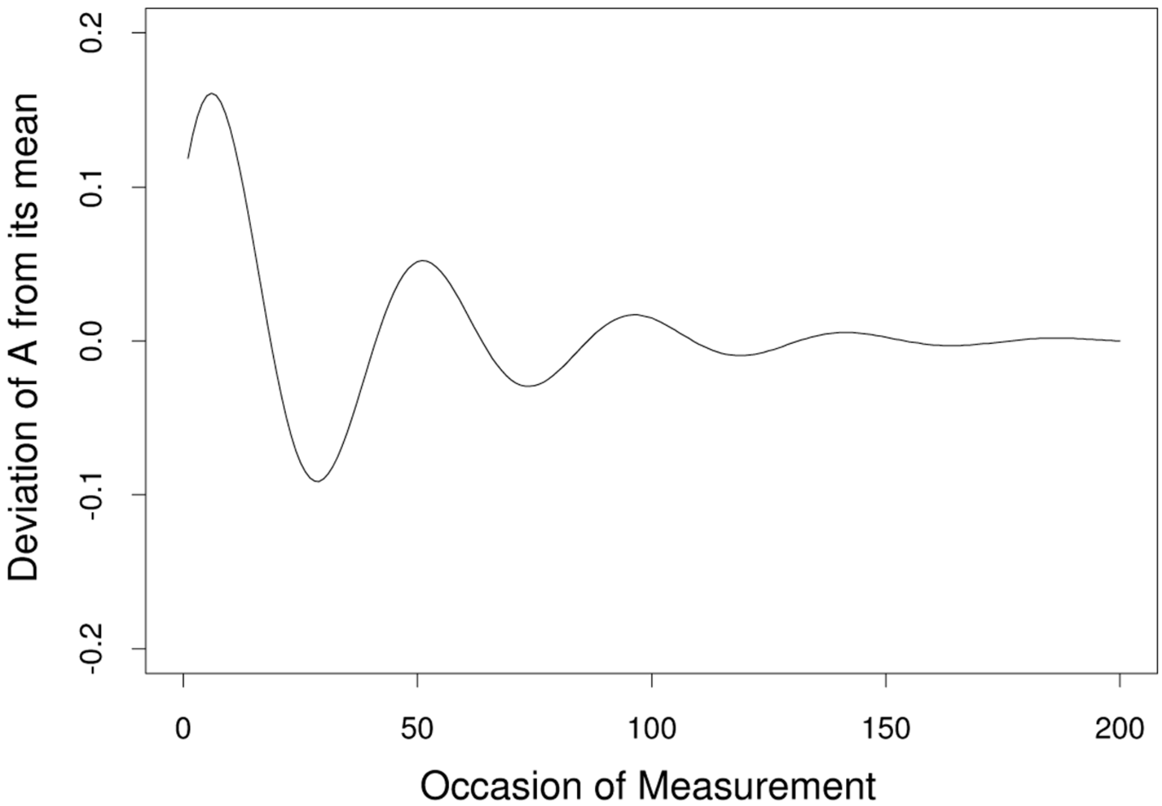

Figure 1.
A time series generated by a damped linear oscillator differential equation model of mood as in Equation 4.

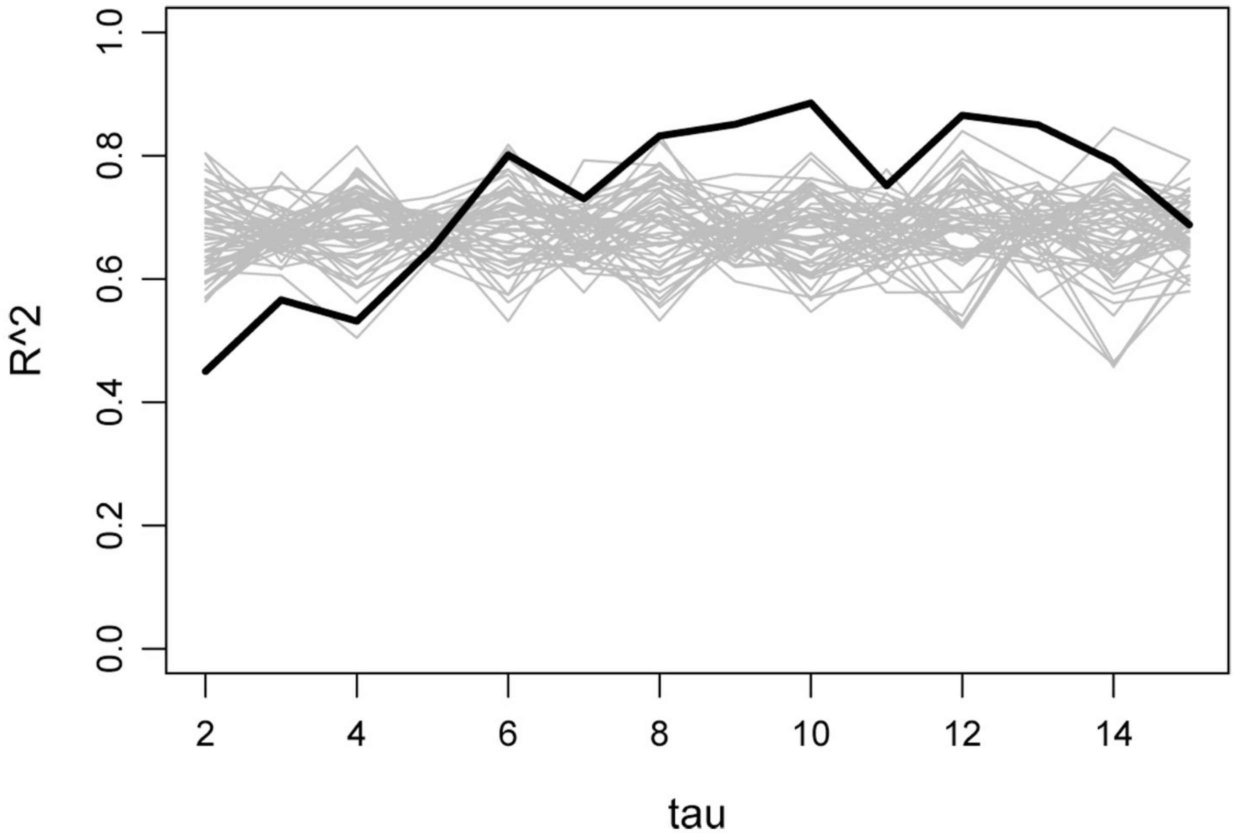

Figure 2.
Plot of variance explained (R^2) versus τ. The bold, black line represents the results from an original time series. Grey lines represent results from the analysis of surrogate data sets.

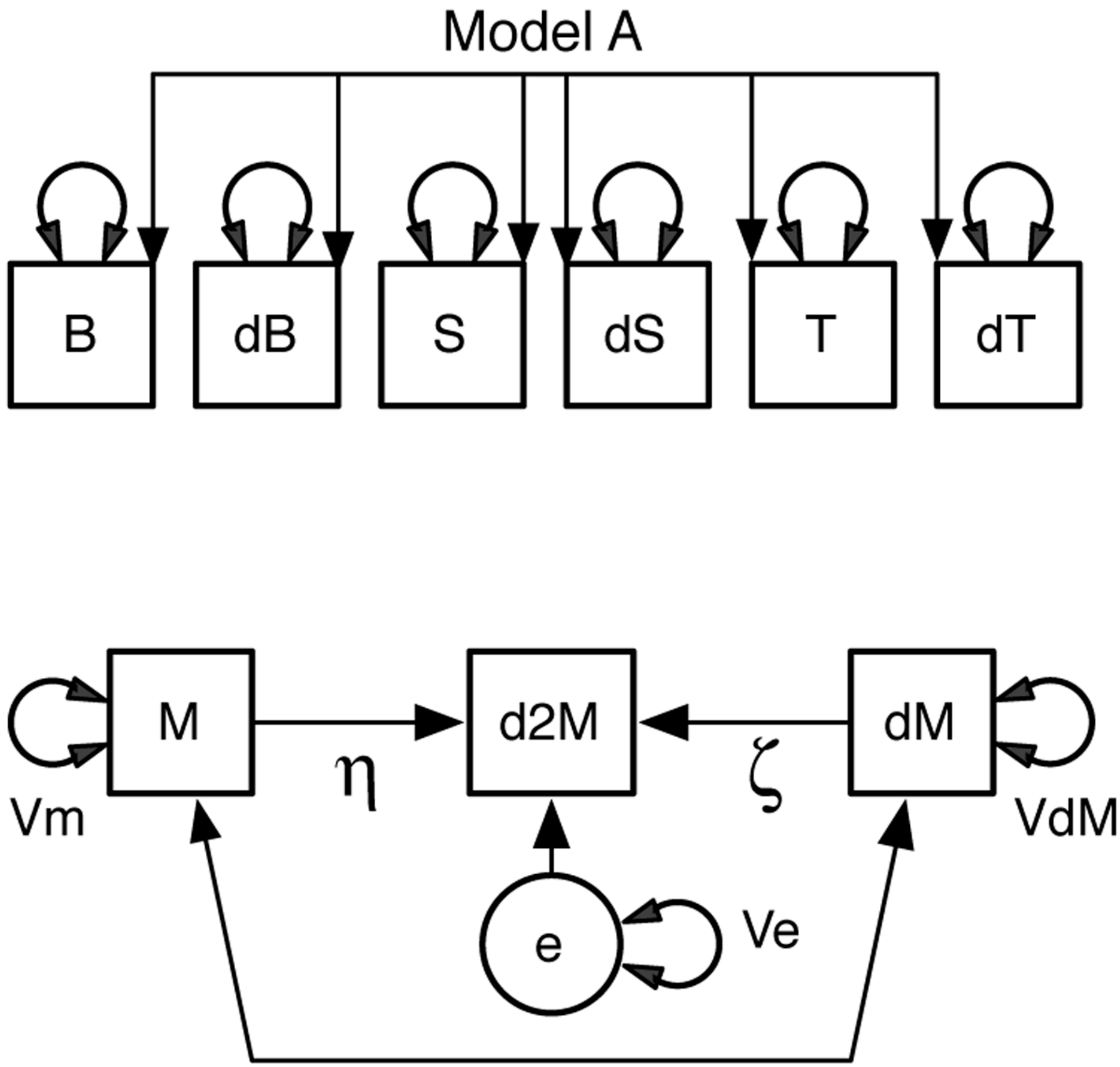

Figure 3.
Path diagram of Model A. This model hypothesizes intrinsic oscillation of mood conforming to a damped linear oscillator, but no coupling between weather and mood.

NIH-PA Author Manuscript
NIH-PA Author Manuscript

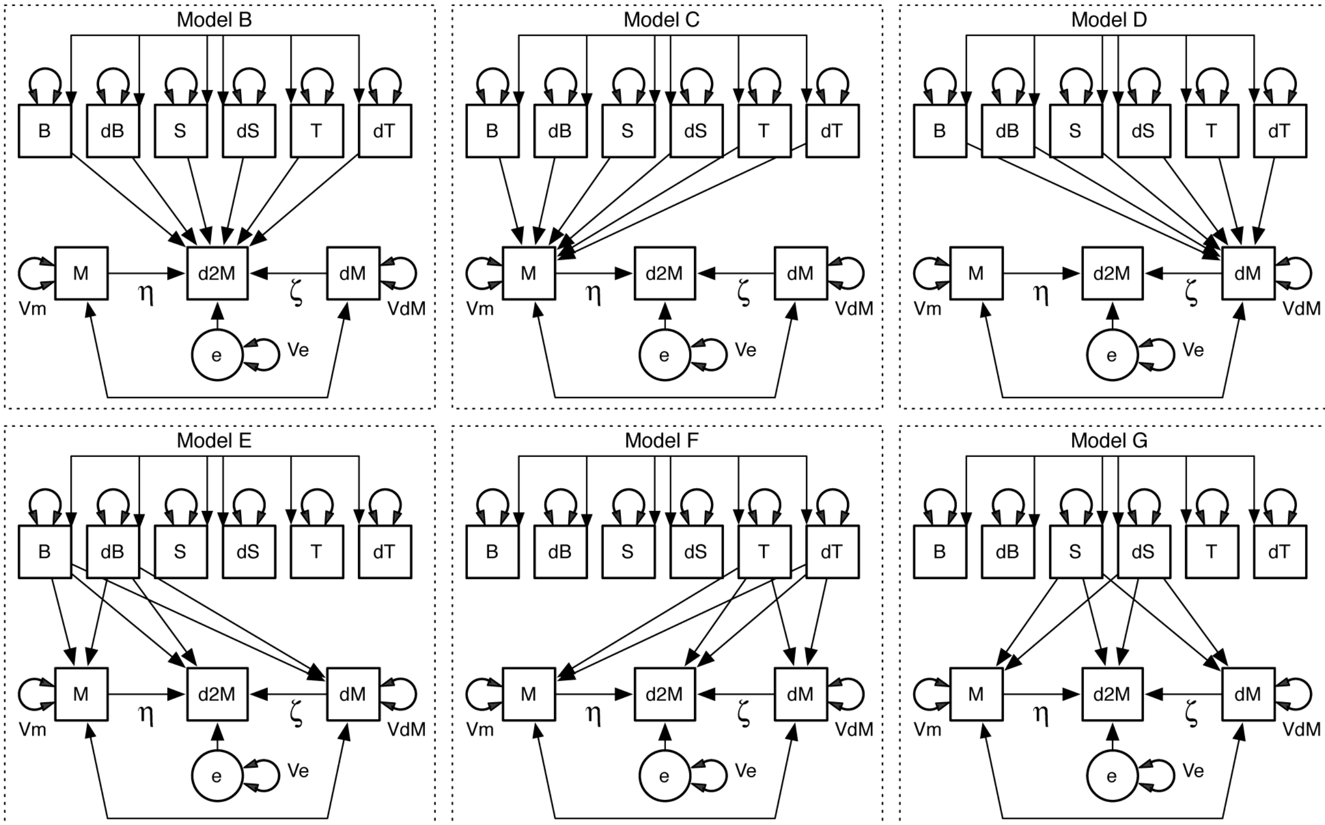

Figure 4.
Path diagrams of the structural equation models used to estimate the self-regulation of mood as a damped linear oscillator and the relationship between weather variables and mood. Models B, C, and D construct different hypotheses about the type of coupling between weather variables and mood. Models E, F and G test the weather variables individually.

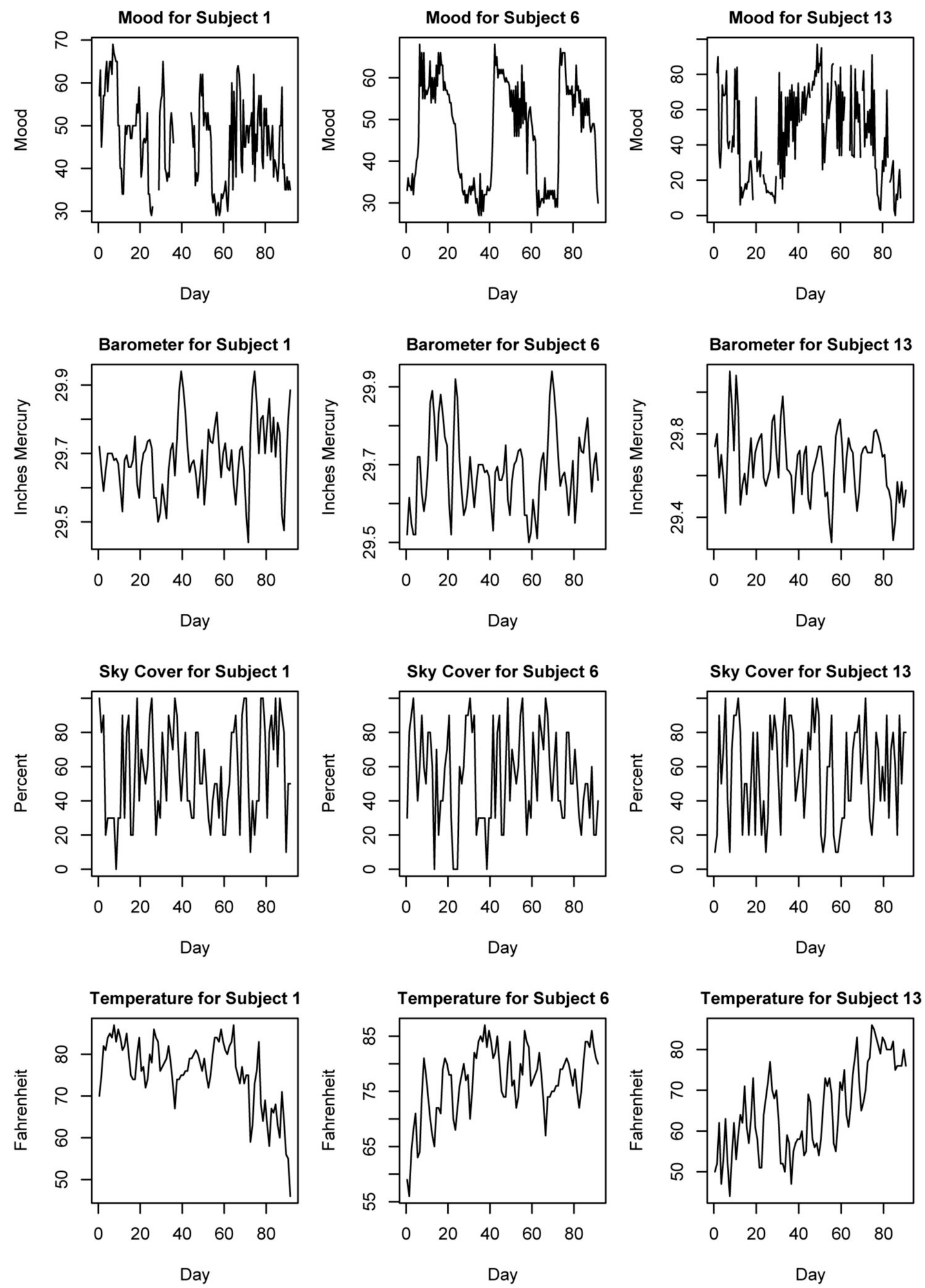

Figure 5.

Time series plots of Mood (Morning & Evening), Barometric Pressure, Sky Cover and Mean Temperature for three patients.

Table 1

Age, sex, diagnoses, and medication for the 15 patients that participated in the study.

Patient	Age	Sex	Diagonses		Medication
			Bipolar	Comorbid Axis I	
1	33	F	I		Valproate Bupropion
2	32	F	II	Simple Phobia Agoraphobia	Carbamazepine Fluoxetine
3	43	F	II	Simple Phobia	Lithium Phenelzine
4	54	F	I	Panic Disorder	Lithium, Calproate Sertraline
5	43	F	II	Social Phobia, OCD Panic Disorder	Carbamazepine, Clonazepam Levothyroxine, Phenelzine
6	47	M	I		Valproate, Nortriptyline Tranylcypromine
7	39	M	I		Lithium, Bupropion Carbamazepine
8	50	F	I	Social Phobia, OCD Panic Disorder	Valproate Tranylcypromine
9	40	F	II	Social Phobia	Lithium, Fluoxetine Levothyroxine
10	47	F	I	Simple Phobia	Lithium, Venlafaxine Clonazepam
11	38	F	I		Lithium, Doxepin Propranolol
12	45	M	II		Lithium
13	48	M	I		Lithium, Bupropion Levothyroxine
14	40	F	II		Lithium Fluoxetine
15	37	F	I	Social Phobia	Levothyroxine Sertraline

Table 2

Descriptive statistics for Mood, Barometric Pressure, Sky Cover and Temperature for all 15 subjects.

Subj.	Observations		Mood Mean(SD)		Barometer (0.1 in.) Mean(SD)	Sky Cover (%) Mean(SD)	Temp. (°F) Mean(SD)
	Total Days	Missing AM/PM	AM	PM			
1	92	11/10	47.1(9.7)	46.8(10.5)	296.9(1.0)	57(28)	75.8(8.0)
2	92	2/3	44.5(15.0)	48.0(11.3)	296.5(1.3)	61(27)	72.0(10.4)
3	92	0/0	46.1(15.5)	45.8(15.7)	296.9(1.0)	57(28)	75.7(8.0)
4	92	0/2	45.1(15.3)	45.9(16.5)	296.8(1.2)	64(27)	76.7(5.5)
5	92	5/10	43.9(20.1)	57.5(19.7)	296.8(1.0)	54(27)	76.8(6.2)
6	92	0/0	48.5(13.1)	45.9(11.4)	296.8(1.0)	54(27)	76.8(6.2)
7	92	0/0	41.1(8.1)	48.6(10.9)	296.9(1.0)	57(28)	75.7(8.0)
8	92	9/18	43.4(13.0)	40.5(12.4)	296.9(1.0)	57(28)	75.7(8.0)
9	91	0/1	60.3(20.4)	53.0(24.0)	297.6(1.9)	63(31)	56.3(12.6)
10	92	8/8	25.9(13.0)	32.9(9.8)	296.8(1.2)	64(27)	76.7(5.5)
11	92	0/1	50.4(17.7)	52.5(17.2)	297.2(1.5)	60(29)	67.2(12.0)
12	92	1/2	37.6(5.2)	38.1(5.6)	296.5(1.3)	61(27)	72.0(10.4)
13	91	4/15	38.6(21.5)	53.8(27.7)	296.6(1.6)	58(28)	65.6(10.6)
14	92	34/33	17.6(18.4)	16.7(18.3)	296.9(1.0)	57(28)	75.8(8.0)
15	92	9/20	44.4(11.9)	42.2(9.0)	296.8(1.2)	64(27)	76.7(5.5)

NIH-PA Author Manuscript

NIH-PA Author Manuscript

Table 3

Estimated τ values for morning and evening data.

Subj.	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14***	**15**
τ AM	6	16	4	6	4	6	6	11	4	12	5	16	12	-	16
τ PM	5	16	5	6	2	7	3	9	11	11	5	15	13	-	15

*Was not analyzed due to a large percentage (36%) of missing data.

NIH-PA Author Manuscript
NIH-PA Author Manuscript

Table 4

Estimated parameters from fitting the seven damped linear oscillator models for mood.

	Model A	Model B	Model C	Model D	Model E	Model F	Model G
η	−1.092	−1.093	−1.092	−1.092	−1.091	−1.098	−1.089
ζ	0.039	0.027	0.039	0.039	0.035	0.022	0.045
$B \rightarrow M$			0.608		0.217		
$B \rightarrow dM$				−0.155	−0.340		
$B \rightarrow d2M$		−0.026			−0.187		
$dB \rightarrow M$			0.739		0.128		
$dB \rightarrow dM$				−0.188	−0.364		
$dB \rightarrow d2M$		−0.645			−0.680		
$T \rightarrow M$			0.136			0.094	
$T \rightarrow dM$				0.080		0.090	
$T \rightarrow d2M$		0.170				0.181	
$dT \rightarrow M$			0.031			−0.003	
$dT \rightarrow dM$				−0.071		−0.049	
$dT \rightarrow d2M$		0.022				0.074	
$S \rightarrow M$			0.410				0.292
$S \rightarrow dM$				0.068			0.102
$S \rightarrow d2M$		−0.309					−0.271
$dS \rightarrow M$			0.067				0.092
$dS \rightarrow dM$				0.193			0.180
$dS \rightarrow d2M$		−0.323					−0.215
N	1749	1749	1749	1749	1749	1749	1749
R^2	0.617	0.625	0.617	0.617	0.618	0.623	0.619
-2LL	77.74	40.20	59.77	54.84	65.84	30.02	58.63
AIC	41.74	16.20	35.77	30.84	41.84	6.02	34.63
DOF	18	12	12	12	12	12	12

NIH-PA Author Manuscript

NIH-PA Author Manuscript

Table 5

AIC fit statistics for each individual, for all seven models. The best-fitting model within individual is shown in the final column, and the mean and median result within model are shown in the last two rows.

Patient	Model A AIC	Model B AIC	Model C AIC	Model D AIC	Model E AIC	Model F AIC	Model G AIC	Best Model
01	−7.320	−1.389	−2.323	−10.972	−1.207	−6.419	−0.884	D
02	49.717	39.181	41.689	18.476	43.820	37.838	37.029	D
03	6.089	−2.994	9.764	4.603	13.915	13.594	−8.485	G
04	21.603	13.545	21.140	8.032	3.332	25.962	20.259	E
05	1100.123	29.785	238.277	293.169	63.344	6.755	361.488	F
06	−9.409	−6.754	−6.269	−5.986	−14.725	−1.146	−4.092	E
07	−15.669	−9.406	−9.959	−11.860	−10.028	−9.334	−13.185	A
08	21.197	26.009	18.525	−2.563	14.399	12.003	7.286	D
09	30.171	27.394	15.309	17.839	20.237	3.296	34.249	F
10	9.568	13.337	−3.953	12.371	10.349	−13.782	17.839	F
11	91.726	45.161	46.329	92.175	87.890	20.458	84.801	F
12	78.980	71.430	83.442	17.472	81.301	5.835	84.392	F
13	−1.126	−11.490	8.066	1.057	4.893	−9.924	4.550	B
15	1.756	11.639	−8.470	1.410	4.420	−9.203	9.687	F
Mean	98.386	17.532	32.255	31.087	22.996	5.424	45.352	-
Median	15.383	13.441	12.537	6.317	12.132	4.566	13.763	-