Mental health improves on sunnier days of the year.

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Despite the standing of seasonal affective disorder as a construct in clinical practice, there is little theoretical clarity on what seasonality means, and almost no epidemiological evidence of circannual patterns in population-wide mental health. Two global geospatial datasets reveal that incident solar radiation (sunniness), modeled as a function of latitude and time of year, predicts mental health worldwide. Internet searches indicative of mental disorders declined on sunnier days of the year, as did prevalence of self-reported depression and anxiety. Crucially, factors specific to location or time do not explain the association.

Keywords: mental health, seasonal affective disorder, photoperiod, daylength, insolation, irradiance

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Conflict of Interest

I have no source of funding or conflict of interest to declare concerning this study.

Ethical Review

This study did not undergo ethical review.

Data and Code Availability

All data used in this study are publicly available. All code will be made available upon publication.

Author Names in References

Author names in references are written in Latin alphabets.

Life on planet Earth depends on light from our Sun. How much solar radiation falls on a point on Earth’s surface depends on where Earth is on its orbit around the Sun. The periodicity of Earth’s annual orbit gives rise to seasons that vary in phase and intensity by latitude, and dictates the rhythm of biological life.

Does the state of the human mind exhibit the same seasonality? The question has endured for over three decades [1–6]. The notion of seasonal affective disorder characterizes an annual pattern in mental health, a decline during winters and recovery during summers. Some of the most prominent taxonomies classify seasonal affective disorder not as a clinically distinct construct, but as a specifier for other mental disorders [7, 8]. Since the amount of sunlight is thought to be behind it, clinicians commonly treat the condition with exposure to artificial light among other therapeutics [9].

Despite its standing in clinical practice, scientists debate whether seasonal affective disorder is a valid construct at all [6, 10, 11]. Indeed, there is considerable inconsistency in what researchers mean by season, the independent variable of interest [6]. Largely, if implicitly, it seem that the intention has been to study the association between mental health and photoperiod—the duration between sunrise and sunset. A few studies [12–14] have explicitly used measures of irradiance—the amount of sunlight falling on a given surface on Earth.

Photoperiod is an incomplete measure of the amount of sunlight. It ignores the angle at which sunlight is incident on a point on Earth’s surface, which affects how much energy the light delivers. The Sun appears lower in the sky (closer to the horizon) at places farther from the equator, so they receive solar energy at a lower rate. Photoperiod also does not incorporate the distance between the Sun and Earth, which changes throughout its orbit. Incident solar radiation, or insolation¹ [15–17], accounts for these nuances. Both photoperiod [18] and insolation [15–17] can be modeled as functions of latitude and the time of year (see [Data and Methods](#) section, [figure 2](#), [figure 3](#), and [animation 1](#)). Photoperiod is symmetric about the

¹A note on terminology: Irradiance is a measure of power per unit area (measured in units of watts per square meter) or energy per unit time per unit area (measured in joules per second per square meter) as distinct from irradiation, a measure of energy per unit area (measured in joules per square meter). What I call insolation is referred to by some authors as average daily insolation [15, 16], which is irradiation averaged over the solar day, and hence has units of watts per square meter.

equator as well as about its mode (12 hours). Insolation, neither. Unlike photoperiod, insolation encapsulates sunniness rather than mere daylength. I use insolation as the independent variable. Insolation thus modeled, though, does not account for sunlight’s dispersion in the atmosphere. To account for it, I use satellite-based estimates of solar irradiance reaching Earth’s surface [19]. I also consider photoperiod for comparison with the literature.

Studies on the seasonality of mental health have historically used cross-sectional data [20] to test the latitude gradient hypothesis: If sunlight and mental health covary, then places farthest from the equator, where sunlight varies the most, must also have high prevalence of mental illness [21]. A latitude gradient, though, does not imply an association with sunlight. Place-specific characteristics— geographical features, demographic composition, and so on— rather than sunlight may explain a latitude gradient. Places farther from the equator, for instance, are also known to be more developed and less populated [22]. Time-series data from a single location, likewise, can not distinguish between mental health’s correlation with sunlight and that with time-specific factors— say, academic calendars, or the annual holiday season observed at the end of December in many parts of the world.

In order to establish an association between sunlight and mental health uncontaminated by such confounders, we need frequent measures of mental health at a wide range of latitudes. Traditional surveys can not viably collect data from representative samples of the population as frequently as necessary. Administrative data on the utilization of health services, when they are available, may underestimate disease prevalence since they underrepresent the very individuals most susceptible to mental illnesses [23–27]. So, the question has not received sufficient attention from an epidemiological perspective, and there is little evidence of seasonal shifts in population-wide mood or depressive symptoms [6].

The ubiquity of the internet offers solutions [28, 29]. Marking a turning point, scientists in one study [30] constructed a high-frequency panel dataset of public Twitter posts² from English-speakers around the globe. In their data, after accounting for individual-specific and time-specific factors, photoperiod itself was not associated with mood but the daily rate of change of photoperiod was. Faster photoperiod increased, more the Twitter users expressed positive emotions. Other studies have reported that internet searches³ of mental health related keywords peaked during

²Other studies have shown that individuals with mental disorders differed in their social media posts [31].

³Other studies have used internet searches to detect influenza epidemics [32, 33] and Lyme

winters [35], after violent events [36], and following COVID-19 lockdowns [37]. Crucially, internet searches reveal private health information seeking behavior that social media posts or surveys may not capture due to social desirability bias [38].

Such internet-based data, nevertheless, originate from commercial products, not scientific data collection instruments. The design and usage of the products influence the data they generate. So, the construct validity of internet-based data needs critical evaluation before they can be interpreted with certitude [39, 40]. Social media posts may contain sarcasm, regionalisms, or multimedia that introduce error when we quantify their emotional content [40]. In fact, measures of emotion such as those used in the aforementioned study on photoperiod [30] have since been shown to correlate poorly with other measures of subjective well-being [40]. Internet search engines, likewise, may affect individuals' choice of search terms by recommending keywords. Further, extracting search trends data has traditionally required researchers to use their discretion in formulating search queries and mapping keywords to mental illnesses. Due to these and other reasons, previous health studies using internet search data have had limited replicability [41], and internet searches have shown inconsistent convergent validity [42–45].

With these considerations and context in mind, I begin my investigation with geospatial data of internet searches. Google has publicly released a weekly index of internet search behaviors related to a set of health conditions in sub-national regions of six countries predominantly from the Anglosphere, in both the northern and southern hemispheres of Earth, spanning a period of over 57 months [46]. Unlike search trends data used in earlier generations of studies, the index does not require researchers' discretion in the formulation of search queries, the choice of keywords, or the mapping of keywords to mental illnesses. Rather, Google's researchers have themselves mapped searches to symptoms using a consistent methodology (see **Data and Methods** section), and validated searches related to mental health against independent data sources [47]. The index measures all searches related to each symptom as a proportion of the total number of searches in a given geographical unit in a given week. Data from each location are normalized with a unique scaling. As a result, they do not allow direct comparison of two places. They are nonetheless useful for within-place comparisons that form the basis of my analysis. Over 90% of internet searches in the world are performed on Google's search engine [48]. So, the data represent a large segment of the population with internet access; though the details of the population's demographic characteristics remain unknown— a limitation that

disease [34]

continues to restrict the utility of internet-based data in public health surveillance [29]. Some researchers have used searches related to respiratory symptoms from this dataset to predict COVID-19 cases [49]. In my own analysis, complementary to other efforts [47], searches related to mental disorders from the US when aggregated nationally show (figure 4) convergent and discriminant validity against the number of children and adolescents who visited emergency departments with presentations of mental illnesses [50]. By contrast, searches characteristic of mental disorders show low and even negative correlations with prevalence of anxiety or depression in American adults as estimated using the US census bureau’s pulse household surveys [51]. These comparisons, nonetheless, could be biased due to ecological correlation; comparisons of smaller geographic units may yield different correlations. Still, the data suggest that internet searches related to mental disorders are likely to reflect the mental health of children and adolescents if not that of adults.

The data show (figure 1) a clear correlation between insolation and mental health. Internet searches indicative of mental disorders declined on sunnier days of the year. Since I residualized the variables to account for within-year place-fixed and within-country time-fixed unobserved variables, culture, food, environmental factors, or the quality of healthcare do not account for the association, nor do holidays, elections, academic calendars, or national events.

Figure 1

Next, I turn to data from online surveys of adults on Facebook [52, 53], a platform used by 36% of the world's population— 2.8 billion people— every month [54]. The

survey data, aggregated from over 67.54 million individual responses, represent over 100 countries in multiple languages and span over 25 months. Unlike the internet search data, these data measure mental health with direct questions, leaving little ambiguity about how the measurement relates to the construct. The authors of this dataset have applied sampling and weighting procedures designed to minimize non-response bias and to ensure that the data represent the adult population. Since they observe only a few demographic dimensions, the authors have incomplete information on how the respondents differ from non-respondents. Cultural and linguistic differences impede a direct comparison of measures across geographies. Nonetheless, the data are useful for within-place comparisons. Researchers have used signals from the data to predict recorded COVID-19 cases in the population [52, 53]. In my analysis, the prevalence of anxiety and depression in social media survey data from US states correlate well with prevalence estimates from US census bureau’s household pulse surveys [51], but not with emergency department presentations by children and adolescents with mental illnesses [50] (figure 4).

Results from the social media surveys (figure 1) are consistent with those from internet searches. Prevalence of self-reported anxiety and depression also declined on sunnier days of the year. One in 400 people (0.25 percentage points) ceased to be anxious and depressed when insolation increased by one hectowatt—roughly how much it ranges between the two solstices in Cambodia and Nigeria (around 12.8 degrees latitude), or Tanzania (around -7.1 degrees latitude).

Substituting insolation as a dependent variable with either satellite-based estimates of solar irradiance (figure 5) or photoperiod (figure 6) retrieves the same association in both datasets. In contrast with previous studies [30], my analysis uncovers an improvement in mental health on longer days of the year. A model linear in insolation approximates mental health better than one linear in photoperiod as evidenced by the magnitude of the residuals’ deviations from the models’ predictions.

The results withstand several falsification tests (figures 7 and 8). Using insolation at geometric centroids and population centroids produces similar results. Scale effects do not explain the association as it is manifest in two datasets that largely represent different geographic units. In internet searches, the magnitude of the association depends on the scale of the geographic unit. Nevertheless, a negative association persists for searches pertaining to all mental disorders regardless of scale. Since the relationship is evident in internet searches preceding the COVID-19 pandemic, the pandemic can not explain it. Allowing for spatial heteroskedasticity and temporal autocorrelation using previously developed methods [55] yields lower estimates of

uncertainty.

I draw a few lessons. Formulating clear, falsifiable theories of circannual seasonality in human biology requires an appreciation of the distinction between solar insolation, photoperiod, time of year, and latitude. Testing theories with data from multiple sources is equally important, particularly when the correspondence between the data and the construct under study is unclear.

My analysis does not speak to whether the association between sunlight and mental health translates into a strain on public health resources. If the relationship is not apparent in, say, hospital visits, it could point to a failure in service delivery. Hormonal changes, vitamin D levels, changes in physical activity [4, 9], and all other possible etiological mechanisms require further study too.

1 Data and Methods

Photoperiod and Insolation

Figure 2

Animation 1 <https://osf.io/4jt2p/>

Figure 3

Farther we go from the equator, more photoperiod and insolation oscillate between the two solstices (figures 2 and 3). Two places in two different hemispheres of Earth that are equally far from the equator, as measured in longitude, would have the same photoperiod at the peak of their respective summers (half a year apart). However, the one in the southern hemisphere would have higher insolation because the Earth is closer to the Sun during southern summers than it is during northern summers. At places closest to the poles, the Sun never sets on the longest days of the year. So, the longest days in these places are twice as long as the longest days at the equator. Comparing the highest values of insolation at the same places, the differences are less stark. The highest values of insolation at all points on Earth are comparable.

Unless otherwise stated, I calculate insolation and photoperiod on a given day by averaging their values at a place's geometric centroid and points sampled at every 0.5 degree latitude by 0.5 degree longitude.

Satellite Data on Irradiance on Earth's Surface

The National Aeronautics and Space Administration has made available estimates of the amount of solar radiation reaching Earth’s surface based on satellite recordings (all-sky surface shortwave downward irradiance⁴) [19]. These data account for atmospheric conditions. To calculate irradiance on a given day, I average its value at a place’s geometric centroid and points sampled at every 0.5 degree latitude by 0.5 degree longitude.

Internet Searches

Google has released data on internet searches related to over 400 health symptoms for six countries at varying geographic resolutions [46]. The data span over 57 months and are available at day or week levels of aggregation. To calculate the index, Google divided the total number of searches ascribed to a given symptom in a given geographic unit in a given time period by the total number of searches in that geographic unit in that time period. In the initial release, the ratio was scaled so that the maximum for each geographic unit was 100. Later releases may have values higher than 100 if the ratio exceeded its initial maximum. Searches by a single user on a given day were counted only once per symptom for up to three symptoms. Google added artificial noise to the data to preserve the privacy of individuals and did not report data when there were too few searches for a particular symptom in a given location at a given time. This censoring means data are not missing at random. Missing data represent the lowest search volumes. Aggregation by larger temporal and geographic units makes it more feasible to preserve privacy with minimal artificial noise and censoring [46]. For this reason, weekly data have fewer missing values than daily data at the same geographic unit. And aggregation at larger geographic levels have fewer missing values than data at smaller geographic levels. I set missing values to the lowest non-missing value in the location and standardize each symptom to have mean zero and standard deviation one.

Surveys on a Social Media Platform

Researchers from the Delphi group at Carnegie Mellon University [53] and at the University of Maryland [52] partnered with Facebook to survey a random sample of the social media platform’s adult (over 18) users every day for over 25 months. They collected data on COVID-19 symptoms, beliefs and behaviors, mental health, and other variables. They weighted the data to correct for non-response bias and to ensure that the data represent the population. The survey asked how often the

⁴I convert the units to watts per square meter unless stated otherwise.

respondents felt anxious or depressed in the previous five to seven days. Using responses to these questions, the researchers estimated the proportion of individuals in a given place and time who reported feeling anxious or depressed most or all of the time in the reference period.

Emergency Department Visits

I obtained data on emergency department visits from researchers at the Centers for Disease Control and Prevention [50]. The data represent about 71% of non-federal emergency departments in the US. At the time of writing, I have been unable to obtain more disaggregated data.

Household Pulse Survey

The US census bureau surveyed adults above 18 from American households to measure changes in employment, spending, food security, housing, disruptions to education, and dimensions of physical and mental health during the COVID-19 pandemic [51]. The bureau invited respondents through email and text message to fill an internet questionnaire. Estimates from the survey are weighted to account for nonresponse bias and to match the population by gender, age, race, ethnicity, and education. Estimates of anxiety and depression are based on the reported frequency of symptoms in the reference period of past seven to 14 days.

Construct Validity

Figure 4

Construct Validity of Internet Searches and Social Media Survey Data

Demonstrating convergent validity, internet searches indicative of certain mental disorders showed high correlation with the number of American children and adolescents visiting emergency departments with mental illnesses (see figure 4). Visits exclude those related to substance use, developmental disabilities, and dementia [50], which explains the lower correlation with searches related to these disorders. Further demonstrating discriminant validity, searches related to allergies and similar symptoms had low (negative) correlation with visits. Prevalence of anxiety and depression from social media survey data show low correlation with the visits. The low correlation is expected since the surveys excluded children and adolescents. These comparisons, however, are between nationally aggregated data. I use data aggregated at sub-national units from the US for my primary analysis.

By contrast, social media survey data show high correlation with the prevalence of anxiety or depression of American adults as measured by the pulse household survey [51]. Internet searches indicative of mental disorders show low and sometimes negative correlation with the pulse household survey data. Searches related to allergies and similar symptoms show negative correlations.

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Supplementary Materials

Alternate Independent Variables

Figure 5

Mental health improved on sunnier days of the year.

Figure 6

Falsification Tests

Figure 7

Figure 8