The Geography of Insufficient Sleep in the Contiguous United States (CONUS)

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Abstract

Insufficient sleep is becoming increasingly prevalent, partially because of the accelerated pace of modern life, and is linked to a wide range of adverse physical and mental health outcomes. While several social, physical, and environmental factors are known to influence sleep duration, the underlying mechanisms and their geographic variability remain poorly understood. The growing availability of geospatial data, such as satellite observations, nationwide health surveys, and census datasets, offers new opportunities to observe sleep behaviors and potential determinants at large geographical scales with improved precision and efficiency. This study explores the geographical patterns of insufficient sleep and their associations with social, physical, and environmental factors. We obtained the latest county-level insufficient sleep rates in the Contiguous U.S. and explored their relationship with outdoor nighttime light exposure, day length, greenness, climate, air pollution, mental and physical health conditions, and social-demographic characteristics. Results reveal a distinct geographic boundary extending from the Southwest to the Northeast that delineates two regions: the Southeastern High-Prevalence of Insufficient Sleep Zone and the Northwestern Low-Prevalence of Insufficient Sleep Zone. Statistical and machine learning models demonstrate that insufficient sleep is significantly associated with environmental exposures (precipitation, temperature, air pollution), sociodemographic characteristics (race-ethnic minorities), and health-related variables (obesity, diabetes, and physical distress). By integrating spatial data science and public health perspectives, this study advances understanding of the environmental and social determinants of sleep behaviors, offering valuable insights to guide location-based interventions and policies that can potentially promote healthier sleep across communities.

Keywords

Insufficient Sleep, Sleep Health, Social-Environmental Determinants, Spatial Analysis, Machine Learning

1 Introduction

Human sleep is a complex, vital physiological process regulated by the brain and influenced by circadian rhythms and homeostatic mechanisms. Regular, sufficient sleep is essential for maintaining human physical and mental health. Sleep facilitates critical restorative functions, including energy conservation, tissue repair, immune regulation, and metabolic homeostasis. Sleep also plays a vital role in brain plasticity, emotional regulation, and cognitive performance. Nevertheless, sleep disturbances, especially insufficient sleep, have become prevalent among adults (Chattu et al., 2018). The American Academy of Sleep Medicine (AASM) and the Sleep Research Society (SRS) define insufficient sleep as less than 7 hours of sleep per night. In 2022, more than one third of U.S. adults reported insufficient sleep issues, according to the latest data from the Centers for Disease Control and Prevention (CDC 2022). More recently, ResMed's 2025 Global Sleep Survey, encompassing over 30,000 participants across 13 countries, revealed that 71% of responders reported inadequate sleep problems.

Abundant literature has demonstrated strong links between insufficient sleep and a wide range of adverse health outcomes across physical, mental, and cognitive domains. Short sleep duration disrupts hormonal regulation of appetite and increases the risk of obesity and type 2 diabetes (Spiegel et al., 2004). Besides, inadequate sleep can significantly lead to elevated sympathetic activities and inflammation, inducing cardiovascular diseases (Liu et al., 2016). Insufficient sleep also increases vulnerability to depression and anxiety through altered emotional regulation and heightened stress reactivity (Baglioni et al., 2011). Furthermore, sleep deprivation impairs attention, memory, and executive function, diminishing reaction time and decision-making abilities (Lim and Dinges, 2010).

The availability and accessibility of geospatial data have been rapidly growing recently, bringing new opportunities to investigate human sleep behaviors and their associations with diverse factors across multiple spatial and temporal scales. Remote sensing products, such as nighttime light (NTL) images from the VIIRS Day/Night Band, satellite-derived air pollution measures (e.g., PM 2.5 concentrations), and climate indicators including temperature and precipitation, provide valuable information on environmental factors that may shape sleep health. These environmental datasets can be complemented with rich demographic and socioeconomic information from census data as well as health-related outcomes from county-level or city-level health surveys. The fusion of these diverse geospatial datasets enables the analysis and comparison of sleep behaviors and potential determinants across different communities.

This investigation aims to decipher the geographical disparities of insufficient sleep in the Contiguous U.S. (CONUS) and its underlying social-physical-environmental factors through multisource geospatial data. The specific objectives are twofold: (1) unravel the geographical characteristics and disparities of county-level insufficient sleep in the CONUS; (2) delineate the relationship between insufficient sleep and a range of social, physical, and environmental determinants. This study addresses two key research questions. First, do rates of insufficient sleep across the CONUS exhibit distinct geographic clustering patterns? Second, how do individual physical and mental health factors and social-environmental conditions interact to shape the spatial variability of insufficient sleep? The results will help decision-makers and local communities to identify populations at risk, monitor disparities, and inform location-based interventions.

This article proceeds as follows. We first briefly review previous work investigating the multifaceted determinants of sleep health in Section 2. Section 3 describes data collection, attributes, and preprocessing in detail. Section 4 presents the methodological framework of analyzing insufficient sleep and its relevant human-environmental variables. The geographical disparities in insufficient sleep and its associations with social, physical, and environmental variables are summarized in section 5. Section 6 discusses the key findings and limitations of the study. Finally, Section 7 concludes this investigation and outlines future research directions.

2. Background

2.1 Sleep and Environments

Recently, several studies have examined the effect of environmental factors, e.g., light exposure, climate, air quality, and green infrastructures, on sleep health. For example, exposure to lights, including natural and artificial nighttime lights, plays a crucial role in regulating sleep rhythms by influencing the human body’s internal clock that governs sleep-wake cycles. Ohayon et al. (2016) evaluated the association between artificial outdoor nighttime light and human sleep behaviors in the U.S. They found that people living in areas with greater exposure to artificial outdoor nighttime light exhibited delayed bedtime and wake up time, shorter sleep duration, and increased daytime sleepiness. Casiraghi and de la Iglesia (2022) reviewed studies examining sleep behaviors in preindustrial communities to assess how access to electric light influences sleep time. They noted that increased exposure to artificial light at night tends to delay sleep onset while having a smaller effect on wake time, ultimately resulting in shorter overall sleep duration.

Climate factors including temperature and humidity can also significantly affect sleep behaviors by influencing the body’s ability to regulate internal temperature during the night. Brockmann et al. (2017) designed a population-based survey from the Tropic of Capricorn to the Antarctic Circle to explore the relationship between climatic zones and sleep durations. Their results revealed that people living in higher latitude areas (colder regions) reported longer sleep durations. This observation was further confirmed with sensor-based measurements. Minor et al. (2022) collected over 7 million sleep records from wearable devices across 68 countries with local daily meteorological data. The study identified a significant association between higher temperatures and shorter sleep duration, with the effect of temperature on sleep loss being amplified in regions with warmer climates.

Exposure to air pollution is increasingly recognized as a significant factor that shapes sleep behaviors. Air pollution disturbs normal breathing during sleep and increases the risk of mental illness, leading to sleep disorders. Chen et al. (2019) collected 29,722 surveys, ground measurements of air pollutant types and concentrations, remote sensing images, meteorological data, and land use information to test the associations between human sleep quality and the long-term exposure to air pollution in China. They revealed that exposure to high concentrations of PM 2.5, PM 10 and NO_2 for extended periods was significantly correlated with poor sleep quality, particularly in rural regions.

Meanwhile, greenness exposure and accessibility have been shown to promote sleep quality by enhancing mood, encouraging physical activity, and reducing exposure to environmental pollution. Liu et al. (2023) analyzed survey-based sleep data in combination with geospatial measures of residential greenness and air pollution conditions. Their findings indicate that frequently engaging with green spaces can mitigate the side effects of air pollution in affecting sleep quality. Stenfors et al. (2023) adopted geographic information system (GIS) technologies to spatially analyze the associations between residential greenspace and sleep quality. Using multilevel general linear models, they revealed that higher greenspace availability in residential surroundings was significantly associated with less sleep difficulties.

2.2 Sleep and Social Characteristics

Social characteristics play essential roles in sleep behaviors and health. Sleep behaviors are influenced by biologically embedded factors such as age and gender, which reflect underlying physiological, hormonal, and brain structural differences. A meta-analysis by Zhang & Wing (2006) found that females had 1.4 - 2.0 times higher odds of experiencing insomnia symptoms than males. A regression analysis by Torbjörn et al. (2017) shows a significant reduction in sleep duration as age increases, i.e., sleep duration decreases by 2.2 minutes per 10 years. In addition, sleep health is intertwined with race-ethnic identity and cultural context. Grandner (2010) analyzed population-based survey data from CDC to examine ethnic and socioeconomic differences in sleep complaints. Using regression models that adjusted for demographic and health-related covariates, they found that racial/ethnic minority groups and individuals with lower income or less education were more likely to report short sleep duration, insomnia symptoms, and poor sleep quality. Similarly, Patel et al. (2010) conducted a population-based, cross-sectional survey of 9,714 randomly selected U.S. adults to examine socioeconomic and ethnic disparities in sleep quality. Their regression analyses showed that poor sleep quality was more common among individuals living below poverty and Africa-American groups. Sosso et al. (2021) conducted a systematic review and meta-analysis to examine the relationship between socioeconomic status (SES) and objectively measured sleep parameters. Their findings indicated that lower SES was associated with shorter total sleep time, longer sleep latency, greater sleep fragmentation, and higher variability in sleep onset and latency, while higher SES indicators such as education, income, and perceived economic well-being were linked to improved sleep efficiency and longer sleep duration. Moreover, Casiraghi et al. (2025) conducted a longitudinal study of Toba/Qom communities in northern Argentina (2012–2024), tracking over 12,000 sleep events as rural villages gained electricity and comparing them with semi-urban groups that already had electric power. They found real-time delays in sleep onset and wake time and a shortening of total sleep duration following electrification, reflecting the effect of modernization, such as the widespread use of smartphones and the internet, on sleep patterns.

2.3 Sleep and Physical Conditions

Beyond social-environmental factors, individual health conditions such as stress, psychiatric disorders, and chronic physical illnesses exhibit complex bidirectional relationships with sleep behaviors. Sleep deprivation impairs immune function, which can increase susceptibility to infections and delay recovery from illness. It also promotes systemic inflammation, thereby contributing to metabolic dysfunction and cardiovascular risk. Conversely, chronic illness, such as diabetes, cardiovascular disease, or chronic pain, and elevated psychological stress can disrupt sleep architecture, leading to fragmented sleep, shorter total sleep duration, and delayed sleep onset.

Merrill (2022) systematically compared the associations between several mental health conditions, including anxiety, depression, bipolar disorder, and schizophrenia, and sleep disorders such as insomnia, hypersomnia, and sleep apnea. The results demonstrated that insomnia was particularly and consistently linked to anxiety, bipolar disorder, and schizophrenia. These findings suggest that disturbances in sleep are not only symptoms but also potential risk factors and modifiers of psychiatric illness trajectories. Li et al. (2022) conducted a review of 69 studies to assess the associations between sleep duration and various health outcomes. They found that both short and long sleep durations were significantly associated with increased risks of cardiovascular disease, cognitive decline, coronary heart disease, depression, falls, frailty, lung cancer, metabolic syndrome, and stroke.

2.4 Gaps in Existing Literature

Although previous studies have examined the complex interplay between sleep behaviors and different social, physical, and environmental factors, several limitations exist (Leypunskiy et al., 2018; Martins et al., 2020). First, prior investigations have largely neglected the geographical patterns and disparities of sleep behaviors. There remains a paucity of research that uses spatial methods to delineate the spatial heterogeneity of sleep patterns and disorders across regions. Second, limited attention has been given to investigate the ways in which these disparities are shaped by varying social and environmental contexts and physical health conditions. These gaps limit our understanding of how place-based and individual-based determinants contribute to sleep behaviors and health disparities. Spatial insights are essential for designing place-specific strategies to address the root causes of sleep disparities, as environmental, social, and physical stressors vary widely across communities. For example, in densely populated or industrialized urban areas, interventions may focus on reducing nighttime light and noise pollution, two potential disruptors of circadian rhythms and sleep quality. In regions affected by air pollution, improving ambient air quality through emission control and green infrastructure can mitigate sleep disturbances linked to chronic exposure to fine particulate matter and other pollutants. Meanwhile, urban design strategies such as expanding green space and vegetation cover can alleviate localized heat stress, creating cooler and more restorative sleep environments. These examples illustrate how integrating geospatial approaches into sleep research can enable a place-based understanding of environmental and social determinants of sleep health, guiding targeted interventions and policy decisions across diverse settings.

3 Data

3.1 Human Health Data

The health-related data, including the county-level percentages of population experiencing insufficient sleep, were obtained from Behavioral Risk Factor Surveillance System (BRFSS), a comprehensive, population-based public health surveillance system established by CDC in 1984. It is designed to collect and provide data on health-related risk behaviors, chronic health conditions, and the use of preventive services among adults in the U.S. Table 1 lists the human health-related data used in this research, including insufficient sleep rate, the percentage of adults reporting 14 or more days of poor physical and mental health per month, and diabetes and obesity prevalence. It is noteworthy that BRFSS applies an age adjustment to enable fair comparison of prevalence across populations in counties with different age structures.

Table 1. Descriptions of human health indicators obtained from CSC's BRFSS.

<table>
<tr><th>Health Data</th><th>Description</th><th>Source</th></tr>
<tr><td>% Insufficient Sleep</td><td>Percentage of adults reporting fewer than 7 hours of sleep per 24 hours (age-adjusted).</td><td rowspan="5">Behavioral Risk Factor Surveillance System (BRFSS):

https://www.cdc.gov/brfss/index.html</td></tr>
<tr><td>% Frequent Physical Distress</td><td>Percentage of adults reporting 14 or more days of poor physical health per month (age-adjusted).</td></tr>
<tr><td>% Diabetes Prevalence</td><td>Percentage of adults aged 18 and above with diagnosed diabetes (age-adjusted).</td></tr>
<tr><td>% Adult Obesity</td><td>Percentage of the adult population (age 18 and older) reports a body mass index (BMI) greater than or equal to 30 kg/m2 (age-adjusted).</td></tr>
<tr><td>% Frequent Mental Distress</td><td>Percentage of adults reporting 14 or more days of poor mental health per month (age-adjusted).</td></tr>
</table>

For insufficient sleep data, BRFSS asks participants to self-report the average number of hours of sleep they obtain in a 24-hour period every two years from 2014 to 2022, providing an accessible, subjective measure of sleep duration. Figure 1 shows the geographical pattern of the precent of people experiencing insufficient sleep in the U.S. in 2022 (the latest data available). Insufficient sleep rates were significantly higher in southeast regions (Texas, Oklahoma, Missouri, Arkansas, Louisiana, Mississippi, Alabama, Georgia, and Florida) than in northwest regions (Washington, Oregon, Idaho, Montana, Wyoming, Nebraska, South Dakota, and North Dakota).

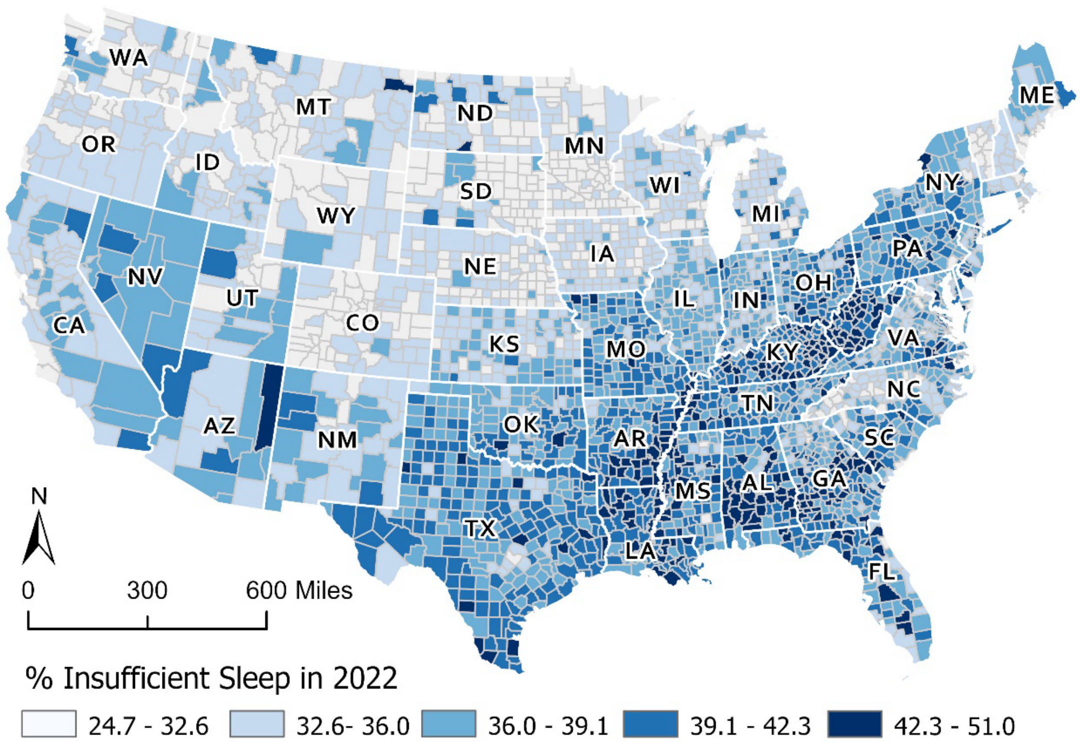

Figure 1. Geographical distribution map % of insufficient sleep in 2022 (Data Source: BRFSS)

3.2 Geographical Factors

Four county-level geographical factors in 2022, including geographic regions, climate zones, metro and nonmetro counties, and race-ethnic minority prevalence, were included in this investigation. According to the U.S. Census Bureau classification standard, the CONUS can be divided into four geographic regions including West (421 counties), South (1422 counties), Northeast (217 counties), and Middle West (1055 counties) regions (Figure 2a). The CONUS can also be classified into four climate categories based on Köppen-Geiger climate classification (Beck et al. 2018): Marine (52 counties located at the west coast), Cold (1210 counties mainly distributed in areas north of 39-degree N), Mixed Dry (191 counties concentrated in California, Arizona, and New Mexico State), and Mixed Humid (1647 counties mainly located at South region) (Figure 2b). Meanwhile, counties can be classified as large, medium, and small metropolitan (433, 387, and 353 counties respectively) or nonmetropolitan (1927 counties) based on their relationship to metropolitan areas (Figure 2c), as defined by the U.S. Office of Management and Budget (OMB). Metropolitan areas are focused on West/East Coasts and east inland areas.

Furthermore, using data from the U.S. Census Bureau's 2022 Population Estimates Program, we categorized counties according to the predominant racial or ethnic group. Specifically, if the share of a county's population belonging to a particular group exceeded that group's share of the national population, the county was classified as having a prevalence of that group. The national averages used for comparison were 19.1% for Hispanics, 12.1% for African Americans, 6.1% for Asians (including Native Hawaiians and Other Pacific Islanders), and 4.8% for American Indians/Alaska Natives (or multiracial populations). The race-ethnic minority prevalence is displayed in Figure 2d and shows six categories: Hispanics (279 counties), American Africa (584 counties), Asians, Native Hawaiians and Other Pacific Islanders (32 counties), American Indians/Alaska Natives (249 counties), Two or more minorities (233 counties), No minority (1733 counties). Figure 2d revealed that counties with above national average American Africa population concentrated along the Gulf and the Eastern Coast in 2022. Concurrently, there was an above-national-average proportion of Hispanics and two or more minorities in Texas and counties along the West Coast.

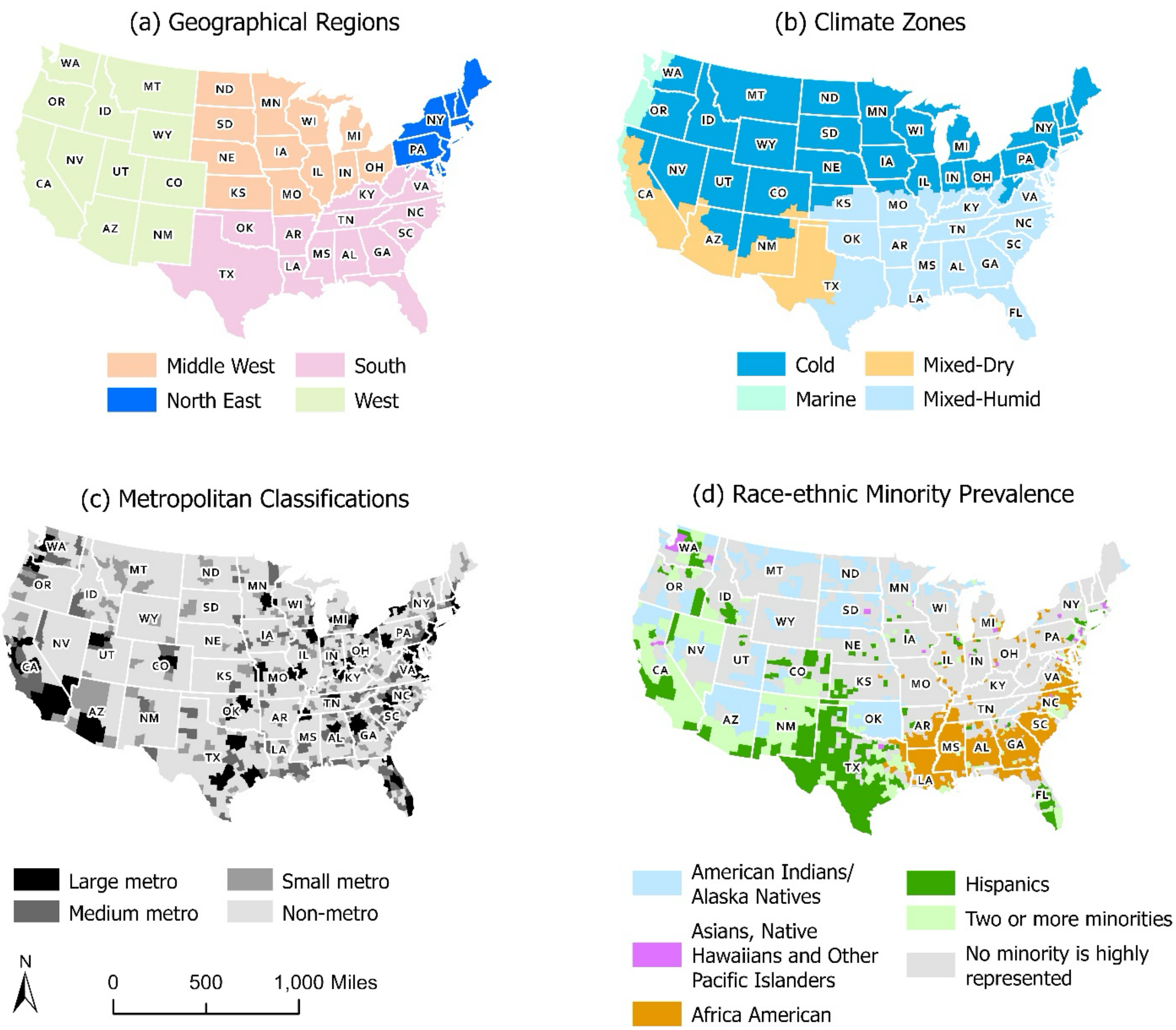

Figure 2. Spatial distributions of four geographical factors across the CONUS: (a) geographic regions, (b) climate zones, (c) metropolitan classifications, and (d) racial and ethnic minority prevalence.

3.3 Environmental Conditions

Table 2 summarizes the environmental variables used in this study, including light, climates, air pollution, and greenness, which were identified based on a review of prior investigations mentioned in Section 2. Light-related factors include both artificial outdoor nighttime light and the duration of natural daylight (Day Length). Climate factors include average yearly temperature, total yearly precipitation, and average yearly relative humidity. The annual average concentration of PM 2.5 data and Normalized Difference Vegetation Index (NDVI) that measures the greenness and health of vegetation are adopted in this research. All those natural environmental variables were acquired from the year 2022 and calculated at the county level for subsequent analysis.

Table 2. Environmental Factors description

Natural Environments	**Description**	**Source**
Outdoor Nighttime Light	Radiance from artificial lighting emitted from the Earth's surface at night, representing anthropogenic light exposure.	Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB)
Air Pollution ($PM_{2.5}$)	Average daily concentration of fine particulate matter ($PM_{2.5}$, $\mu g/m^3$) at the county level, indicating ambient air quality.	Environmental Public Health Tracking Network
Annual Average Temperature	Mean annual land surface temperature derived from remote sensing observations.	NASA MODIS MOD11A2 data product
Annual Precipitation	Total annual accumulated precipitation in each county.	UCSB Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS) (https://www.chc.ucsb.edu/data/chirps)
NDVI (Greenness)	Normalized Difference Vegetation Index representing vegetation density and photosynthetic activity.	NASA MODIS MOD13A1 data product
Day Length	Duration of natural daylight, measured as the number of daylight hours per day on average.	National Renewable Energy Laboratory
Humidity	Mean relative humidity (%) representing the proportion of water vapor in the air.	TerraClimate dataset from the University of Idaho Climatology Lab

		(https://www.climatologylab.org/datasets.html)

3.4 Social-Demographical Characteristics

Social variables such as demographics, race, education, and economics were collected. Demographic factors contain variables describing gender, age distributions, and the proportion of rural populations. Race and ethnicity are represented by the percentage of population identifying as American Indian or Alaska Native, Native Hawaiian or Other Pacific Islander or Asian, Hispanic, Non-Hispanic American Africa and White at the county level. Educational attainment is measured by high school and college completion rates. Economic indicators include the rate of unemployment, income ratio, and traffic volume. Detailed descriptions of these variables are provided in Table 3.

Table 3. Environmental Factors description

Social Variable	Description	Source
% of Under 18 Years	Percentage of the population below 18 years old.	Census Population Estimates Program (PEP)
% of Aged 65 and Older	Percentage of the population aged 65 years and older.	Census PEP
% of Female	Percentage of the population identifying as female.	Census PEP
% of American Indian or Alaska Native	Percentage of the population identifying as American Indian or Alaska Native.	Census PEP
% of Asian	Percentage of the population identifying as Asian.	Census PEP
% of Hispanic	Percentage of population identifying as Hispanic.	Census PEP
% of Native Hawaiian or Other Pacific Islander	Percentage of population identifying as Native Hawaiian or Other Pacific Islander.	Census PEP
% of Non-Hispanic American Africa	Percentage of population identifying as non-Hispanic American Africa or African American.	Census PEP

% of Non-Hispanic White	Percentage of population identifying as non-Hispanic White.	Census PEP
% of Rural population	Percentage of population residing in a census-defined rural areas.	Decennial Census Demographic and Housing Characteristics File
Traffic Volume	Average traffic volume (vehicles per meter) along major roadways within the county.	EJSCREEN: Environmental Justice Screening and Mapping Tool
% of Unemployed	Percentage of population aged 16 years older who are unemployed and looking for work	Bureau of Labor Statistics
Income Ratio	Ratio of household income at the 80th percentile to income at the 20th percentile	American Community Survey (ACS), five-year estimates
Higher Education	Percentage of adults ages 25-44 with some post-secondary education.	ACS, five-year estimates
High School Completion	Percentage of adults ages 25 and over with a high school diploma or equivalent.	ACS, five-year estimates

4 Methods

This research consists of three steps (Figure 3), including (a) detecting the geographical patterns and variations of insufficient sleep in the CONUS, (b) statistical exploration of the association between insufficient sleep rates and different factors, and (c) modeling county-level insufficient sleep using machine learning methods.

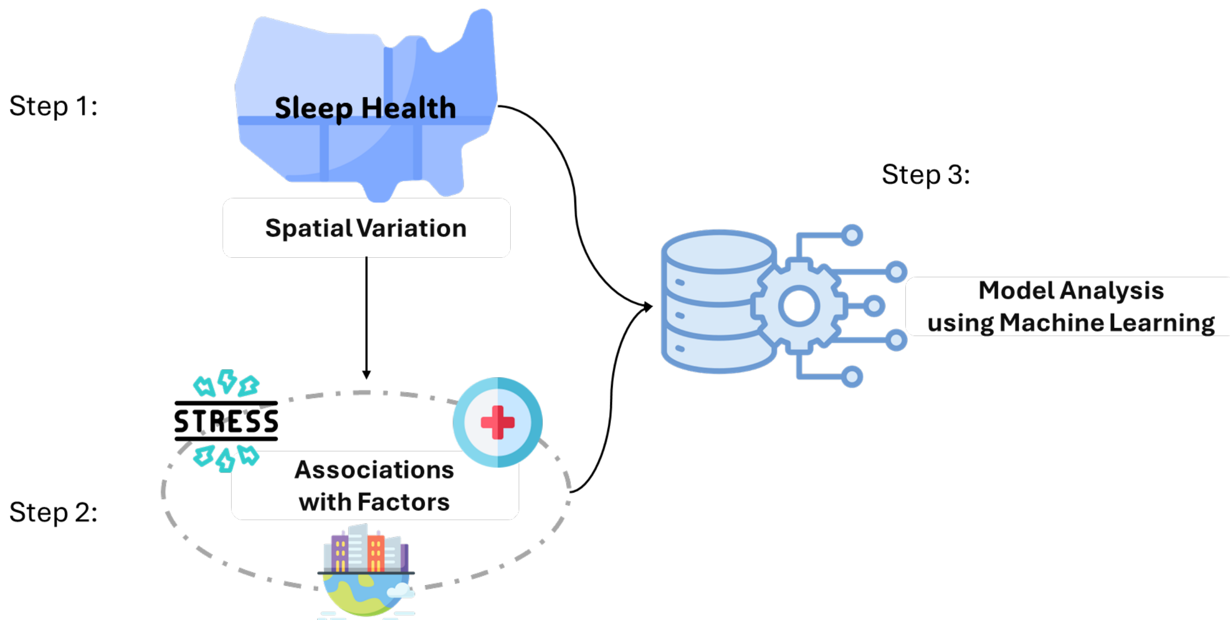

Figure 3. The workflow of this research

The first step is to delineate the geographic patterns of insufficient sleep at the county level in the U.S. to answer the first research question (do rates of insufficient sleep across the CONUS exhibit distinct geographic clustering patterns). We conducted two analyses in this step, Pearson correlation and hotspot analysis. Pearson correlation is applied to evaluate the strength and direction of linear relationships between geographical locations (latitudes/longitudes of county centroids) and insufficient sleep rates. The Pearson correlation is calculated using Equation 1, in which x_i and y_i are the individual observations of variables, $\bar{x}$ and $\bar{y}$ are the means of variables, and n is the total number of observations.

$$r = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2 \sum_{i=1}^{n}(y_i-\bar{y})^2}} \tag{1}$$

We then applied Global Moran's I (Equation 2) to assess whether the insufficient sleep rate exhibits spatial autocorrelation across the CONUS. In Equation 2, N is the number of spatial units and w_{ij} are spatial weights. Moran's I value ranges from –1 to +1. A statistically significant positive Moran's I indicates that neighboring areas tend to have similar values, suggesting the presence of spatial clustering.

$$Moran's\ I = \frac{N}{\sum_i \sum_j w_{ij}} \cdot \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{N}(x_i-\bar{x})^2} \tag{2}$$

After that, we performed a Hot Spot Analysis using the Getis–Ord Gi* statistic (Getis and Ord, 1992) to identify the specific geographic locations where significant clusters occur. This local spatial analysis distinguishes areas with high values surrounded by other high values (hot spots) and low values surrounded by low values (cold spots), providing detailed spatial insight into the distribution patterns across regions. The Getis-Ord Gi* statistic for location i (i.e., a county in this study) is calculated using Equation 3:

$$\text{Getis} - \text{Ord } G_i^* = \frac{\sum_{j=1}^{n} w_{ij} x_j - \bar{X} \sum_{j=1}^{n} w_{ij}}{S \sqrt{\left[\frac{n \sum_{j=1}^{n} w_{ij}^2 - (\sum_{j=1}^{n} w_{ij})^2}{n-1}\right]}} \quad (3)$$

Where x_j is the attribute value at location j, w_{ij} is the spatial weight between locations i and j, $\bar{X}$ is the mean of all x, S is the standard deviation of x, and n is the total number of observations.

The second step examines the associations between insufficient sleep and various physical conditions and social-environmental variables. Paired t-tests were adopted to compare the means of insufficient sleep rate under different categorical geographical conditions, aiming to determine whether these differences are statistically significant across the CONUS. The t-test statistics are calculated using Equation 4:

$$t = \frac{\bar{d}}{s_d / \sqrt{n}} \quad (4)$$

Where $\bar{d}$ is the mean of the paired differences, s_d is the standard deviation of the differences, and n is the number of pairs. Pearson correlation was also applied to evaluate the strength and direction of linear relationships between insufficient sleep rate and factors including demographics, race-ethnics, natural environments, stress and disease.

The last step is modeling insufficient sleep rates across the CONUS using three machine learning approaches, including general linear regression, random forest (RF), and Extreme Gradient Boosting (XGBoost). This step estimates the combined effects of multiple explanatory variables on insufficient sleep rates. Before implementation, we calculated the Pearson's correlation coefficients between each pair of the 26 variables to assess and eliminate multicollinearity (Cai et al., 2018). If the correlation coefficient between any two variables was greater than 0.6, we selected the factor that has a higher correlation with insufficient sleep rate for the subsequent modeling.

The general linear regression model is a statistical approach used to examine the linear relationship between a dependent variable and one or more independent variables using Equation (5):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + \varepsilon \quad (5)$$

Where Y is the dependent variable (county-level percentage of people reporting insufficient sleep), X_1, X_2, …, X_p are the independent variables, β_0 is the intercept term, β_1, β_2, …, β_p are the regression coefficients, and ε is the error term.

RF is an ensemble classification algorithm that uses decision trees as base classifiers (Leo, 2001). Each decision tree is trained using a subset of data randomly sampled from the whole input dataset and taking a random selection of features. The Gini index was used in this study to select the attribute at each node, which measures the impurity of cases classified by one attribute. The Gini index is calculated by Equation 6:

$$Gini\ index = 1 - \sum_{k=1}^{n}(P_i)^2 \tag{6}$$

where P_i is the probability of a case belonging to a distinct class. The Gini index varies from 0 to 1, and lower values of the Gini index yields better classification.

XGBoost is a scalable and highly efficient machine learning algorithm based on the gradient boosting framework (Chen and Guestrin, 2016). It builds an ensemble of decision trees sequentially, where each new tree attempts to correct the prediction errors made by the preceding ensemble. The algorithm minimizes a regularized objective function that incorporates both a loss term (e.g., mean squared error for regression or logistic loss for classification) and a regularization term to penalize model complexity.

We used three accuracy estimation matrics, R-squared (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) to evaluate the performance of each model. Also, the Shapley Additive exPlanations (SHAP) method was applied to interpret the results from RF and XGBoost models by quantifying each variable's contribution to the prediction of insufficient sleep rates. Based on cooperative game theory, SHAP assigns each feature a SHAP value representing its average marginal effect on the model output. A positive SHAP value indicates that the feature increases the predicted insufficient sleep rate relative to the model baseline, whereas a negative value indicates a decreasing effect.

5 Results

5.1 Geographical Disparities in Insufficient Sleep in the CONUS

Figure 4 displays the geographical disparities of insufficient sleep rates across the CONUS. The county-level rates in 2022 follow a normal distribution with the mean value of 37.30% and the standard deviation of 4.06% (Figure 4a). Figure 4b and 4c presents scatterplots illustrating the associations between latitudes/longitudes of county centroids and insufficient sleep rates across the CONUS. Figure 4c shows a negative relationship between latitude and insufficient sleep (Pearson R = -0.55, $p < 0.001$), indicating that counties located at higher latitudes (colder regions) tend to have less people reporting insufficient sleep. Conversely, Figure 4b demonstrates a positive correlation between longitude and insufficient sleep (Pearson R = 0.35, $p < 0.001$), with higher percentages observed in counties further east.

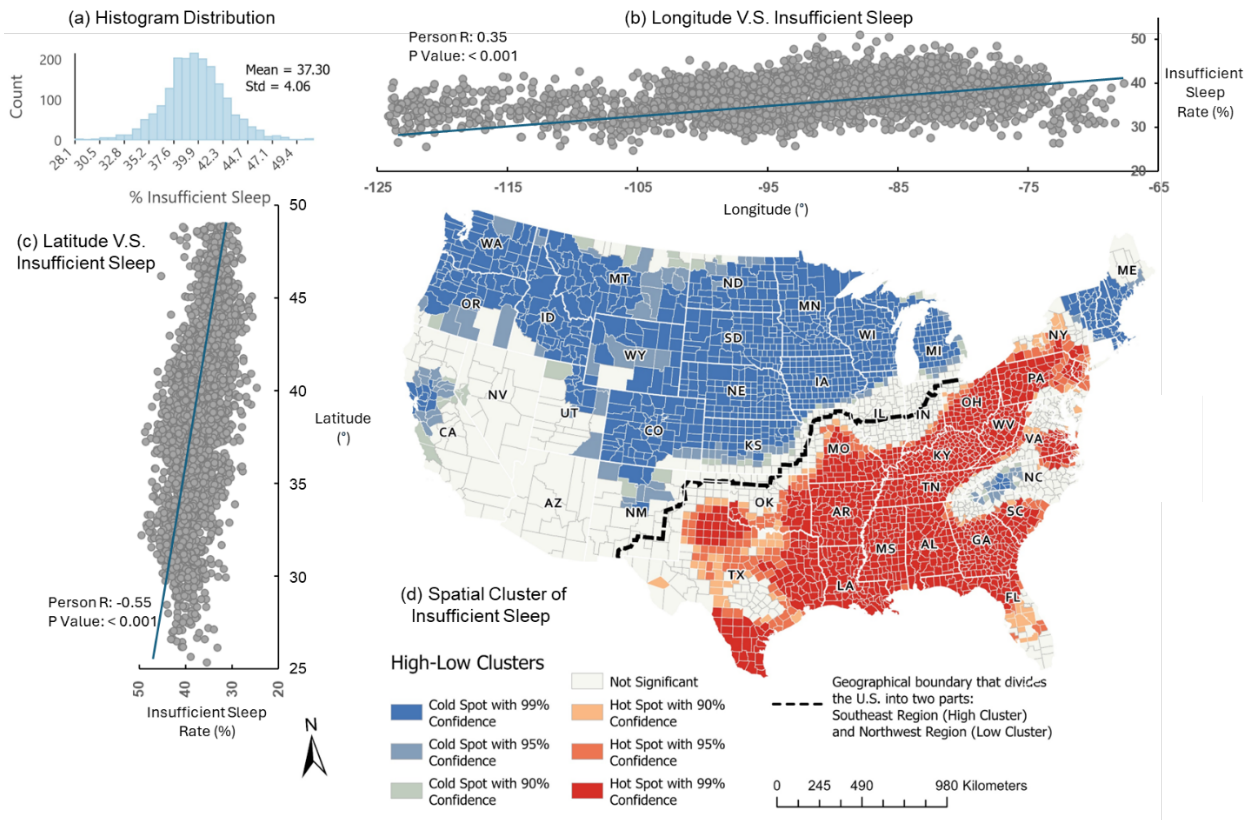

Figure 4. Geographical disparities map of insufficient sleep rate in the U.S.

The spatial autocorrelation analysis results demonstrate the non-random spatial distribution of insufficient sleep in the U.S. The global Moran's I value is 0.60, indicating a strong positive spatial autocorrelation. It means that counties with similar levels of insufficient sleep rates are geographically clustered rather than randomly distributed. The Getis-Ord Gi* statistics identified hot spots and cold spots of insufficient sleep prevalence at the county level (Figure 4d). Counties classified as hot spots (positive Moran's I value), indicating that significantly higher levels of insufficient sleep are primarily concentrated in the Southeastern U.S., including much of the South and parts of the Midwest and Northeast. These areas are shaded in deep red, with varying confidence levels (90%, 95%, and 99%). Conversely, cold spots (negative Moran's I value, blue colored counties in Figure 4d), representing significantly lower levels of insufficient sleep, are predominantly located in the Northwestern and Upper Midwestern regions, including states such as Montana, the Dakotas, Minnesota, and parts of the Pacific Northwest. In addition, two prominent cold spots were identified: one in the Northeastern United States (covering Vermont, New Hampshire, Massachusetts, Rhode Island, and parts of New York and Maine) and another along the border region of North Carolina, Tennessee, Georgia, and South Carolina.

Figure 4d also exhibits a distinct isolation zone between the southeast hot spots (red areas) and the northwest cold spots (blue areas) based on the Moran's I values. We drew a separation line to delineate the two regions by tracing the geometric midline through the interior of the polygons in between. This geographic divide is indicated by a dashed centerline in Figure 4d, which passes through or along the borders of the following states: Texas, Oklahoma, Arkansas, Missouri, Kentucky, Indiana, and Ohio. These results underscore a statistically significant spatial pattern, i.e., spatial gradient, in insufficient sleep prevalence, revealing regional disparities that may be influenced by social and natural environmental determinants.

5.2 Relationships Between Insufficient Sleep and Social-Physical-Environmental Factors

Figure 5 displays comparative boxplots assessing differences in insufficient sleep prevalence across four categorical environmental and sociodemographic factors: U.S. Census geolocation areas, climate zones, race-ethnic minority prevalence, and metro versus non-metro classifications. Significant geographical disparities can be observed. Initially, variation in insufficient sleep is evident across geographic regions (Figure 5a). The Southern (S) region exhibits the highest median percentage of insufficient sleep, while the Western (W) region shows the lowest. Pairwise comparisons confirm that the South differs significantly from all other regions, particularly from the West and MW. Meanwhile, climate conditions appear to influence sleep patterns (Figure 5b). Individuals living in Mixed-Humid zones report the highest prevalence of insufficient sleep, followed by those in Cold, Mixed-Dry, and Marine climates. All pairwise group comparisons are statistically significant. These environmental contexts may affect thermal comfort during sleep and circadian regulation through light exposure and seasonal variation.

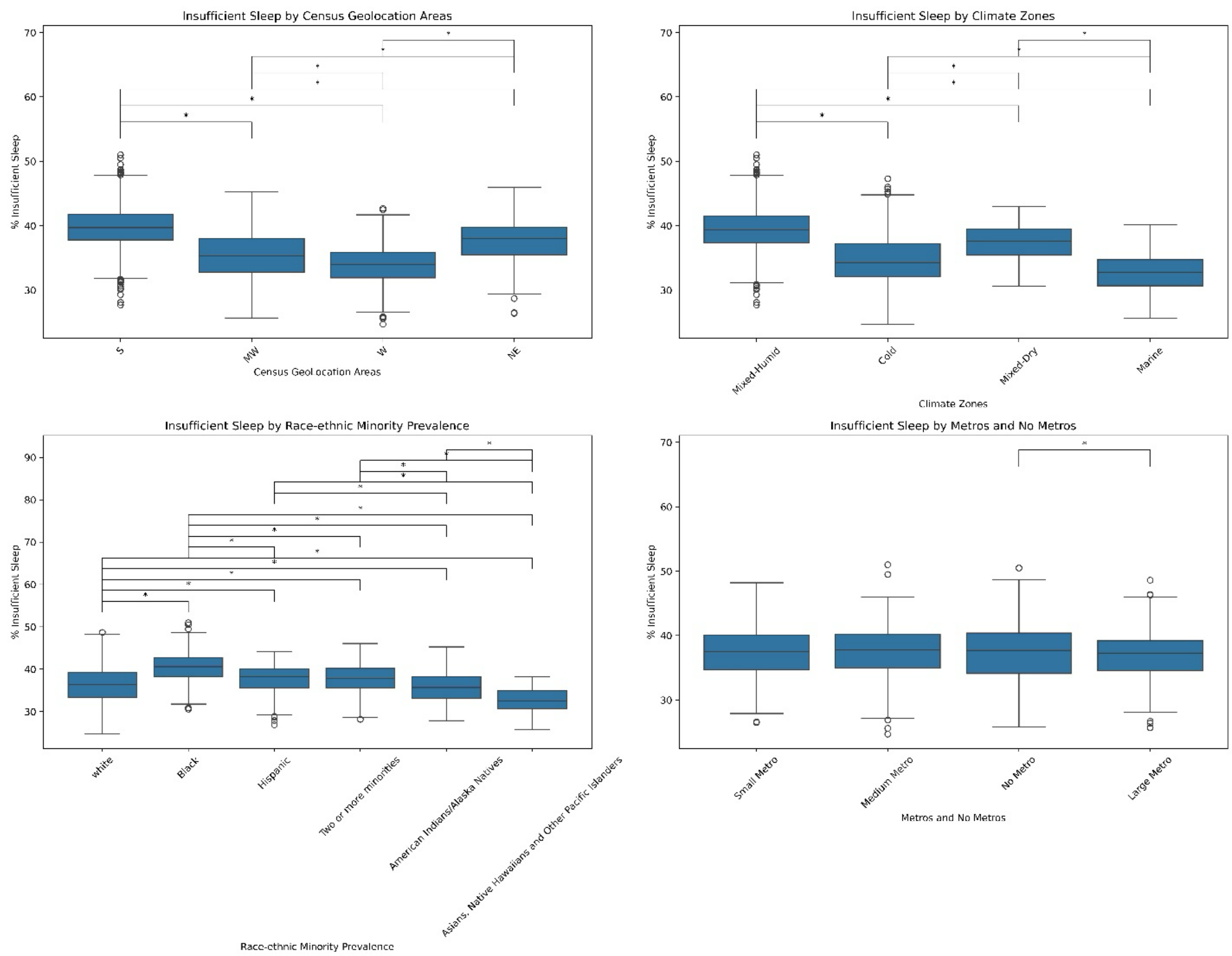

Figure 5. Boxplot with race, geolocation, climate, and urbanization

Pairwise t-tests indicate that insufficient sleep rates differ significantly across all pairs of counties with different predominant racial or ethnic groups (Figure 5c). The highest rates of insufficient sleep are observed in counties with a predominance of non-Hispanic Black populations, followed by counties with above-average proportions of Hispanic and multiracial residents. In contrast, counties where Asian, Native Hawaiian, or Pacific Islander populations reported the lowest levels of insufficient sleep. Differences across levels of urbanization are relatively modest (Figure 5d). Large metropolitan areas exhibit slightly lower insufficient sleep rates than nonmetropolitan counties, with the difference reaching statistical significance. However, small and medium metropolitan areas do not differ significantly from one another or from nonmetropolitan regions.

Figure 6 illustrates the relationship between insufficient sleep prevalence and the selected social, physical, and environmental factors using pairwise Pearson correlation matrices. As shown in Figure 6a, demographic factors exhibit generally weak correlations with insufficient sleep rates. The percentage of the population under age 18 ($r = 0.07$) and female ($r = 0.05$) are marginally and positively associated with the insufficient sleep rate. In contrast, the percentage of the population aged 65 and older shows a modest negative correlation ($r = –0.18$), suggesting that counties with a higher proportion of older residents tend to report lower rates of insufficient sleep. The proportion of the rural population also displays a negligible relationship (r = 0.07), indicating limited spatial variation in insufficient sleep associated with rurality. This result is consistent with the t-test in Figure 5.

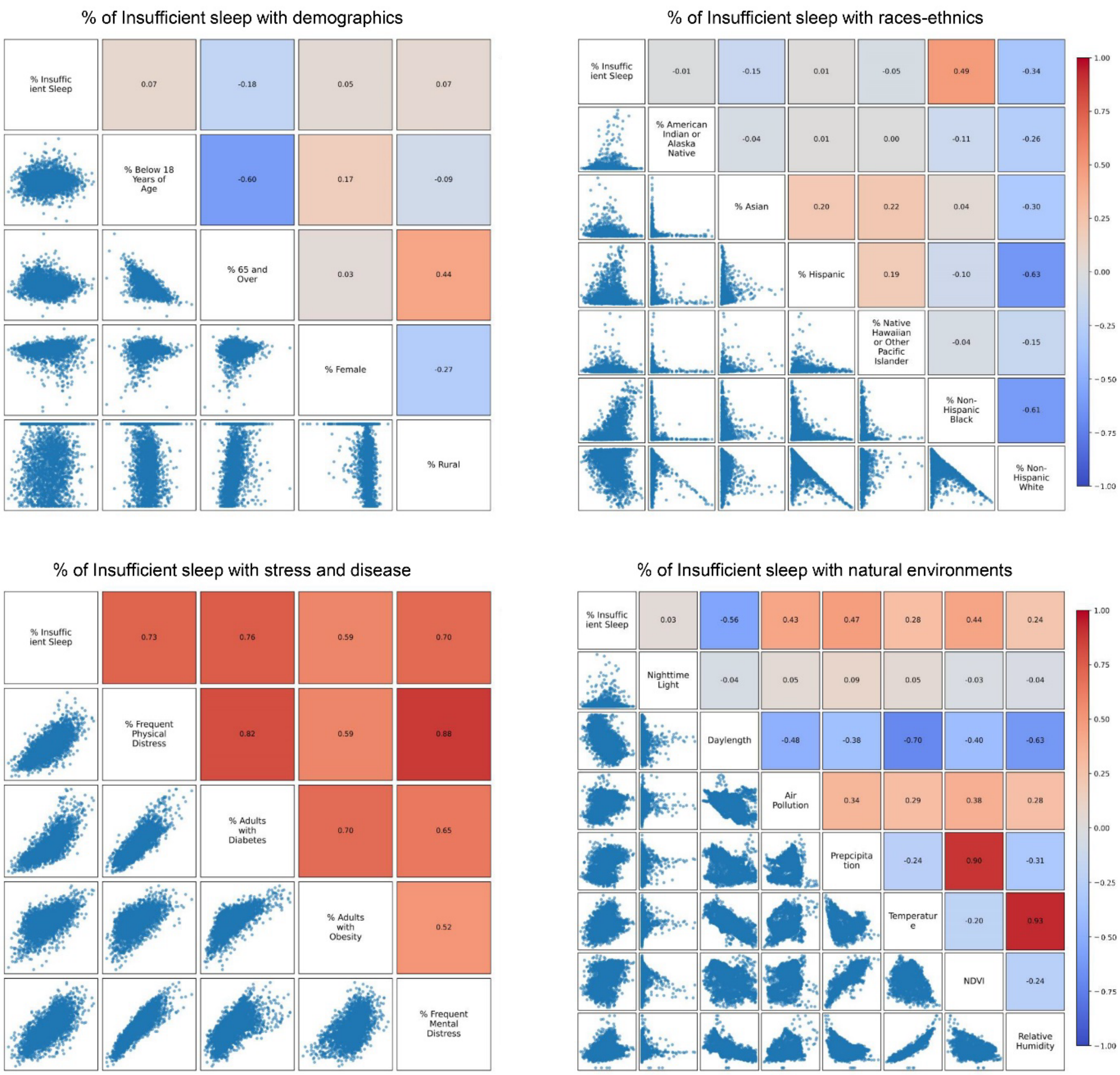

Figure 6. Scatter plots and correlation results between % of insufficient sleep and factors

Figure 6b shows substantial associations between race-ethnic compositions and insufficient sleep rates. Non-Hispanic American Africa populations exhibit a moderate positive correlation with insufficient sleep (r = 0.49), while Non-Hispanic White populations show a negative correlation (r = -0.34). Proportations of other race groups (e.g., Hispanic, Asian, Native populations) show weaker or near-zero correlations with insufficient sleep rates. The strongest associations with insufficient sleep are observed in the stress and disease domain (Figure 6c). The percentage of adults with diabetes shows a strong and positive correlation with insufficient sleep rate with an r value of 0.76. Other variables such as mental distress (r = 0.70), obesity (r = 0.59), and physical distress (r = 0.73) also exhibit strong associations with the percent of insufficient populations, supporting the robust link between poor physical and mental health and inadequate sleep duration.

Environmental determinants reveal mixed and complex effects on insufficient sleep, as indicated in Figure 6d. Day length is negatively correlated with insufficient sleep, suggesting that people who live in lower latitude regions are more likely to report inadequate sleep issues. Temperature (r = 0.28), Precipitation (r = 0.47) and Relative Humidity (r = 0.24) are positively correlated with insufficient sleep, indicating that muggy or sultry climates may impair sleep quality. Air pollutions, i.e., PM 2.5 concentrations, are positively correlated with insufficient sleep (r = 0.43).

However, community greenness measured by NDVI is positively correlated (r = 0.44) to insufficient sleep rate, implying that people who live in more green areas experience shorter sleep, contrary to prior findings that more vegetated environments may support better sleep. This counterintuitive finding may be explained by several factors. First, communities with higher NDVI values are predominantly located in the southeastern CONUS, where warmer temperatures and higher humidity create favorable conditions for vegetation growth but are also associated with sleep disturbances due to increased nighttime heat exposure and discomfort. Previous studies reporting positive associations between greenness and sleep quality were often conducted at finer spatial scales or within smaller regions of similar climate conditions, which may not fully capture these large-scale climatic variations. Second, at the county level, higher NDVI values do not necessarily translate into accessible or usable green spaces for residents. Extensive vegetation cover in southeastern regions may consist of forests, wetlands, or agricultural lands with limited human access, rather than parks, trails, or neighborhood green infrastructure that directly supports recreation or psychological restoration. Consequently, NDVI-based greenness measures may overestimate the availability of functional green spaces, limiting their explanatory power for human health outcomes such as sleep.

5.3 Machine Learning Modeling of Insufficient Sleep in the U.S.

The last analysis quantitatively investigated the collective effects of social-physical-environmental factors on sleep health through machine learning models. After the collinearity and significant test, 11 variables were excluded, and a total of 10 variables were included in the models. Table 4 presents the performance of the three models. The XGBoost model yielded the best predictive performance with an R^2 value of 0.805, the lowest RMSE (1.852) and the lowest MAE (1.413). The RF model exhibited slightly lower performance, with an R^2 of 0.787, RMSE of 1.935, and MAE of 1.429. The General Linear Regression model showed the weakest performance, with an R^2 of 0.717, RMSE of 2.231, and MAE of 1.714.

Table 4. The comparison results based on three machine learning models

Model	R-square	RMSE	MAE

General Linear Regression	0.717	2.231	1.714
Random Forest	0.787	1.935	1.429
XGBoost	0.805	1.852	1.413

Figure 7 summarizes the effects of each variable on insufficient sleep rates as estimated by different models. According to the multiple linear regression results (Figure 7a), the percentage of adults experiencing frequent physical distress exhibits the strongest positive association with insufficient sleep. Other influential factors showing positive relationships include the percentage of adults with obesity, high school completion rate, percentage of non-Hispanic Black population, nighttime light exposure duration, unemployment rate, and percentage of Asian population. In contrast, day length, percentage of adults with some college education, and percentage of American Indian or Alaska Native population demonstrate significant negative associations with insufficient sleep.

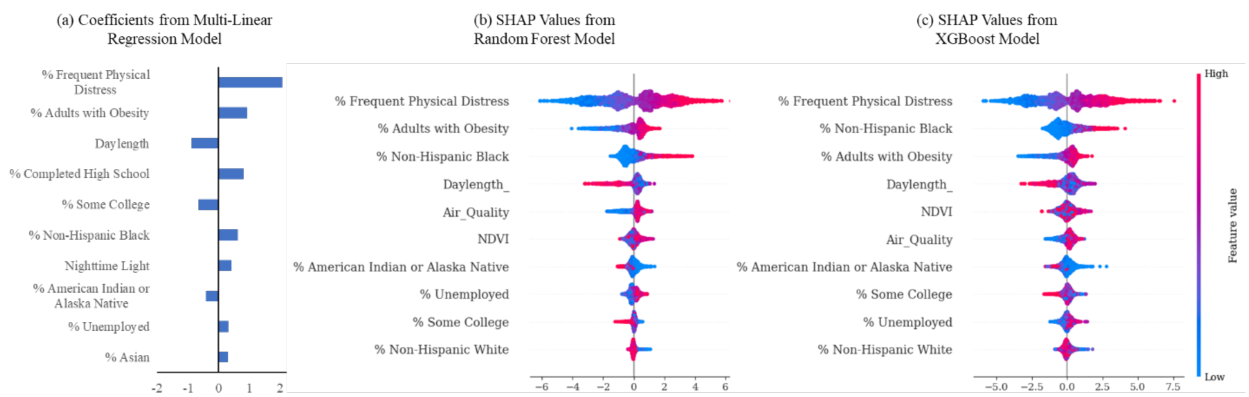

Figure 7. The importance of social-physical-environmental factors in (a) linear regression model, (b) SHAP for random forest model, and (c) SHAP for XGBoost model.

Figures 7b and 7c illustrate the importances and directional effects of the ten most influential social, physical, and environmental factors on insufficient sleep, as estimated by RF and XGBoost models using the SHAP framework. Consistent with the multiple linear regression results, the percentage of adults experiencing frequent physical distress and the percentage of adults with obesity remain the strongest positive contributors, confirming the bidirectional relationship between physical health and sleep deprivation. Insufficient sleep rates are also positively associated with day length, unemployment rate, NDVI, and the percentage of non-Hispanic Black population, while negatively associated with the percentage of adults with some college education, the percentage of American Indian or Alaska Native population, and the percentage of non-Hispanic White population. However, unlike the linear model, both the Random Forest and XGBoost analyses reveal a notably strong positive influence of air pollution on insufficient sleep rate, suggesting that environmental hazard exposures may have nonlinear and amplifying effects on sleep health across U.S. counties.

6 Discussion

6.1 Significant Findings and Implications

This study demonstrates clear geographical disparities in insufficient sleep across the CONUS, suggesting that sleep health is not randomly distributed but rather geographically structured, shaped by local living environments and broader social-ecological systems (CDC, 2022; Hale et al., 2020). Latitudinal and longitudinal gradients reveal the role of geographical and circadian mechanisms in regulating sleep duration. Insufficient sleep tends to decrease with latitude and increase with longitude in CONUS, consistent with the influence of natural daylight cycles on circadian alignment (Foster & Kreitzman, 2014; Roenneberg et al., 2007). Regions at higher latitudes experience extreme photoperiod variations, where prolonged daylight in summer can delay sleep onset and extended winter darkness may lengthen sleep or shift its timing. Evidence from smartphone-based and chronobiological studies (Walch et al., 2016; Friborg et al., 2012) supports this interpretation. It highlights how environmental light regimes, through photoperiodic entrainment, interact with human physiology to produce spatially patterned sleep behaviors.

Beyond geographical influences, the findings reveal that environmental exposures, socioeconomic conditions, and health factors jointly shape the spatial patterns of insufficient sleep across the CONUS. Among environmental determinants, air pollution, temperature, and humidity exert substantial impacts on sleep health. Poor air quality has been shown to disturb respiratory and circadian functions, while high nighttime temperatures and humidity disrupt thermoregulation and hinder the body's ability to initiate and maintain restful sleep (Chen et al., 2019; Minor et al., 2022). These associations highlight the vulnerability of populations in regions facing both environmental degradation and climatic stressors.

It is worth mentioning that the analysis reveals a positive correlation between NDVI and insufficient sleep, challenging the conventional assumption that greener environments universally promote better sleep. This counterintuitive pattern likely reflects the contextual and ecological complexity of greenness. Many high-NDVI counties are located in hot, humid regions such as the southeastern United States, where environmental conditions are less favorable for restorative sleep despite high vegetation cover. Furthermore, NDVI primarily captures vegetation density rather than green space accessibility. Forests, wetlands, or agricultural lands may inflate greenness metrics without providing usable or health-promoting green infrastructure. Thus, the relationship between greenness and sleep depends not only on vegetation abundance but also on accessibility, quality, and microclimatic context.

Socioeconomic and demographic characteristics also shape sleep adequacy patterns. Counties with higher proportions of non-Hispanic Black populations consistently exhibit greater prevalence of insufficient sleep. Similarly, unemployment correlates with higher sleep deprivation, likely due to chronic stress, financial insecurity, irregular work schedules, and reduced access to healthsupportive resources. Higher education like college completion, conversely, acts as a buffer by fostering awareness of healthy behaviors and facilitating more stable lifestyles.

Finally, health-related variables, particularly the prevalence of frequent physical distress and obesity, emerge as the most robust predictors of insufficient sleep. These relationships illustrate a bidirectional feedback loop: chronic illness and pain disrupt sleep continuity, while prolonged sleep deprivation worsens metabolic, cardiovascular, and inflammatory conditions (Adir et al., 2021). Together, these findings demonstrate that insufficient sleep is a multifactorial and spatially embedded phenomenon, emerging from the interplay among environmental stressors, social inequalities, and health conditions. Addressing these disparities therefore requires integrated, place-based strategies that can improve environmental quality, enhance healthcare access, and reduce structural differences to promote healthier sleep environments across regions.

6.2 Limitations and Future Research Directions

A key limitation of this study arises from the spatial scale of analysis using county-level data, which may obscure substantial within-county heterogeneity in insufficient sleep and its associated determinants. Counties in the United States vary greatly in demographic characteristics, socioeconomic composition, and environmental conditions. Aggregating data to the county level can therefore lead to the modifiable areal unit problem (MAUP) and ecological fallacy (Stewart and Wong, 1991; Stan, 1984), in which relationships identified at aggregated spatial scales may not accurately reflect associations at finer geographic or individual levels. Such aggregation can mask spatial variability within urban and rural areas, potentially underestimating localized effects of environmental stressors and social disparities. Furthermore, the precision and reliability of BRFSS-derived estimates may differ across counties due to sampling variability, uneven response rates, and population density differences, which may in turn introduce spatial bias and affect model performance and interpretability. To improve precision, future studies could employ multi-scale or hierarchical spatial frameworks, integrate higher-resolution data (e.g., census tract, ZIP code, or individual level), and use spatially explicit models such as geographically weighted regressions (GWR) or GeoAI approaches to better capture local variability and spatial non-stationarity.

Another limitation arises from the lack of occupational and other detailed population subgroup information in the county-level BRFSS data, which constrains the ability to examine disparities in insufficient sleep across different workforce and demographic categories. Occupation is a key determinant of sleep health, as work schedules, shift types, and job-related stress levels vary by occupation and can profoundly affect sleep duration and quality (Luckhaupt et al., 2010; Magnavita et al., 2017). Without such data, it is difficult to disentangle occupational effects from other socioeconomic or environmental factors aggregated at the county level, potentially leading to residual confounding and biased associations. Moreover, other unobserved within-county differences, such as commuting time, or exposure to occupational hazards, further obscure the heterogeneity in sleep patterns among specific groups. Future research could integrate occupational health and other detailed population subgroup information, to capture these group-specific disparities. Linking BRFSS data with employment statistics or detailed population subgroup data could provide a better understanding of how work-related contexts interact with social and environmental determinants of sleep. Such approaches are essential for developing occupation-specific interventions and policy recommendations aimed at reducing sleep disparities and improving overall sleep health.

Finally, the scope of sleep indicators available in BRFSS limits the depth of analysis. The dataset only measures the prevalence of insufficient sleep, lacking other crucial dimensions such as sleep timing, regularity, efficiency, and quality (Moore et al., 2011; Chaput et al., 2020). Sleep health is inherently multidimensional, and duration alone cannot capture the full spectrum of sleep behavior or its physiological and psychological correlations. Future studies should incorporate richer, temporally detailed datasets derived from wearable sensors, mobile apps, or smart devices, which can capture daily and seasonal variations in sleep patterns. Combining these individual-level observations with high-resolution environmental data such as nighttime light exposure, temperature fluctuations, or indoor environmental conditions would enable more nuanced analyses of the spatial and contextual factors shaping sleep health. Such multimodal integration is essential for building a comprehensive, geospatially informed database of population sleep behaviors that connect environmental, social, and biological dimensions.

7. Conclusion

This study provides a comprehensive spatial epidemiological assessment of insufficient sleep across CONUS counties by integrating environmental, demographic, and health-related variables. A key finding is the identification of a distinct geographic boundary traversing from the Southwest to the Northeast that delineates two regions: the Southeastern High-Prevalence Zone and the Northwestern Low-Prevalence Zone. The presence of this geographical disparity signifies a transition in the underlying environmental and social determinants of sleep health. In addition to spatial clustering, multivariate analyses demonstrate that insufficient sleep is significantly associated with both natural environmental exposures, including precipitation, temperature, air pollution, sociodemographic and health-related variables, such as race-ethnicity, obesity, diabetes, and physical distress. Among all variables, frequent physical distress and chronic disease prevalence emerged as the most influential contributors to insufficient sleep at the population level. Overall, these findings indicate that effective sleep health interventions must account for geospatial disparities, environmental exposures, and coexisting health burdens. An integrative approach, leveraging spatial data, machine learning models, and health surveillance tools, is essential to identify high-risk communities and develop tailored public health strategies that address both root causes and contextual drivers of insufficient sleep.

Building upon the current findings, the next phase of this research will focus on developing a spatiotemporal analytical framework to explore the dynamic evolution of insufficient sleep from 2014 to 2022. A time-series analysis will be conducted to quantify temporal trends and fluctuations in insufficient sleep prevalence across U.S. counties, capturing the effects of social, economic, and environmental transitions over nearly a decade. To further reveal local spatial variations and contextual influences, future work will incorporate spatial-explicit neural network models to integrate spatial dependence and nonlinear relationships simultaneously. This modeling approach will help uncover how the strength and direction of associations between insufficient sleep and its determinants vary geographically, evolve over time, and are reshaped by disruptions like pandemics. By integrating time-series trends with spatial modeling, the future research aims to construct a spatiotemporal landscape of insufficient sleep, providing valuable insights into the interplay between sleep health and social-environmental dynamics.

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