Geographic Distribution of Insufficient Sleep across the US:

A County-Level Hotspot Analysis

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ABSTRACT

INTRODUCTION: Insufficient sleep is associated with cardiometabolic risk and neurocognitive impairment. Determinants of insufficient sleep include many social and environmental factors. Assessment of geographic hot/coldspots may uncover novel risk groups and/or targets for public health intervention. The aim of this study was to discern geographic patterns in the first dataset to include county-level sleep data.

METHODS: The 2009 Behavioral Risk Factor Surveillance System was used. Insufficient sleep was assessed with a survey item and dichotomized. Data from N=2231 counties were available. Tests for significant spatial concentrations of high/low levels of insufficient sleep (hotspots/coldspots) used the Getis-Ord G* statistic of local spatial concentration, chosen due to the nature of missing data.

RESULTS: 84 counties were hotspots, with high levels of insufficient sleep ($p<0.01$), and 45 were coldspots, with low insufficient sleep ($p<0.01$). Hotspots were found in Alabama (1 county), Arkansas (1), Georgia (1), Illinois (1), Kentucky (25), Louisiana (1), Missouri (4), Ohio (7), Tennessee (12), Texas (9), Virginia (6), and West Virginia (16). Coldspots were found in Alabama (1 county), Georgia (2), Illinois (6), Iowa (6), Michigan (2), Minnesota (1), North Carolina (1), Texas (7), Virginia (12), and Wisconsin (6). Several contiguous hotspots and coldspots were evident. Notably, the 17 counties with the highest levels of insufficient sleep were found in a contiguous set at the intersection of Kentucky, Tennessee, Virginia and West Virginia (all $p<0.0002$).

CONCLUSIONS: Geographic distribution of insufficient sleep in the US is uneven. Some areas (most notably parts of Appalachia) experience disproportionately high amounts of insufficient sleep and may

be targets of intervention. Further investigation of determinants of geographic variability need to be explored, which would enhance the utility of these data for development of public health campaigns.

INTRODUCTION

Insufficient sleep is increasingly recognized as an important public health issue.[1] Population-based studies have shown that short sleep duration, which may represent insufficient sleep for many individuals, is associated with elevated risk of obesity, cardiovascular disease, diabetes, and a number of other significant health outcomes.[2-6] Self-reported insufficient rest or sleep, the outcome studied in this paper, has been linked with obesity, hypertension, hyperlipidemia, heart attack and stroke.[7] In order to address this public health issue, the social and environmental determinants of insufficient sleep need further examination.[2, 3, 8, 9] One possible determinant that has received little attention is geographical location.

Several recent studies have examined social environmental influences on sleep at the national level[6, 10-12] but these generally did not address geographic patterning insufficient sleep. Hale and colleagues have examined whether unhealthy neighborhoods influence the relationship between sleep and physical and mental health[13-17], but those studies focused on the characteristics of neighborhoods, not on the geographic region in which they were located. However, one recent study used the 2006 Behavioral Risk Factor Surveillance System data for 36 U.S. states to show that those in Southern states were more likely to report difficulty sleeping over the past 2 weeks. The states with the highest rates of sleep disturbance included West Virginia, Oklahoma, Missouri, Arkansas, Mississippi and Alabama, but notably, data on some nearby states (e.g., Kentucky or Ohio) were unavailable, making it difficult to observe clustering of insufficient sleep across states.

One issue with the limited existing research that examines geographical patterning of insufficient sleep is that the state maybe too broad a level of geographic aggregation. There may be particular regions within a state that are particularly susceptible to sleep problems, and also regions that are relatively free of problems. Studies of the links between neighborhood characteristics and sleep suggest that geographic patterning operates at a more local level than the state. Until recently, no data have been available to address the question of whether insufficient sleep is geographically patterned at the local level, using data that represents the entire United States. These findings would be relevant to many stakeholders, including members of the public and health authorities at the national, regional and state levels, who could use these data to discern the public health burden of sleep disturbance relative to geography.

Accordingly, the present study leveraged a large, national sample of US adults to assess whether insufficient sleep is differentially reported across counties. Specifically, county-level data from the 48 mainland US states were examined to discern hotspots and coldspots of insufficient sleep. Hypotheses included: (1) regional differences in the percent of adults reporting insufficient sleep would be evident, and most prominent in those states previous identified as having high levels of sleep disturbance; and (2) these regional patterns would elucidate a number of hotspots of abnormally high insufficient sleep and coldspots of abnormally low insufficient sleep.

METHODS

Data from the 2009 Behavioral Risk Factor Surveillance System (BRFSS) were used [18]. The BRFSS is an annual, state-based, random-digit-dialed telephone survey of adults in the United States. It is conducted by the Centers for Disease Control and Prevention and designed to monitor health-related behaviors in the general population. Data from all 48 contiguous states and Washington, DC were included in these analyses. Response rates varied by state, with a median of 53.86% (range: 37.90% (Oregon) to 66.85% (Nebraska)).

The outcome of interest was perceived insufficient rest or sleep (insufficient sleep). This was measured using the item, "During the past thirty days, for about how many days have you felt you did not get enough rest or sleep?" Responses were dichotomized, with those reporting ≥15/30 days being categorized as reporting insufficient sleep. This dichotomization was chosen for several reasons. First, a dichotomized variable allows for much more interpretable prevalence estimates. Second, the cutoff of 15 days was chosen to mirror the diagnostic criteria for insomnia, which suggests that symptoms should exist for approximately half of nights to be clinically relevant[19]. Second, this dichotomization at 50% of nights is consistent with other BRFSS studies that similarly dichotomized global sleep disturbance[20-25]. Third, preliminary evaluation of different cutoffs (3, 7, 15, or 30 days) did not result in noticeably different patterns of findings regarding insufficient sleep and outcomes.

To examine the prevalence of insufficient sleep, the BRFSS data were analyzed 3 ways. First, prevalence of insufficient sleep was estimated for all available counties and mapped at the county level. Second, these county-level prevalence estimates were evaluated using a spatial clustering technique to identify regionally anomalous areas of counties that demonstrate unusually high or low values (i.e., "hotspots" and "coldspots"). Third, linear regression analyses aimed to assess characteristics of individuals who live in hotspots and coldspots versus the majority of counties, which were identified as neither.

Regarding the clustering analysis, tests for significant spatial concentrations of high percentage values (or low percentage values) were conducted. These tests evaluate the percentage of respondents within a specific county that reported insufficient sleep, relative to neighboring counties. Typically, this analysis would involve comparing frequency of insufficient sleep to immediate neighbors. However, there were many missing counties that would make this approach problematic, since counties were not missing at random (since these were generally the most sparsely-populated counties) and all counties neighboring one of these missing counties would typically be excluded. Also, the number of responses per county was highly variable, generally in proportion with the population density of that county. Therefore, a method is needed to account for this variability and missing data. To address this, the Getis-Ord G^*statistic of local spatial concentration was used[26]. For any given set of n spatial units, this local statistic is constructed for each spatial unit, i, by first identifying some appropriate measure, w_{ij}, of "closeness" to each other unit j (including i). Here we choose the standard *contiguity measure* defined by $w_{ij} = 1$ if counties i and j share a common border (including the case, $i = j$, and $w_{ij} = 0$ otherwise. For any given set of nonnegative data $(x_i: i = 1, \dots, n)$ associated with these n spatial units (such as our three percentages above), the G^* statistic is then defined for each unit, i, by:

$$(1)\quad G_i^* = \frac{\sum_{j=1}^{n} w_{ij} x_{ij}}{\sum_{j=1}^{n} x_j}, i = 1, \dots, n$$

Equivalently, if the *immediate neighborhood* of i is denoted by $N_i = \{j: w_{ij} = 1\}$ then in our case this statistic takes the more easily interpretable form:

$$(2)\quad G_i^* = \frac{\sum_{j \in N_i} x_j}{\sum_{j=1}^{n} x_j}, i = 1, \dots, n$$

In these terms, G_i^* is simply the fraction of all individuals reporting insufficient sleep in the immediate neighborhood of county i. If this fraction is "unusually high" (or "unusually low") relative to levels that would be expected by chance alone, then it can reasonably be concluded that there is "significant insufficient sleep" (or "significant lack of insufficient sleep") in the neighborhood of county i.

These notations can be made precise in terms of the *null hypothesis* that the observed value, say $G_i^{*(0)}$, is not statistically distinguishable from values that would be observed if the given percentages $(x_i: i = 1, \dots, n)$ were randomly distributed among spatial units. The actual distribution of G_i^* under this null hypothesis can then be approximated by randomly reassigning these percentages to spatial units many times and computing the statistic in each case. More formally, if $G_i^{*(k)}$, $k = 1, .., M$, denotes the values obtained from M random reassignments (permutations) of percentages to spatial units, then this constitutes a sample of size M of G_i^* under this null hypothesis. Assuming that the observed value, $G_i^{*(0)}$, is coming from the same population, this yields a sample $[G_i^{*(0)}, G_i^{*(1)}, \ldots G_i^{*(M)}]$ of size $M + 1$. So if k_i^+ denotes the number of these samples with values *at least as high* as $G_i^{*(0)}$, then the chance of obtaining a value as high as $G_i^{*(0)}$ is estimated by:

(3) $P_i^+ = \frac{k_i^+}{M+1}$

and yields a natural p-value for an *upper-tailed* test of this null hypothesis. For example, if $P_i^+ = 0.05$ then there is only a 5% chance of observing a value as high as $G_i^{*(0)}$ if this null hypothesis were true. Conversely, if k_i^- denotes the number of these samples with values *no higher than* $G_i^{*(0)}$, then:

(4) $P_i^- = \frac{k_i^-}{M+1}$

yields the equivalent p-value for a *lower tailed* test of this hypothesis.

Finally, it should be noted this G_i^* statistic is asymptotically normally distributed under the above null hypothesis[26]. However, the present approach is generally more reliable for small samples, such as those obtained for many of the counties in this study. Hence the results reported below are for this direct-sampling approach. The asymptotic approach (as implemented in ArcGIS software) was assessed for purposes of comparison, and was found to yield very similar results (not reported here).

These tests were applied using $\mathrm{M} = 9{,}999$ random permutations. A p value of <0.01 was chosen to denote significant high or low levels of insufficient sleep, corresponding to a level in the top (or bottom) 100 values among the 10,000 permutations. A value in the top 100 would be considered a "hotspot" and a value in the bottom 100 would be considered a "coldspot." Confidence intervals around percentages were computed using the Clopper and Pearson exact method, as implemented by the *binofit* program in MATLAB, based on the implementation by Daly[27].

To examine differences between individuals who reside in a "hotspot" or "coldspot" county relative to counties that were not identified as either one, multinomial logistic regression analyses were used, with county type coded as hotspot, coldspot, or neither (reference) as the outcome variable and demographic, socioeconomic, and health variables from the BRFSS survey used as predictors. These included the following: age (18-24, 25-29, 3034, 35-39, 40-44, 55-59, 60-64, 65-69, 70-74, 75-79, and 80+(reference)), sex, education (college graduate (reference), some college, high school, less than high school), race/ethnicity, overall health (excellent (reference), very good, good, fair, poor), consumption of at least 5 servings of fruits/vegetables per day (yes or no), sedentary lifestyle (any exercise within the past 30 days), employment (low-intensity (reference), moderate-intensity, manual labor, and unemployed), heavy alcohol use (2 or more drinks per day for women, 3 or more for men), current smoking, overall mental health (#days in the past month of poor mental health), household size, access to health insurance, and obesity. These variables were entered simultaneously so that unique effects of each factor could be examined.

The present analysis allows for not only the enumeration of county-level prevalence estimates for insufficient sleep, but also the spatial analysis of potential areas of the country with unusually high and low concentrations of insufficient sleep. There are a number of important limitations to this approach (see below), but there are also many distinct advantages. Importantly, this approach is unique in that it allows for spatial analysis in the presence of data that is not missing at random.

RESULTS

Respondents and Counties

Data for the present study were drawn from 424,989 respondents to the 2009 BRFSS. Those who did not respond to the insufficient sleep item, or responded “Don’t know/Not Sure” or “Refused” were excluded (7,618 respondents, 1.76% of responses). Responses were aggregated by county. Of the 3,109 counties/county-equivalents in the mainland US, N=2,231 counties were represented among respondents who participated in the BRFSS. Geographic distribution of insufficient sleep by quintile is reported in Figure 1.

Hotspots of Insufficient Sleep

Table 2 lists the 84 counties identified as “hotspots,” reporting significantly high levels of insufficient sleep (p<0.01 level). Table 2 includes the state and name of each county, the percent of insufficient sleep observed, 95% confidence interval, the G_i^* value for each county *i*, and the p-value P_i^+. The largest aggregation of counties identified as hotspots includes an area at the intersection of Kentucky, Tennessee, West Virginia, and Virginia. This area includes a contiguous set of counties that comprise the top 19 counties categorized as hotspots (all with p-values ≤0.0002). In addition, over half of the 84 counties identified as hotspots come from this region. Other regions identified as hotspots include areas of Ohio and Texas, and Missouri, and single counties in other states. Figure 2 presents a map of hotspots and coldspots. Figure 3 shows the region with the largest number of hotspots in detail, including the 15 counties with p<0.0001 for their G* value.

Coldspots of Insufficient Sleep

Table 3 lists the 45 counties identified as reporting “coldspots” with significantly low levels of insufficient sleep (p<0.01 level). Table 3 includes the state and name of each county, the percent of insufficient sleep observed, 95% confidence interval, the G_i^* value for each county *i*, and the p-value P_i^-.

Unlike the large aggregation of hotspots identified above, there are no coldspots of comparable intensity. However, there were several regions that contained smaller aggregations of coldspots, including areas of Texas, northern Virginia, and the northern Midwest.

Differentiating Hotspots and Coldspots

Multinomial logistic regression analyses including age, sex, race/ethnicity, household size, education, insurance access, employment, fruit and vegetable consumption, sedentary lifestyle, heavy drinking, smoking, obesity, overall health, and mental health, included N=373,176 respondents with complete data for analysis. Results can be seen in Table 3. Overall, individuals in hotspot counties were more likely to be younger to middle-aged, White, living with only one other person, less educated, with health insurance, and unemployed. They are also more likely to be sedentary, smokers, obese, and in overall fair or poor health, and they are less likely to be heavy drinkers and less likely to report poor mental health only 1-7 days in the past month. Individuals in coldspot counties were more likely to be White, and have only a high school education, and no individuals in coldspot counties lived in households with 10 or more people.

DISCUSSION

Insufficient sleep is an important health risk factor, but little is known about its geographic distribution. The present study evaluated, at the county level, whether self-reported insufficient sleep is disproportionately distributed across the US. Overall, we found that there are several notable hotspots, particularly one very large concentration in the Appalachia region that connects Tennessee, Virginia, West Virginia, Kentucky, and Ohio. Other hotspots were identified, particularly in the southeast and Midwest US. A number of coldspots were also identified, primarily in the Midwest, Texas, and northern Virginia.

The main finding of this study is that the region that represents the largest aggregation of hotspots lies in a region of Appalachia that traverses West Virginia, Kentucky, Tennessee, Virginia and Ohio. There have been a number of studies of this region that have shown that Appalachia is a region that has one of the highest obesity rates in the nation[28, 29]. In addition, individuals living in this region are at greater risk of cardiovascular disease[30, 31], diabetes[20, 21], lung diseases[32-34], and several types of cancer[30, 32, 33, 35], relative to individuals in other areas. Some reasons for this may be the general lack of education in this region, low socioeconomic status, unemployment, lack of access to care, and lack of infrastructure[36]. It is unclear why this region, in particular, has such a high rate of insufficient sleep relative to other regions. It may be the case that so many of the risk factors that are particularly prevalent in this area are also commonly identified as either risk factors for poor sleep or potential effects of poor sleep[3, 37, 38].

In examining differences between individuals in hotspot and coldspot counties relative to counties that were neither, no clear pattern emerged for predicting individuals in coldspot counties, suggesting that the examined factors may not be the most relevant predictors. Regarding hotspot counties, the general pattern emerged that relatively younger individuals of lower socioeconomic status and poorer health were more likely to live in hotspot counties. It is interesting to note that racial/ethnic minority status was negatively associated with living in either a hotspot or coldspot county.

Although no previous studies have examined geographic patterning of insufficient sleep at the county level, two previous studies have used BRFSS data to investigate geographic patterning of other sleep-related variables. McKnight-Eily and colleagues[39] assessed the prevalence of insufficient sleep using the 2008 BRFSS. The measure of insufficient sleep was the same survey item, though it was categorized as 0/30 days, 1-13/30 days, 14-29/30 days, or 30/30 days, (instead of 15-30/30 days versus 0-14/30 days , used in the present study). Their analysis showed that among the 48 continental US states and Washington, DC, the states with the highest rates of insufficient sleep every night were (in order), West

Virginia (19.3%), Tennessee (14.8%), Kentucky (14.4%), Oklahoma (14.3%), Florida (13.5%), Georgia (13.4%), Missouri (13.4%), Alabama (13.2%), Mississippi (13.1%), Louisiana (13.0%), North Carolina (13.0%). In the present study, hotspots were identified in nearly all of these states, particularly the three with the highest rates: West Virginia, Tennessee, and Kentucky, replicating these findings. The findings from the present study also extend these findings by identifying which areas of these states are at heightened risk, since hotspots were generally confined to specific areas and were not state-wide.

One other previous study has examined geographic patterning of sleep. Using BRFSS 2006, our group[20] examined state-level prevalence of general sleep disturbance (which included difficulty falling asleep, difficulty maintaining sleep or sleeping too much), as well as daytime tiredness/fatigue. This analysis also found that the states with the highest concentrations both sleep disturbance and daytime/fatigue included West Virginia, Alabama, Mississippi, Missouri, and Oklahoma. As with the previously-described study by McKnight-Eily and colleagues, the present study replicates the finding that states in Appalachia and the Southeast US are at high risk of unhealthy sleep, and it extends these findings by suggesting regions within those states at highest risk.

The present data suggest that there are several areas of the country, most notable Appalachia, which may experience disproportionately high rates of insufficient sleep. To the degree to which this represents undiagnosed or untreated sleep disorders, this suggests that the areas identified as hotspots might be good targets for intervention. Notably, there are relatively few AASM-accredited sleep centers in the central Appalachia region. Perhaps resources could be directed to this region to screen for and treat sleep disorders at these centers. Also, this area may be ideal for adding sleep to existing health education programs.

Limitations

The most important limitation of the current study is that we are unable to explore reasons for this geographic variation. The previous study by Grandner and colleagues[20] found that variation in sleep disturbance at the census region level was driven by regional differences in mental health, race/ethnicity, access to healthcare, socioeconomics, smoking, and weather patterns. The limitations of the county-level analyses preclude similar analyses in this context. For example, although several previous studies have identified Appalachia as a region that is particularly high risk of chronic disease and a number of other adverse outcomes (see above), the present study is unable to determine whether these factors mediate the geographic relationship, due to limitations in the ability of this survey to capture these factors and limitations to the statistical techniques to leverage covariates.

Another important limitation of this approach is that the G statistic can be somewhat unpredictable when a county exhibits prevalence of insufficient sleep that is very different from its neighbors. This could result in a county (such as Falls County, Texas) where the estimated prevalence is 0% yet it is identified as a hotspot, since all of its neighbors have high prevalence. Clearly, it is at the center of a hotspot, though it could be a “donut hole” or it could have been misclassified due to small sample size. Also, counties may be classified as coldspots, despite relatively high prevalence. This could result in a county (such as Erath County, Texas), where observed prevalence is high but it is classified as a coldspot due to all of its neighbors having very low prevalence. This is an inherent limitation to the clustering approach in that some of the counties identified may not meet all of the typical characteristics of the cluster. These relatively uncommon anomalies may be due to limited sample sizes or complex regional patterns that cannot be adequately captured with this approach.

Other limitations of these analyses exist as well. For example, cross-sectional data collection precludes assessments of causality. Although it is likely that residence predates sleep disturbance, it is not possible to determine whether changing residence will alter sleep. Also, the insufficient sleep survey item is limited in its clinical utility, as it is not diagnostic of any particular sleep disorder, it may or may not reflect sleep duration, and it assesses a construct that has not been thoroughly evaluated psychometrically. Therefore, conclusions should be interpreted with appropriate caution.

Conclusions

Overall, insufficient sleep was found to be differentially distributed among US counties, with several hotspots and coldspots identified. In particular, a prominent hotspot was found in an Appalachian region at the intersection of Kentucky, Tennessee, West Virginia, and Virginia, with that hotspot extending into parts of Ohio. These findings could be utilized by stakeholders, including members of the public and health authorities at the national, regional and state levels, who could use these data to discern the public health burden of sleep disturbance relative to geography.

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Table 1. Counties identified as hotspots of insufficient sleep

State	County	% Insufficient Sleep	95%CI		G*	P+
Tennessee	Union	14.29	0.36	57.87	0.0048	0.0001
Kentucky	Whitley	27.78	17.86	39.59	0.0057	0.0001
Tennessee	Scott	28.57	3.67	70.96	0.0054	0.0001
Kentucky	Perry	29.13	21.41	37.85	0.0047	0.0001
West Virginia	Mingo	29.79	20.79	40.10	0.0060	0.0001
Kentucky	Bell	30.00	18.85	43.21	0.0056	0.0001
West Virginia	Logan	30.00	20.79	40.57	0.0041	0.0001
Virginia	Wise	30.51	19.19	43.87	0.0063	0.0001
Kentucky	Letcher	30.56	22.05	40.16	0.0048	0.0001
Kentucky	Pike	30.60	25.14	36.49	0.0060	0.0001
Virginia	Lee	32.61	19.53	48.02	0.0047	0.0001
Tennessee	Claiborne	35.29	14.21	61.67	0.0059	0.0001
Kentucky	Knott	37.50	27.40	48.47	0.0052	0.0001
West Virginia	Lincoln	39.29	26.50	53.25	0.0057	0.0001
Tennessee	Campbell	52.17	30.59	73.18	0.0053	0.0001
West Virginia	Kanawha	24.54	20.99	28.38	0.0062	0.0002
Kentucky	Magoffin	25.58	13.52	41.17	0.0044	0.0002
West Virginia	Boone	32.14	22.36	43.22	0.0046	0.0002
Kentucky	Harlan	37.50	27.40	48.47	0.0046	0.0002
Ohio	Vinton	40.00	12.16	73.76	0.0050	0.0002
West Virginia	Cabell	24.27	18.58	30.72	0.0050	0.0003
Virginia	Buchanan	29.17	12.62	51.09	0.0051	0.0003
West Virginia	Wayne	29.91	21.80	39.07	0.0050	0.0003
Kentucky	McCreary	28.00	16.23	42.49	0.0049	0.0004
Kentucky	Montgomery	26.60	18.01	36.71	0.0032	0.0005
Ohio	Meigs	26.67	12.28	45.89	0.0049	0.0005
Ohio	Gallia	30.77	14.33	51.79	0.0048	0.0005
West Virginia	Wyoming	35.71	23.36	49.64	0.0048	0.0005
Ohio	Hocking	30.00	11.89	54.28	0.0049	0.0006
Virginia	Dickenson	26.09	10.23	48.41	0.0039	0.0007
Virginia	Scott	26.32	13.40	43.10	0.0048	0.0007
Kentucky	Floyd	32.95	26.00	40.49	0.0038	0.0007
Texas	Falls	0.00	0.00	33.63	0.0042	0.0008
Tennessee	Hamblen	28.57	14.64	46.30	0.0044	0.0008
Texas	Angelina	31.03	15.28	50.83	0.0053	0.0008
Tennessee	Greene	24.19	14.22	36.75	0.0047	0.0009
Tennessee	Hawkins	25.00	15.02	37.40	0.0048	0.0010
Kentucky	Lawrence	31.25	20.24	44.06	0.0042	0.0010
Texas	Newton	28.57	3.67	70.96	0.0048	0.0011
Ohio	Athens	31.82	18.61	47.58	0.0053	0.0012
Arkansas	Mississippi	21.13	12.33	32.44	0.0064	0.0013
Kentucky	Laurel	23.02	15.99	31.35	0.0052	0.0013

Tennessee	Anderson	31.58	17.50	48.65	0.0047	0.0013
West Virginia	Raleigh	27.70	20.67	35.65	0.0046	0.0015
Kentucky	Knox	35.71	23.36	49.64	0.0036	0.0015
Texas	Jasper	55.56	21.20	86.30	0.0042	0.0015
West Virginia	Mercer	20.81	14.60	28.21	0.0047	0.0016
Kentucky	Johnson	27.38	18.21	38.20	0.0036	0.0016
Texas	Milam	37.50	8.52	75.51	0.0046	0.0018
Kentucky	Clark	26.67	7.79	55.10	0.0046	0.0020
Kentucky	Harrison	15.38	1.92	45.45	0.0035	0.0021
Kentucky	Breathitt	28.07	16.97	41.54	0.0029	0.0021
West Virginia	McDowell	21.88	12.51	33.97	0.0040	0.0022
Kentucky	Boyd	25.14	19.03	32.07	0.0040	0.0023
Texas	Orange	18.18	5.19	40.28	0.0040	0.0024
West Virginia	Putnam	23.66	16.68	31.88	0.0040	0.0025
Kentucky	Bourbon	46.15	19.22	74.87	0.0040	0.0027
Kentucky	Clay	31.25	18.66	46.25	0.0040	0.0028
Virginia	Russell	42.22	27.66	57.85	0.0051	0.0028
Missouri	Howell	33.33	19.09	50.22	0.0024	0.0031
Texas	Tyler	26.32	9.15	51.20	0.0034	0.0035
Kentucky	Carter	28.74	19.54	39.43	0.0039	0.0036
Tennessee	Lauderdale	36.84	21.81	54.01	0.0040	0.0036
West Virginia	Summers	22.86	10.42	40.14	0.0045	0.0037
Kentucky	Morgan	28.21	20.28	37.27	0.0034	0.0042
Texas	Burleson	33.33	4.33	77.72	0.0039	0.0044
Kentucky	Pulaski	20.34	14.67	27.03	0.0050	0.0045
Texas	Trinity	28.57	3.67	70.96	0.0039	0.0045
Georgia	Polk	13.64	2.91	34.91	0.0044	0.0047
Illinois	Mason	25.00	5.49	57.19	0.0034	0.0047
West Virginia	Fayette	25.42	17.86	34.26	0.0038	0.0060
Tennessee	Grainger	50.00	18.71	81.29	0.0044	0.0068
Tennessee	Jefferson	12.90	3.63	29.83	0.0039	0.0069
Tennessee	Haywood	19.35	7.45	37.47	0.0043	0.0070
West Virginia	Mason	30.67	20.53	42.38	0.0039	0.0070
West Virginia	Jackson	21.95	13.56	32.46	0.0044	0.0073
Alabama	Calhoun	16.67	11.76	22.60	0.0038	0.0074
Missouri	Cape Girardeau	24.59	14.46	37.29	0.0033	0.0075
Kentucky	Hardin	19.49	14.17	25.75	0.0059	0.0076
Missouri	Cedar	25.00	3.19	65.09	0.0022	0.0079
Missouri	Texas	25.00	9.77	46.71	0.0049	0.0079
Ohio	Ross	25.81	11.86	44.61	0.0048	0.0082
Ohio	Lawrence	25.81	15.53	38.50	0.0048	0.0091
Louisiana	Rapides	20.50	16.82	24.58	0.0047	0.0099

Table 2. Counties identified as coldspots of low insufficient sleep

State	County	% Insufficient Sleep	95%CI		G*	P+
Texas	Howard	0.00	0.00	52.18	0.0000	0.0000
Texas	Pecos	0.00	0.00	45.93	0.0000	0.0000
Texas	Erath	33.33	11.82	61.62	0.0011	0.0000
Virginia	Harrisonburg	0.00	0.00	45.93	0.0002	0.0008
Wisconsin	Iowa	15.25	7.22	26.99	0.0017	0.0009
Illinois	Christian	20.00	4.33	48.09	0.0010	0.0009
Michigan	Iosco	3.23	0.08	16.70	0.0004	0.0011
Illinois	Montgomery	0.00	0.00	16.84	0.0022	0.0014
Virginia	Chesterfield	17.29	11.29	24.81	0.0033	0.0015
Texas	Colorado	18.18	2.28	51.78	0.0016	0.0015
Wisconsin	Adams	12.50	5.18	24.07	0.0022	0.0019
Illinois	Madison	18.87	13.11	25.83	0.0030	0.0019
Wisconsin	Grant	15.09	6.75	27.59	0.0023	0.0020
Wisconsin	Brown	14.29	8.39	22.16	0.0019	0.0021
Virginia	Colonial Heights	0.00	0.00	84.19	0.0006	0.0026
Virginia	Rockingham	6.52	1.37	17.90	0.0023	0.0026
Michigan	Aremac	0.00	0.00	19.51	0.0012	0.0027
Georgia	Mitchell	11.11	1.38	34.71	0.0020	0.0027
Wisconsin	Buffalo	15.56	6.49	29.46	0.0013	0.0031
Alabama	Jackson	11.11	2.35	29.16	0.0020	0.0032
Texas	Dawson	0.00	0.00	60.24	0.0006	0.0033
Georgia	Toombs	13.64	2.91	34.91	0.0009	0.0035
Iowa	Carroll	6.25	0.77	20.81	0.0003	0.0038
Virginia	Greensville	15.00	3.21	37.89	0.0017	0.0038
Illinois	Shelby	0.00	0.00	21.80	0.0024	0.0044
Texas	Brown	21.74	7.46	43.70	0.0010	0.0051
Wisconsin	Richland	7.55	2.09	18.21	0.0017	0.0052
Virginia	Waynesboro	0.00	0.00	97.50	0.0003	0.0060
Virginia	Staunton	0.00	0.00	84.19	0.0003	0.0061
Texas	Austin	5.00	0.13	24.87	0.0021	0.0063
Virginia	Petersburg	5.26	0.13	26.03	0.0013	0.0063
North Carolina	Hertford	11.11	0.28	48.25	0.0010	0.0068
Iowa	O'Brien	11.11	2.35	29.16	0.0017	0.0069
Virginia	Floyd	6.67	0.17	31.95	0.0021	0.0070
Virginia	Goochland	4.17	0.11	21.12	0.0021	0.0074
Minnesota	Winona	9.09	3.02	19.95	0.0025	0.0080
Virginia	Wythe	20.69	7.99	39.72	0.0013	0.0083
Iowa	Clayton	18.18	6.98	35.46	0.0029	0.0085
Wisconsin	Dane	16.67	10.98	23.78	0.0025	0.0087
Iowa	Sioux	11.24	5.52	19.69	0.0014	0.0088
Iowa	Harrison	14.29	4.81	30.26	0.0010	0.0088
Illinois	Stephenson	16.67	4.74	37.38	0.0021	0.0089

Virginia	Henrico	14.79	9.39	21.71	0.0021	0.0094
Illinois	Jersey	6.67	0.17	31.95	0.0014	0.0095
Iowa	Crawford	4.44	0.54	15.15	0.0010	0.0097

Table 3. Multinomial Logistic Regression Analyses Examining Demographic, Socioeconomic, and Health Factors that Differentiate Individuals in Hotspots and Coldspots.

		Hotspot (vs Neither)			Coldspot (vs Neither)		
Variable	Category	OR	95% CI	p	OR	95% CI	p
Age	18-24	1.65	(1.23, 2.23)	0.001	1.16	(0.73, 1.82)	0.532
	25-29	2.81	(2.08, 3.81)	<0.001	0.78	(0.47, 1.29)	0.338
	30-34	2.39	(1.82, 3.15)	<0.001	0.96	(0.63, 1.45)	0.838
	35-39	2.06	(1.58, 2.69)	<0.001	0.79	(0.53, 1.16)	0.221
	40-44	2.21	(1.70, 2.87)	<0.001	0.84	(0.58, 1.21)	0.344
	45-49	1.91	(1.51, 2.41)	<0.001	0.71	(0.49, 1.01)	0.059
	50-54	1.89	(1.52, 2.35)	<0.001	0.83	(0.59, 1.15)	0.256
	55-59	1.82	(1.48, 2.24)	<0.001	0.80	(0.57, 1.11)	0.180
	60-64	1.58	(1.30, 1.93)	<0.001	0.89	(0.65, 1.20)	0.436
	65-69	1.54	(1.27, 1.86)	<0.001	0.83	(0.61, 1.12)	0.227
	70-74	1.41	(1.16, 1.72)	0.001	0.82	(0.60, 1.12)	0.214
	75-79	1.18	(0.96, 1.46)	0.109	0.75	(0.54, 1.04)	0.088
	80+	1.00	(Reference)		1.00	(Reference)	
Sex	Male	1.04	(0.93, 1.16)	0.500	0.94	(0.80, 1.11)	0.487
	Female	1.00	(Reference)		1.00	(Reference)	
Race/Ethnicity	Non-Hispanic White	1.00	(Reference)		1.00	(Reference)	
	Black/African-American	0.30	(0.24, 0.38)	<0.001	0.55	(0.37, 0.81)	0.003
	Hispanic/Latino	0.10	(0.06, 0.18)	<0.001	0.42	(0.28, 0.64)	<0.001
	Asian/Other	0.34	(0.18, 0.62)	<0.001	0.46	(0.27, 0.79)	0.005
	Multiracial	0.53	(0.40, 0.70)	<0.001	0.86	(0.36, 2.04)	0.732
Household Size	1 (Live Alone)	1.00	(Reference)		1.00	(Reference)	
	2 People	1.15	(1.04, 1.28)	0.007	1.21	(1.02, 1.43)	0.0310
	3-5 People	0.98	(0.87, 1.11)	0.766	1.09	(0.90, 1.34)	0.378
	6-9 People	0.75	(0.55, 1.02)	0.063	0.70	(0.44, 1.12)	0.133
	10 Or More People	1.58	(0.24, 10.38)	0.636	0.00	(0.00, 0.00)	<0.001
Education	Less Than High School	3.11	(2.58, 3.73)	<0.001	1.15	(0.81, 1.62)	0.432
	High School	2.22	(1.93, 2.56)	<0.001	1.33	(1.10, 1.62)	0.004
	Some College	1.63	(1.39, 1.92)	<0.001	1.03	(0.85, 1.25)	0.770
	College Graduate	1.00	(Reference)		1.00	(Reference)	

Insurance	Yes	1.00	(Reference)		1.00	(Reference)	
	No	1.39	(1.17, 1.659)	<0.001	0.98	(0.71, 1.34)	0.881
Employment	Low-Intensity	1.00	(Reference)		1.00	(Reference)	
	Moderate-Intensity	1.01	(0.84, 1.213)	0.931	1.07	(0.82, 1.40)	0.607
	Manual Labor	1.03	(0.82, 1.301)	0.788	0.79	(0.54, 1.15)	0.218
	Unemployed	1.22	(1.06, 1.397)	0.006	0.83	(0.67, 1.04)	0.106
Fruit/Vegetable Consumption	Less than 1 / Day	1.11	(0.82, 1.498)	0.510	0.91	(0.56, 1.48)	0.708
	1-3 / Day	1.08	(0.94, 1.247)	0.265	1.12	(0.89, 1.41)	0.350
	3-5 / Day	1.07	(0.93, 1.221)	0.368	0.99	(0.81, 1.22)	0.942
	5 or More / Day	1.00	(Reference)		1.00	(Reference)	
Sedentary Lifestyle	No	1.00	(Reference)		1.00	(Reference)	
	Yes	1.37	(1.20, 1.566)	<0.001	0.78	(0.62, 0.97)	0.024
Heavy Drinking	No	1.00	(Reference)		1.00	(Reference)	
	Yes	0.53	(0.39, 0.727)	<0.001	1.04	(0.77, 1.41)	0.792
Smoking	No	1.00	(Reference)		1.00	(Reference)	
	Yes	1.17	(1.02, 1.343)	0.027	0.98	(0.78, 1.23)	0.867
Obesity	No	1.00	(Reference)		1.00	(Reference)	
	Yes	1.17	(1.03, 1.314)	0.012	1.18	(0.96, 1.44)	0.110
Overall Health	Excellent	1.00	(Reference)		1.00	(Reference)	
	Very Good	1.15	(0.95, 1.385)	0.165	1.12	(0.88, 1.40)	0.389
	Good	1.17	(0.97, 1.417)	0.100	1.01	(0.77, 1.33)	0.925
	Fair	1.53	(1.22, 1.912)	<0.001	1.04	(0.72, 1.49)	0.834
	Poor	2.00	(1.57, 2.555)	<0.001	1.66	(0.95, 2.90)	0.075
Mental Health	0 Days	1.00	(Reference)		1.00	(Reference)	
	1-7 Days	0.76	(0.64, 0.916)	0.004	0.92	(0.75, 1.13)	0.435
	8-14 Days	0.95	(0.69, 1.298)	0.738	0.83	(0.50, 1.36)	0.453
	15-21 Days	1.02	(0.82, 1.274)	0.845	0.77	(0.51, 1.17)	0.217
	22 or More Days	1.14	(0.96, 1.361)	0.141	0.78	(0.53, 1.15)	0.216

Figure 1. Percentages of Insufficient Sleep by County

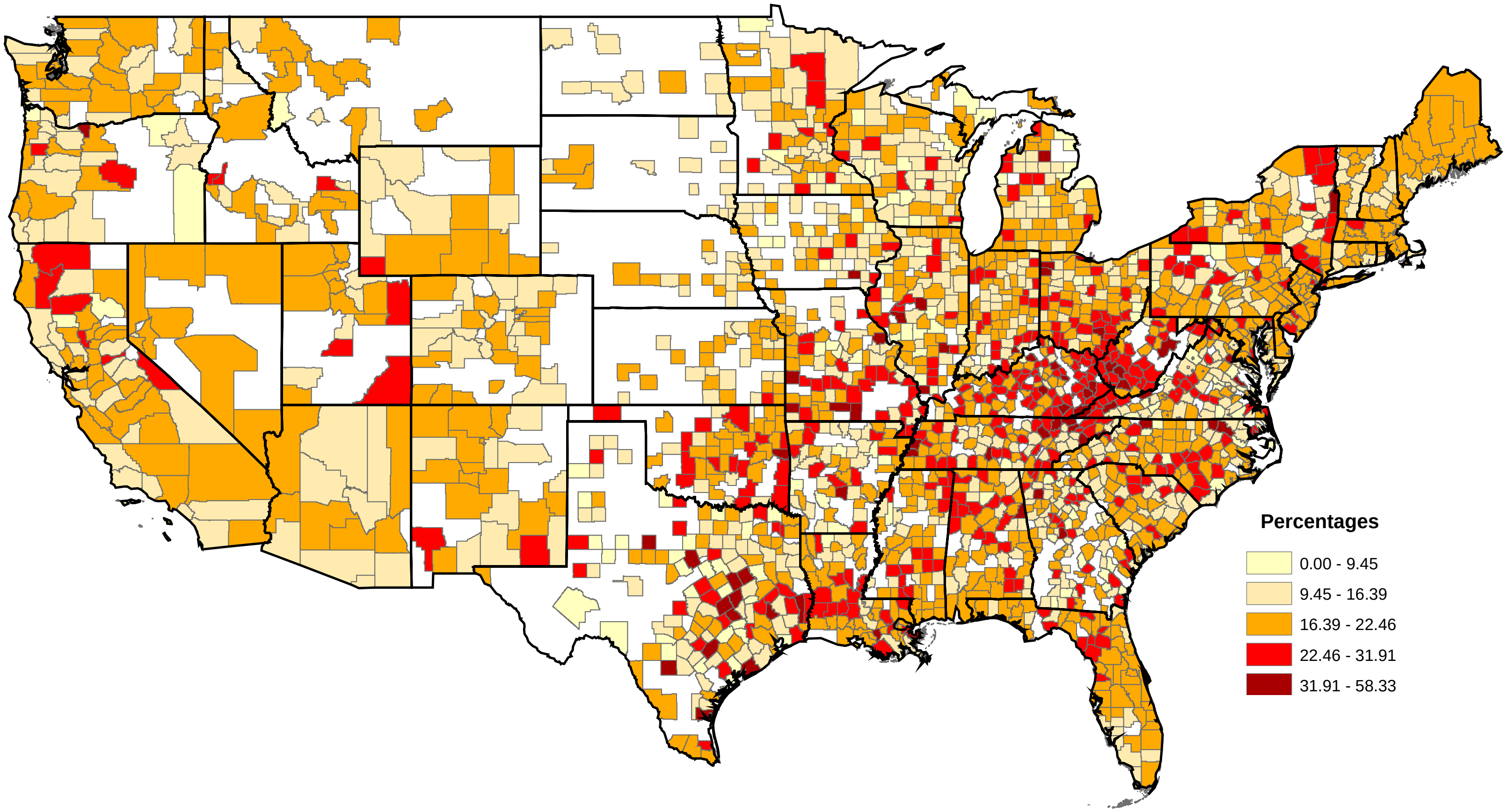

Figure 2. Hotspots and coldspots of insufficient sleep, represented by p-values for both high (red) and low (blue) concentrations of insufficient sleep by county

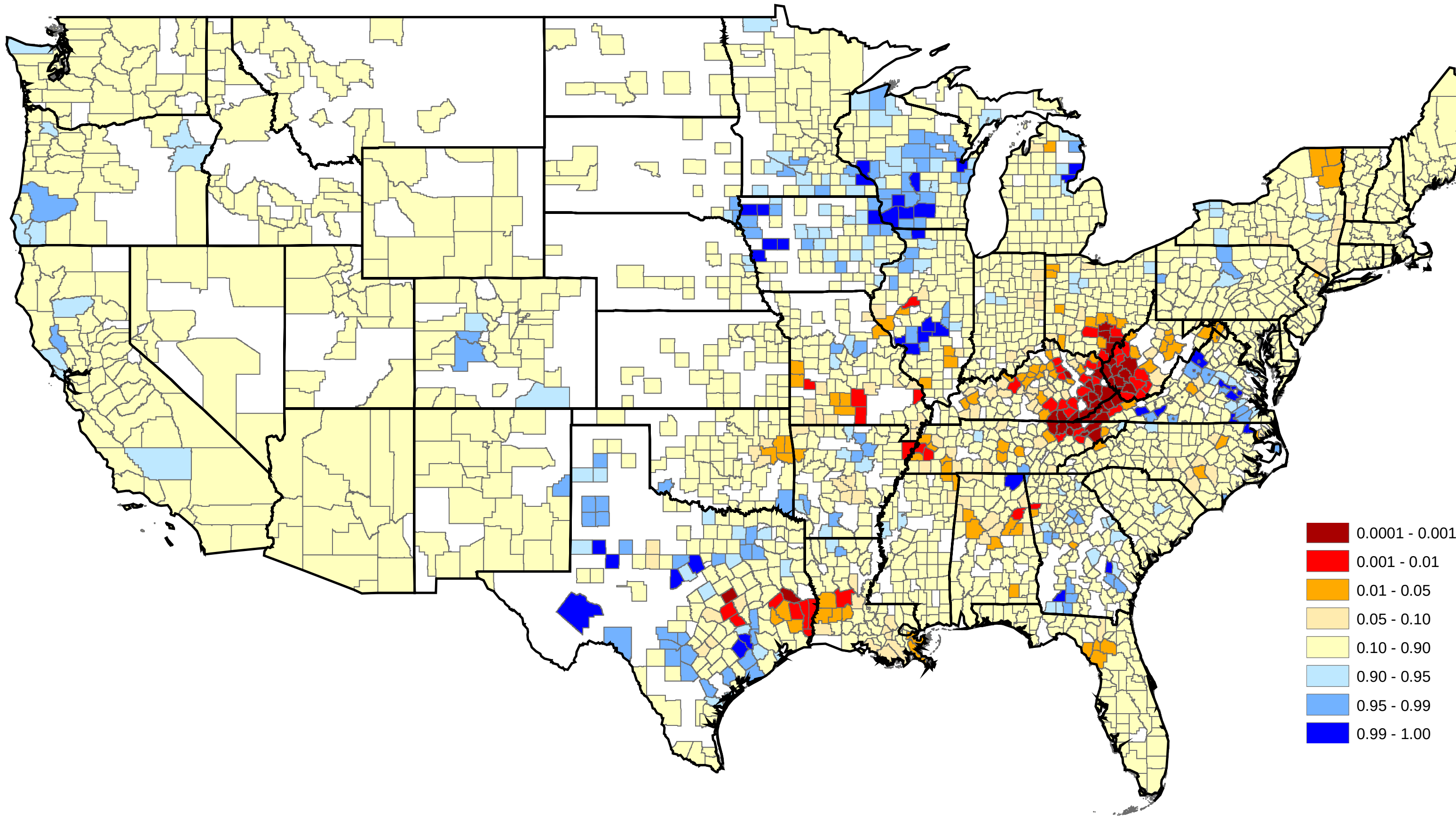

Figure 3. Map of the 15 counties that had the highest percentage of insufficient sleep, all with p<0.0001.