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ARTICLE

County-level USA: No Robust Relationship between Geoclimatic Variables and Cognitive Ability

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ABSTRACT

Using a sample of ~3,100 U.S. counties, we tested geoclimatic explanations for why cognitive ability varies across geography. These models posit that geoclimatic factors will strongly predict cognitive ability across geography, even when a variety of common controls appear in the regression equations. Our results generally do not support UV radiation (UVR) based or other geoclimatic models. Specifically, although UVR alone predicted cognitive ability at the U.S. county-level (β = -.33), its validity was markedly reduced in the presence of climatic and demographic covariates (β = -.16), and was reduced even further with a spatial lag (β = -.10). For climate models, average temperature remained a significant predictor in the regression equation containing a spatial lag (β = .35). However, the effect was in the wrong direction relative to typical cold weather hypotheses. Moreover, when we ran the analyses separately by race/ethnicity, no consistent pattern appeared in the models containing the spatial lag. Analyses of gap sizes across counties were also generally inconsistent with predictions from the UVR model. Instead, results seemed to provide support for compositional models.

1. Introduction

It is well-established that cognitive ability varies across geopolitical divisions such as nations, states, and counties (e.g., nations: [1-2]; Vietnamese provinces: [3]; U.S. states: [4]; U.S. counties: [5]; Argentinian provinces: [6]). These cognitive ability differences have frequently been quite large. Using the fifty U.S. states as an example, the difference between the lowest (Mississippi) and highest (Massachusetts) scoring state was found to be 10.1 IQ-metric points (henceforth just IQ points) [4]. Moreover, these aggregate-level cognitive ability differences have often correlated strongly with other important outcomes including income [7] and education levels [8], health and wellness [9], and rates of various crimes [10].

Although aggregate cognitive scores are potent predictors of important social, economic, and political outcomes [11], consensus about why these relationships exist and for why cognitive ability varies across geography has been lacking. Notably, a recently conducted survey of researchers in this area revealed belief in several potential causes for aggregate cognitive variation including differ-

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ences in education (both quantity and quality), genetics, health, and wealth [12]. Of particular interest for the present study, the surveyed experts generally considered current climate and geography to have relatively small causal effects (only 1 to 3% of the total); nearly all of the experts seemed to dismiss the contemporary effects of climate as a major contributing variable for geospatial differences in cognitive ability.

Despite this, cognitive ability and other behavioral traits show a latitudinal gradient. This led Van der Vliert and Van Lange [13] to propose "latitudinal psychology"; as they note, there are "north-south gradients in cognitive ability, creativity, ingroup-outgroup dynamics, aggressiveness, life satisfaction, and individualism versus collectivism" (p. 43) which need to be accounted for. Indeed, in their review, Lynn et al. [11] reported that 12 of 15 countries exhibited a positive association between absolute latitude and cognitive ability. These intra-country cognitive clines in latitude mirror an international one [14]. Related latitudinal behavioral clines can be found among geographically dispersed non-human animals [13].

Geo-climatic models are in line with the traditional view that latitude-related differences in human behavior are in part caused by the direct effects of ecological and geoclimatic factors [15]. In line with this paradigm, geoclimatic variables have been offered to explain differences in cognitive outcomes (e.g., cognitive ability, future orientation, innovation, state intelligence, educational attainment). Specific latitude-associated causal factors include cold weather ([16-17]; see, relatedly, [18,19,13,20]), latitude-dependent infectious disease ([21-23]), and ultraviolet radiation (UVR) ([21,24-27]; also [13]). These variables may share overlapping causal pathways. Unlike typical sociocultural factors (e.g., socioeconomic status, family values, quality of school curriculum), they are proposed primarily to account for regional variation, and less so for individual variation within regions since the effects of the proposed causal factors are geographically stratified.

The most extensively developed model with respect to cognitive ability specifically is that of Federico León and colleagues. They have argued that geographic differences in UVR have important effects on cognitive ability which are unmediated by genetics. Unlike other UVR models where UVR indexes behaviorally-relevant evolutionary pressures (e.g., [28-29]), this is an environmental model. León et al. have proposed three complementary pathways through which UVR might act on aggregate cognitive ability ([21,24,25-27]). The first pathway involves high UVR exposure exerting an amplifying effect on sex hormone production and fertility which then reduces parental investment in offspring cognitive capital accumulation. The second pathway supposes that UVR exposure increases oxidative stress which is purported to be related to both cognitive impairment and fatigue. The final pathway invokes a supposed immunosuppressive effect of UVR which is claimed to increase disease susceptibility. The implication is that in high UVR regions it may be necessary to divert energy from brain development to the immune system, although it's also possible that the direct effect of developmental insults from disease via increased exposure and vulnerability could be explanatory. Based on a literature review, Meisenberg [30] determined that the UVR model was plausible. However, it is notable that, contrary to this model, low Vitamin D, rather than high is associated with cognitive problems [31].

León and colleagues have tested their model in cross-sectional designs using regression and/or path models globally [32], across Europe [33], in the U.S. ([21,27,34,35]), Brazil [35], Italy [35], and Peru [36]. To date, their analyses have indicated UVR has predictive validity for cognitive ability and socioeconomic outcomes even in the presence of several plausible confounders such as ethnicity, absolute latitude, and temperature.

This geoclimatic research programme has several notable shortcomings. First, all analyses thus far have been conducted at the national or subnational level, not the individual level. It has not been shown that increased UVR exposure is associated with decreased cognitive ability for individuals. Second, the regional and national sample sizes have typically been small (though not always; see, e.g., [36]). For example, in the five U.S. studies examining the UVR-cognitive ability relationship at the state level, the Ns ranged from 48 to 50. For Italy, Brazil, Europe, and globally, sample sizes were 19, 26, 32, and 194, respectively. However, multivariate statistics were used to analyze the data. This could result in imprecise parameter estimates when the variables are strongly intercorrelated, as they usually are with highly aggregated data [10]. Third, spatial autocorrelation (SAC) issues are abundant in national and subnational geographic data ([37-39]) but León and colleagues have not taken these into account (excepting one case; [34]). Unmodeled SAC has the potential to bias results due to unmeasured spatially autocorrelated confounders. SAC diminishes the precision of studies since OLS standard errors assume independent data points whereas SAC induces dependencies among them such that errors can be correlated when autocorrelated causes are unmodeled (assuming the causes themselves are autocorrelated). Finally, some research has found that results may be discordant across levels of analysis [40]. For example, U.S. state-level results may not match U.S. county-level results [41]. For this reason, in their review of regional differences in intelligence, Lynn et al. [11] urged authors to examine data at multiple levels in order to ensure robustness.

The main goal of the present study was to alleviate the shortcomings described above, in part by analyzing data at the U.S. county-level. There are many more U.S. counties than there are U.S. states, which allowed us to conduct multivariate analyses avoiding sample size concerns. Additionally, we were able to compare state- and county-level results, and we were able to include spatially lagged variables which allowed us to address the issue of SAC. An advantage of this dataset was that, owing to replacement migration, geography was less confounded with evolutionary history [42]. Thus, geoclimatic effects can be more readily interpreted as representing contemporaneous effects, as opposed to evolutionary ones (e.g., [43]). Importantly, however, these sorts of relationships can also result from processes aligning demography with evolutionarily familiar or novel environments, or from migratory self-selection ([34,44-45]).

A final goal of the present study was to evaluate the UVR and other geoclimatic models (i.e., latitude and cold weather), as advocated by León [21] and others, versus an ethnic composition model, as suggested by, for example, McDaniel [4]. McDaniel [4] argued that U.S. state cognitive differences were in part a result of demography, conjecturing that the regional differences would be stable so long as the racial demographics (and, also, mean self-identified race and ethnicity (SIRE) differences) were. Conversely, León [22] argued that the association between state cognitive ability and racial composition was spurious. That is, the association was due to the distribution of whites in states with low levels of UVR. The reason for testing a racial/ethnic compositional model is that León and Hassall [34] clearly specified this as an alternative to their geoclimatic model for U.S. regional differences. To be clear, though, racial/ethnic compositional models only attempt to account for regional differences in terms of demographics given known racial/ethnic trait differences. They do not attempt to account for the origins of racial/ethnic differences, which ultimately could be due to culture, genetics, or other factors (for expert opinion on cognitive ability differences see: [12], [46]). The point of these analyses is to see if previously found associations between geoclimatic variables and cognitive ability, in the U.S., can be statistically explained by demographic confounding.

2. Method

The analytic strategy involves running regression models with geoclimatic factors (average temperature and UVR) and proxies for these (latitude, longitude, and elevation) as predictors of county-level cognitive ability. While geoclimatic effects can be interpreted as representing contemporaneous effects on cognitive ability, they could also represent evolutionary effects on ability (e.g., [28],[43]) because migration and settlement patterns in the U.S. and other New World countries have not been random ([34]). Moreover, since ancestral populations differentially adapted to geoclimatic effects over evolutionary time (e.g., pigmentary, thermoregulatory, and disease-related adaptations in response to UVR, climatic, and parasite load-related effects [28-29]), contemporaneous geoclimatic effects may be modified by the racial/ethnic composition of a population. For example, in the UVR model, UVR is proposed to act through hormones, including vitamin D; however, perhaps owing in part to skin tone differences, there are well-known vitamin D level differences between U.S. racial/ethnic groups [47]. Thus, we included race/ethnicity variables as predictors, since these act as crude measures of genetic ancestry and the related evolutionary environments ([48-49]); we also run analyses separately by SIRE group.

Beyond race/ethnicity, we added a spatial lag to capture effects of both SAC and unobserved variables. In the supplement, we detailed with simulations how including a spatial lag confers the added benefit of controlling for unmodeled variables ([50-51]). We do not include socioeconomic status as an independent variable in our regression models since these add no analytic leverage when it comes to evaluating geoclimatic models. This is because geographic differences in socioeconomic status is another outcome which geoclimatic models are invoked to explain (e.g., [13,27]). Also, with the current dataset, it is difficult to disentangle the causal relation between socioeconomic status and cognitive ability. As such, we report results with socioeconomic status as the dependent variable for the main analysis. This is because socioeconomic status could be treated as an alternative measure of county-level functioning. Since our primary concern, following León et al. is with measured cognitive ability that is our primary focus.

We used R 3.6.1 for the analyses. All code and data have been made publicly available in the supplementary materials.

2.1 Measures

2.1.1 County Cognitive Ability

We used data from the Stanford Education Data Archive (SEDA v3.0; [52]), which was publicly available at https://cepa.stanford.edu/seda/overview. This resource contained cognitive testing data from many sources in-

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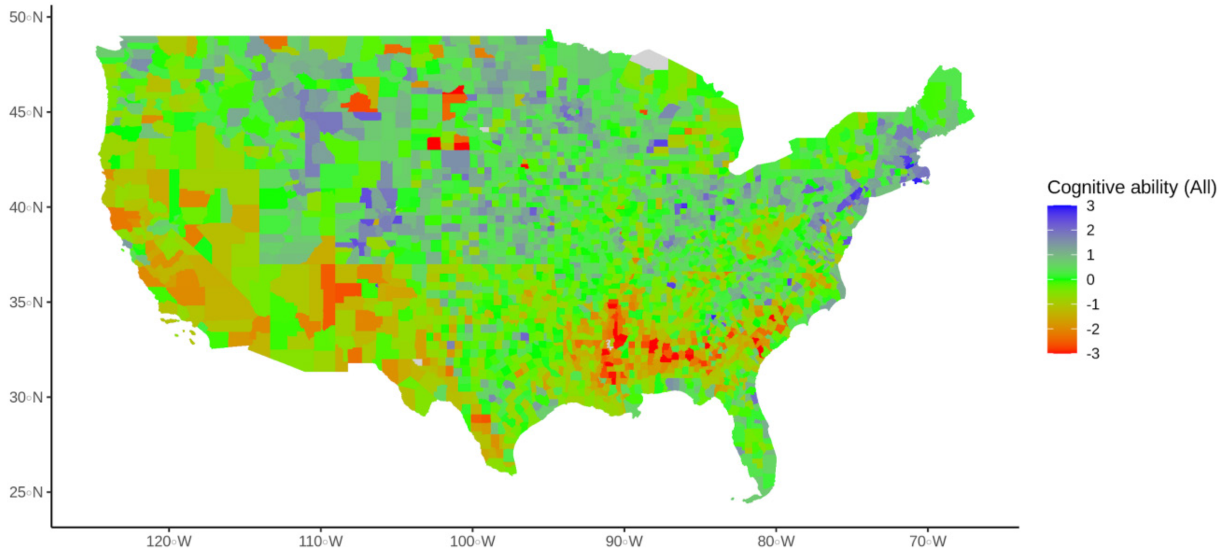

Figure 1. Map of county-level cognitive ability

Note: The scale refers to county-level standardized units, where zero is the mean for all counties.

cluding NAEP and state tests which had been normed to the same scale. The data were available at the U.S. county level for the years 2009-2015. These scores were based on low-stakes math and reading/language tests given to students in grades 3-8. We used the pooled file which had precalculated scores averaged across subjects (math and language), year (2009-2015), and grade (3-8) (seda_county_pool_CS_v30). A detailed description of the method used to compute these is provided by Fahle et al. [53].

The SEDA cognitive scores are based on national and state-level achievement tests. The national tests are The National Assessment of Educational Progress (NAEP) exams. These have been found to relate to measures of intelligence, though they seem to have a greater affinity for crystallized intelligence measures. Regarding these measures, Rindermann and Thompson [54] noted: "Both NAEP scales together measure a mixture of general intelligence and specific knowledge, covered by the construct cognitive ability…. However, compared to figural scales as the Ravens, NAEP scales are more measures of crystallized knowledge." These scores have frequently been used in the intelligence literature as measures of state-level cognitive ability (e.g., [4]). Each state additionally administers state-level assessments (e.g., California Assessment of Student Performance and Progress, Iowa Test of Basic Skills, Ohio's State Test, and Washington Assessment of Student Learning). These have been evaluated, both qualitatively and quantitatively, by the U.S. Department of Education, for the purpose of linking state and national data ([55-59]). Results for the NAEP state assessment mapping analyses can be accessed at https://nces.ed.gov/nationsreportcard/studies/statemapping. The specific methods used by the SEDA for linking the NAEP and state-level tests are detailed on the Educational Opportunity Project website, which can be accessed at https://edopportunity.org/methods. In their validity report, Reardon, Kalogrides, and Ho [60] report correlations of > .90 between the linked district-level scores based on state tests and those based on the NAEP for those school districts involved in the Trial Urban District Assessment and Measure of Academic Progress.

To note, we were unable to assess measurement invariance for these instruments so we cannot make strong psychometric claims about the differences. These may represent general cognitive ability differences or differences in verbal and math abilities (which are stratum I abilities in the three-stratum Cattell–Horn–Carroll model) independent of g. The issue is not immediately relevant to the hypotheses being investigated and it is unlikely that there is bias given the consistent lack of bias in other U.S. samples.

Figure 1 is a map of the distribution of average cognitive ability in our dataset, with zero as the mean for all counties and each unit increase representing an increase in one county-level standard deviation (equivalent to 3.6 individual-level IQ points). Consistent with state-level results, the preponderance of low-scoring counties could be found in the southeast and southwest. Additionally, there were low-scoring counties scattered across the Midwest and west which corresponded to Indian reservations and other counties with high percentages of native Americans.

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2.1.2 County Socioeconomic Status

The SEDA dataset also included several important covariates for research use. Among these were precomputed measures of socioeconomic status based on six indicators, including: (1) median family income, (2) the proportion of adults with a bachelor's degree or higher, (3) the proportion of unemployed adults, (4) the household poverty rate, (5) the proportion of households receiving SNAP benefits, and (6) the proportion of households with single mothers. The component loadings and descriptive statistics for the SES indicators are shown in Table 1 below.

Table 1. Descriptive statistics and component loadings for the SES indicators.

Variable	Loadings	Mean	SD
Median Family Income	0.904	10.90	0.33
Adults with BA or higher	0.721	0.28	0.14
Unemployed adults	-0.921	0.20	0.11
Household poverty rate	-0.925	0.12	0.72
Households receiving SNAP	-0.778	0.10	0.04
Households with single mothers	-0.805	0.20	0.08

Importantly, the SES scores provided here were computed for each race/ethnicity as well as for the overall population in the same way as the cognitive scores were, thus allowing for comparison of values within groups. Figure 2 is a map of the distribution of average SES in our dataset. As seen, the distribution of county-level SES parallels that of cognitive ability.

2.1.3 Demographics

The SEDA covariate files (SEDA v3.0; [52]) provided self-identified race and ethnicity (SIRE) composition data for students (e.g., "percent Whites in the grade"). These proportions are based on the 2006-2010 Common Core of Data (CCD). The CCD is an annual survey of all public elementary and secondary schools. These percentages were somewhat different from the county population percentages based on the American Community Survey (ACS). This was because they represented the percent of students in public schools, not the percentage of adults in the county. We used the CCD values since the percentage of students was the more relevant indicator for controlling the effect of school demographics on student test scores.

2.1.4 Cognitive and SES SIRE Gaps

The SEDA data file provided precomputed cognitive and composite socioeconomic SIRE standardized differences for each county. Black/White, Hispanic/White, and Asian/White *d* values were available. Standard errors for the *d* values were also provided, the inverse of which were used as analytic weights. Note, SEDA's SES *d* values

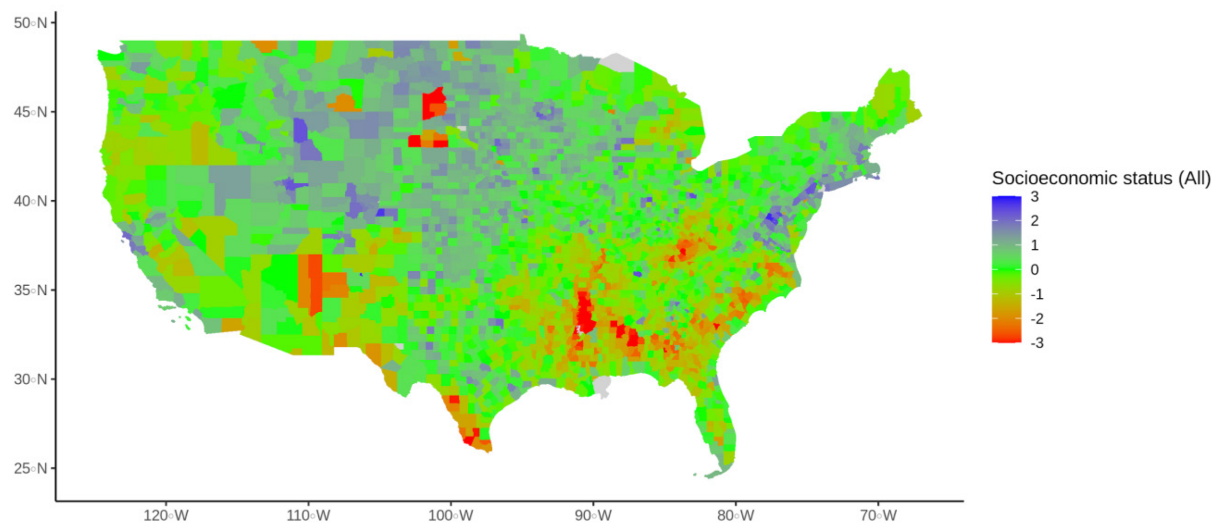

Figure 2. Map of county-level socioeconomic status

Note: The scale refers to county-level standardized units, where zero is the mean for all counties.

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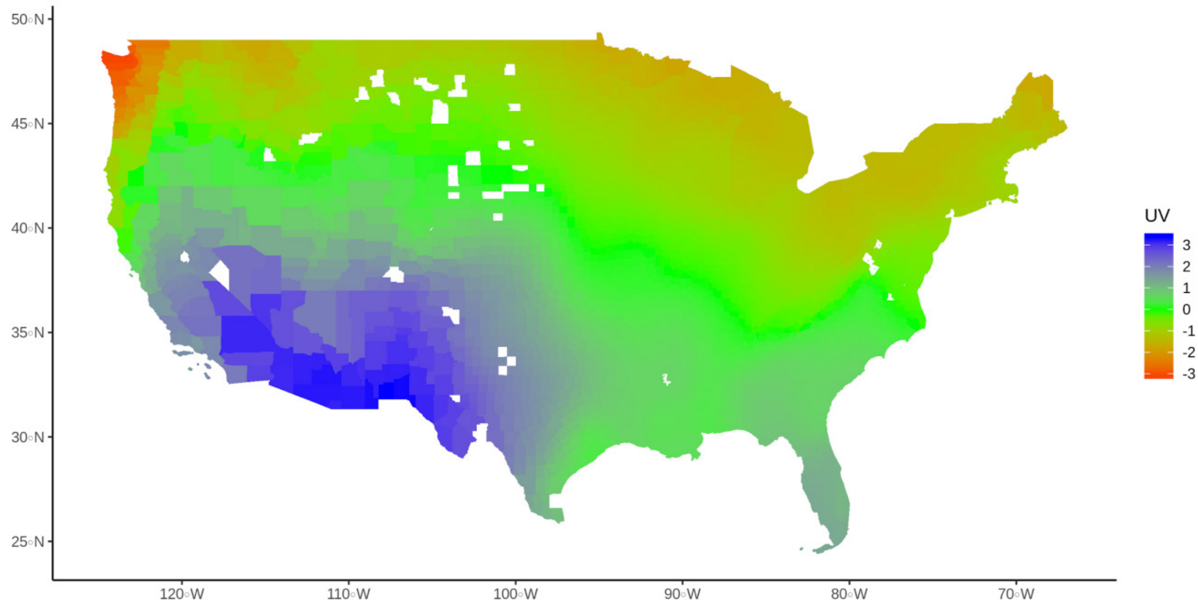

Figure 3. Map of county-level UVR

Note: The scale refers to county-level standardized units, where zero is the mean for all counties

were based on SES composite variables.

2.1.5. Ultraviolet Radiation and Climate Data

Our primary geoclimatic variables are UVR, average temperature, latitude, longitude, and elevation. The National Cancer Institute [61] provided county UVR levels measured in units of Wh/m². These were based on a 30-year average (1961-1990). Figure 3 is a map of the distribution of average UVR, standardized at the U.S. county level. Additionally, the Centers for Disease Control and Prevention [62] provided averaged yearly county-level temperature (yearly mean °C). These were based on data collected from 1979-2011.

León and colleagues have pointed out that absolute latitude is an imperfect proxy for UVR. While these variables covary very strongly at the national level (r = -.89, unweighted, our calculation), there are some sizable deviations, especially when looking at subnational data. Case in point, in our dataset, while the correlation between UVR and latitude was strong (r = -.74, unweighted; absolute values were unneeded because all values had the same sign), New Orleans county (which contained the city of New Orleans) in Louisiana lies at latitude 30.1, and has a UVR level of 0.54 (i.e., a bit above average), while Salt Lake county (which contained Salt Lake City) in Utah lies at latitude 40.9 but has a UVR level of 0.63. There are several reasons for the discrepancies between latitude and UVR including cloud coverage, ozone layer thickness (which partially blocks UVR) and altitude (with higher UVR levels at higher altitudes because of less atmospheric air for the sun's rays to pass through). In the U.S., these factors varied longitudinally and, as a result, Rocky Mountain regions tended to have higher UVR levels than eastern ones at the same latitude [21].

To capture unmeasured geoclimatic factors we included latitude, longitude, and elevation (altitude). Latitude is included since Van der Vliert and Van Lange [13] argued that latitude gradients explained geographic variability in behavior and were an important tool for the behavioral sciences. Longitude was included since León [24] argued that it was yet another dimension along which UVR acts. Elevation was included since this was a component in Cabeza de Baca and Figueredo's [63] brumal (i.e., cold) factor, which was constructed based on temperature, latitude, and altitude. The brumal factor played a central role in Cabeza de Baca and Figueredo's [63] human cognitive ecology model, according to which cold weather and higher altitudes were to be positively associated with cognitive ability. Additionally, according to León and Avilés [36], higher altitude should be related to cognitive ability, though negatively so, owing to increased UVR. Finally, for each county's latitude and longitude, we coded the U.S. census internal point. This is approximately the same as the centroid of the geographical unit, except for cases

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where the centroid does not lie inside the polygons(s) of the unit, in which case the closest internal point was chosen. Van der Vliert and Van Lange [64] additionally proposed steady rain as a "remote climatic predictor". However, the type of mediating effects noted (e.g., droughts, flooding, landslides) are not realistic causes of social and behavioral differences between U.S. counties so we did not include them in our analyses. As a robustness test, we ran the model with additional variables from the Center for Disease Control's reported major communicable diseases (tuberculosis, HIV, respiratory infections, hepatitis, meningitis, and diarrheal diseases) since León et al. sometimes include them in their models. However, as these variables did not substantially alter the other relations, and as they suffer from endogeneity problems (being a partial consequence of cognitive differences), we did not report these results but nonetheless provided them in the supplement.

2.1.6 Spatial Lag

Hassall and Sherratt [38] raised concerns about confounding due to spatial autocorrelation (SAC). Thus, we calculated a spatial lag term for each county by averaging the cognitive ability scores for each of the county's three closest counties (termed k-nearest spatial neighbor regression with k = 3). We used the three nearest neighbors as this was shown in a prior study to produce the most interpretable results [65]. For the SIRE specific regressions, the lag variable was computed based on the cognitive scores for the specific SIRE groups.

3. Results

3.1 Descriptive Statistics, Bivariate Correlations and Main Regression Results

The descriptive statistics for the variables used in the main regression analyses are reported in Table 2. When noted, we reported the descriptives for the original variables, before standardizing them for the regression analyses. This allowed comparison with individual differences since county and individual cognitive differences were on the same scale. For example, Figure 1 shows a range of 6 county-level standard deviations; this is equal to a range of 6 county level *SD* x .24 (i.e., the *SD* of CA_all) or 1.44 individual level ones (21.6 IQ points). To note, the availability of cognitive and SES scores varied by SIRE group. This is because scores were suppressed if the total number for a subgroups was less than 95% of the total reported for all students.

Table 2. Descriptive statistics for variables used in tables 3, 4, 5, and 7

	N	Mean	SD	Median	Min	Max
CA_all	3134	-0.03	0.24	-0.02	-1.20	0.66
CA_Asian	1483	0.34	0.33	0.35	-1.60	1.40
CA_Black	2135	-0.42	0.21	-0.43	-1.20	0.26
CA_Hispanic	2647	-0.25	0.20	-0.25	-0.87	0.57
CA_White	3112	0.10	0.21	0.11	-0.97	0.94
SES_all	3124	-0.08	0.69	-0.03	-3.60	1.86
SES_Black	2108	-1.95	0.86	-2.00	-4.60	1.10
SES_Hispanic	2624	-0.81	0.50	-0.82	-3.60	1.31
SES_White	3099	0.36	0.55	0.37	-2.20	2.42
% White	3124	0.72	0.25	0.81	0.00	1.00
% Black	3124	0.12	0.20	0.02	0.00	1.00
% Hispanic	3124	0.12	0.17	0.05	0.00	1.00
% Asian	3124	0.01	0.03	0.01	0.00	0.59
% Amerindian	3124	0.03	0.10	0.00	0.00	0.99
UVR	3106	4304.05	420.88	4300.00	3000.00	5722.54
Avg temp	3105	17.94	4.92	18.00	3.90	30.61
Latitude	3140	38.45	5.29	38.00	20.00	69.45
Longitude	3140	-92.27	12.90	-90.00	-180.00	-67.61
Elevation	3075	383.34	443.33	240.00	0.00	3096.16

Note:
[1]The descriptive statistics for the original variables are reported; in the regression models, these were standardized.

Table 3 shows bivariate correlations between all study variables. The unweighted correlations are reported below the diagonal. The correlations weighted by the square root of county population size are reported above. Moderate relationships existed between climatic variables and cognitive ability. UVR, by itself, correlated at r = -.33 (weighted) with cognitive ability. These correlations were in the directions predicted by the respective geoclimatic models. The correlations for latitude and temperature with cognitive ability were r = .33 and r = -.42 (weighted), respectively. All three geoclimatic variables were strongly correlated (r > |.70|). To be clear, these were aggregate-level or ecological correlations, which are usually inflated relative to individual-level ones [40].

To clarify the predictive validity of the variables we

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Table 3. Correlation matrix (weighted above the diagonal and unweighted below)

	CA_All	CA_Asian	CA_Black	CA_Hispanic	CA_White	SES_All	SES_Black
CA_all (3134)	1.00	.45	.67	.60	.76	.73	.43
CA_Asian (1483)	.48	1.00	.31	.39	.53	.25	.25
CA_Black (2135)	.65	.34	1.00	.54	.47	.46	.50
CA_Hispanic (2647)	.61	.39	.59	1.00	.42	.24	.24
CA_White (3112)	.69	.59	.40	.35	1.00	.58	.40
SES_all (3124)	.75	.33	.43	.25	.61	1.00	.65
SES_Black (2108)	.42	.31	.55	.24	.41	.65	1.00
SES_Hispanic (2624)	.34	.29	.27	.35	.33	.56	.55
SES_White (3099)	.40	.44	.21	.08	.76	.73	.56
UVR (3106)	-.37	-.05	-.17	-.16	-.11	-.20	.12
Avg temp (3105)	-.39	.07	-.19	-.03	-.13	-.34	.02
Latitude (3140)	.31	-.13	.13	-.03	.10	.33	.01
Longitude (3140)	.20	.31	.12	.31	.11	-.06	-.15
Elevation (3075)	.05	-.18	.11	-.07	-.02	.12	.08
	SES_Hispanic	SES_White	UVR	Avg temp	Latitude	Longitude	Elevation
CA_all (3134)	.28	.37	-.33	-.42	.33	.08	.13
CA_Asian (1483)	.24	.33	-.07	.05	-.13	.33	-.14
CA_Black (2135)	.22	.20	-.25	-.32	.27	.06	.14
CA_Hispanic (2647)	.28	.10	-.17	-.07	.04	.25	-.09
CA_White (3112)	.29	.65	-.10	-.20	.19	-.01	.11
SES_all (3124)	.50	.73	-.19	-.41	.39	-.15	.24
SES_Black (2018)	.50	.50	-.02	-.12	.15	-.09	.14
SES_Hispanic (2624)	1.00	.46	.05	.01	.00	-.05	.05
SES_White (3099)	.50	1.00	.08	-.12	.20	-.21	.20
UVR (3106)	.10	.06	1.00	.73	-.73	-.34	.30
Avg temp (3105)	.08	-.05	.77	1.00	-.92	.06	-.34
Latitude (3140)	-.07	.08	-.75	-.93	1.00	-.29	.23
Longitude (3140)	-.09	-.08	-.42	-.10	-.09	1.00	-.56
Elevation (3075)	.02	.02	.25	-.27	.18	-.41	1.00

Note: N in parentheses; pairwise deletion fit several regressions, as shown in Table 4. Results were weighted by the square root of population size and standardized betas (β) were used. We ran seven models. Model 1 contained UVR only, while Model 2 had SIRE only. Model 3 included both UVR and SIRE. Model 4 added covariates including temperature, latitude, longitude, and elevation. Model 5 added the spatial lag variable. Model 6 added a spline for UVR to capture nonlinear effects (restricted cubic using the *rcs*() in rms package; Harrell [68]). Finally, Model 7 added interaction terms between UVR and SIRE since León and Hassal [34] predicted them due to differences in pigmentation between groups.

Although UVR had a moderate relationship with cognitive ability by itself (Model 1, β = -.33), the relation shrank by about 50% when demographic and climatic covariates were added (Model 4, β = -.16). It dropped further in Model 5 when the spatial lag variable was included (Model 5, β = -.10). In this model, temperature had a moderate effect ($\beta_{temperature}$ = .35), however, it was in the wrong direction relative to contemporaneous climatic model predictions according to which cold climate is hypothesized to be causally associated with higher cognitive ability. Additionally, latitude, longitude, and elevation had small to medium positive effects (β = .17 to β = .24).

Allowing for nonlinear effects via a spline of UVR did not add much to the model (Model 5→6, R^2 gain = .001). Adding interaction terms for UVR and demographics resulted in a small model improvement (Model 5→7, R^2 gain = .019), but also resulted in a *positive* main effect for UVR (Model 7, β = .09). This pattern of results suggested

Table 4. County-level regression results for cognitive ability

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	β	β	B	β	B	β	B
Intercept	.09***	.13***	.10***	.09***	.07***	.00	.08***
UVR	-.33***		-.11***	-.16***	-.10***	(nonlinear)	.09*
% Black		-.56***	-.53***	-.59***	-.52***	-.53***	-.57***
% Asian		.14***	.18***	.24***	.21***	.21***	.23***
% Hispanic		-.33***	-.29***	-.25***	-.27***	-.26***	-.24***
% Amerindian		-.39***	-.35***	-.31***	-.28***	-.29***	-.29***
Avg_temp				.39***	.35***	.34***	.19***
Latitude				.27***	.17***	.22***	.13**
Longitude				.35***	.24***	.27***	.23***
Elevation				.30***	.22***	.21***	.15***
CA_lag					.28***	.27***	.26***
UVR * % Black							.10***
UVR * % Asian							-.08***
UVR * % Hispanic							-.03**
UVR * % Amerindian							-.03
R2 adj.	0.135	0.426	0.455	0.524	0.574	0.575	0.593
N	3099	3122	3093	3062	3062	3062	3062

Note:
*Weighted by the square root of population size. Values in parentheses are standard errors. * <.01, ** < .005, *** <.001. Model 1: UVR; Model 2: SIRE groups; Model 3: UVR + SIRE groups; Model 4: Model 3 + average temperature & latitude, longitude, and elevation; Model 5: Model 4 + spatial lag; Model 6: Model 5 + spline of UVR; Model 7: Model 6 + UVR*SIRE interactions.*

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that UVR was either not a cause of cognitive ability, its effects were modified by the included covariates, or it had heterogeneous and difficult to isolate causal pathways.

The models without the spatial lag predictor showed some degree of SAC in the residuals, indicating the presence of unmodeled covariates possibly biasing estimates. This was removed after the addition of the spatial lag variable. From the pattern in the model R^2 values, it appeared demography was the main source of validity. This conclusion was confirmed by calculating partial R^2 values for the models and then calculating the proportion of total R^2 attributed to the variables. About half was attributed to demographics and small amounts to the other variables (Model 5: SIRE = .57, climate = .079, UVR = .003). Note, the variance importance metrics for the regression models were made available in the supplement.

To see if the geospatial variables (latitude, longitude, and elevation) were leading to underestimation of the effects of temperature and UVR we ran Model 5 without them. In Model 5b, the β for UVR was not significant (β = -.04); contrariwise, the β for temperature was significant, but again in the wrong direction (β = .11). Thus, the inclusion of the other geospatial variables was not likely to be the reason for the results we found.

A reader suggested that we use county-level general socioeconomic status, instead of test scores, as a measure of county-level "intelligence." The reader cited a conception of societal-level "intelligence" by sociologists Talcott

Table 5. County-level regression results for general socioeconomic status

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	B	β	B	β	B	β	β
Intercept	.11***	.08***	.06***	.07***	.06***	.24	.10***
UVR	-.17***		-.03	.15***	.20***	(nonlinear)	.41***
% Black		-.49***	-.48***	-.45***	-.39***	-.41***	-.44***
% Asian		.21***	.26***	.27***	.24***	.23***	.24***
% Hispanic		-.15***	-.15***	-.13***	-.15***	-.11***	-.07***
% Amerindian		-.25***	-.25***	-.26***	-.24***	-.24***	-.25***
Avg_temp				.16**	.13	.10	-.01
Latitude				.40***	.32***	.41***	.32***
Longitude				.21***	.12***	.14***	.13***
Elevation				.14***	.07**	.05	.01
CA_lag					.23***	.22***	.21***
UVR * % Black							.05
UVR * % Asian							-.05***
UVR * % Hispanic							-.09***
UVR * % Amerindian							-.04
R2 adj.	0.038	0.376	0.403	0.432	0.470	0.479	0.489
N	3093	3122	3093	3062	3062	3062	3062

Note:
*Weighted by the square root of population size. Values in parentheses are standard errors. * <.01, ** < .005, *** <.001. Model 1: UVR; Model 2: SIRE groups; Model 3: UVR + SIRE groups; Model 4: Model 3 + average temperature & latitude, longitude, and elevation; Model 5: Model 4 + spatial lag; Model 6: Model 5 + spline of UVR; Model 7: Model 6 + UVR*SIRE interactions. The dependent, general socioeconomic status, is described in Section 2.1.2.*

Parsons and Gerald Platt [66] which aligns with this idea. These results are reported in Table 5. Since León et alia argue that UVR acts on cognitive ability partially through socioeconomics (e.g.,[21]), these results are germane to their models. As seen, using county-level general socioeconomic status instead of cognitive ability did not substantially change the interpretation regarding the effect of the climatic or other variables. In Model 5, UVR was significant but in the wrong direction, while temperature was not significant and also in the wrong direction. Latitude was positively associated with socioeconomic outcomes just as it was with cognitive ones (Table 4, Model 5).

3.2. County vs. State Results

In order to replicate the results from León [21] and León and Hassall [34], we aggregated county data to the state level and then refitted all the models. This result was placed in Table 6. In the initial model, UVR had a stronger effect on the state level (Model 1, β = -.51) than on the county-level (Model 1, β = -.33). In Model 5 with the spatial lag variable, the magnitude of the effect increased (β = -.82).

There seemed to be an aggregation effect wherein higher-level results based on a small dataset (*n* = 49) gave markedly different results than those based on a much larger set (*n* ~3,100) of lower-level units. This pattern of results can happen due to zonation effects; these are effects resulting from how spatial areas are divided [67], or simply from chance given the small sample size and large standard errors.

Table 6. State-level regression results for cognitive ability

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	Β	β	Β	β	β	β	Β
Intercept	.01	.01	.01	-0.2	-.02	-.09	.16
UVR	-.51***		-.42	-.80**	-.82**	(nonlinear)	.20
% Black		-.65***	-.49**	-.70***	-.68***	-.70***	-.77***
% Asian		.14	.02	.40**	.42**	.35	.32
% Hispanic		-.44***	-.06	-.18	-.19	-.09	-.06
% Amerindian		-.23	-.14	-.13	-.12	-.14	.06
Avg_temp				1.77**	1.83**	1.82**	.20
Latitude				1.11	1.07	1.43	.34
Longitude				.85***	.84***	.94***	.67**
Elevation				.90***	.92***	.80**	.22
CA_lag					.10	-.02	-.07
UVR* % Black							-.08
UVR* % Asian							-.26**
UVR* % Hispanic							-.11
UVR* % Amerindian							-.37
R2 adj.	0.315	0.376	0.657	0.438	0.65	0.637	0.742
N	49	49	49	49	49	49	49

Note:
*Weighted by the square root of population size. Values in parentheses are standard errors. * <.01, ** < .005, *** <.001. Alaska and Hawaii excluded, D.C. included. Model 1: UVR; Model 2: SIRE groups; Model 3: UVR + SIRE groups; Model 4: Model 3 + average temperature & latitude, longitude, and elevation; Model 5: Model 4 + spatial lag; Model 6: Model 5 + spline of UVR; Model 7: Model 6 + UVR*SIRE interactions.*

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One way to test the zonation hypothesis is to examine pseudo-states (i.e. counterfactual state border maps that could have existed) and refit the regression model in the new state-level dataset. We did this using a custom algorithm that began by randomly assigning 48 states one county each before looping over states at random, assigning them one random neighboring (shared borders) county if possible (not already assigned). The algorithm finished when it was no longer possible to assign any more counties to states (meaning that all were assigned). We created 1,000 pseudo-states in this way. We then fit the regression models of interest (models 1-3 from Table 2) to the data. Full summary statistics and more details can be found in the supplement.

Table 7. County-level regression results for cognitive ability decomposed by White, Black, Hispanic, and Asian Sire

SIRE: White				SIRE: Black		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
	B	β	β	β	B	β
Intercept	.18***	.31***	.17***	-.20***	-.15***	-.19***
UVR	-.02	.30***	.02	-.05	-.03	-.04
Avg_temp	.02	-.17	-.04	.05	.03	.06
Latitude		.27***	-.03		.08	-.03
Longitude		.22***	.01		.24***	.14***
Elevation		-.10*	-.03		.28***	.17***
CA_lag	.62***		.62***	.42***		.40***
R2 adj.	0.416	0.042	0.418	0.202	0.064	0.217
N	3079	3049	3049	2124	2095	2095
				•		
SIRE: Hispanic				**SIRE: Asian**		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
	B	β	β	β	B	β
Intercept	-.14***	-.16***	-.14***	.28***	.37***	.28***
UVR	-.12***	-.37***	-.21***	-.15***	-.05	-.09
Avg_temp	.16***	.28***	.13	.19***	-.21	-.06
Latitude		-.19***	-.17**		-.37***	-.23*
Longitude		.29***	.12***		.15***	.05
Elevation		.28***	.14***		-.17***	-.06
CA_lag	.45***		.35***	.43***		.39***
R2 adj.	0.306	0.242	0.333	0.211	0.102	0.224
N	2628	2600	2600	1464	1443	1443

Note:
*These are the county-level results by SIRE subgroups. Weighted by the square root of population size. Values in parentheses are standard errors. * <.01, ** < .005, *** <.001. Model 1: UVR + average temperature + spatial lag; Model 2: UVR + average temperature + latitude + longitude + elevation; Model 3: Model 2 + spatial lag.*

Results show that across pseudostates, UVR generally has the largest effect measured in partial R^2 (.12). UVR was largest in the comparison but 44% of the time demographics combined had the larger partial R^2. The results indicated that while zoning could influence results at the state level, it was unlikely to do so in the present case. Generally, there seemed to be an aggregation effect such that geoclimatic predictors had validity at the state but not county level. The possibility of such paradoxes was the rationale for Lynn et al.'s [11] call for authors to examine data at multiple levels as a robustness check.

3.3 Separate SIRE Regression Results

After failing to find a latitudinal cline in cognitive ability for African and Hispanic Americans, León and Hassall [34] analyzed cognitive scores for non-Hispanic Whites separately and reported a significant effect for this group. They speculated that African and Hispanic Americans were protected from the adverse effects of UVR by darker skin color. Following León and Hassall's [34] lead, we ran separate regressions for Whites, Asians, Hispanics, and Blacks. For these analyses, we used the SIRE-specific cognitive scores. Since the dependent variable was the SIRE-specific cognitive score we did not include SIRE percentages as covariates. Model 1 had UVR, temperature, and a spatial lag, while Model 3 added geospatial covariates. Model 2 was an alternative that repeated Model 3 without the spatial lag. Results were placed in Table 7.

Among Whites in Models 1 and 3 (spatial lag included), none of the geoclimatic variables were significant. Among Blacks, only longitude and elevation were significant (both positive). For Asians and Hispanics, temperature was either in the wrong direction (Model 1) or not significant (Model 3). For Hispanics, UVR was a significant predictor in the correct direction. However, this negative association was explicitly predicted to not exist by León and Hassall [34], who noted "the explanatory strength of UV radiation is shown not only by its ability to account empirically for [north-south cognitive decline among Whites] but also by its capacity to explain the absence of the north-south cognitive decline among non-White communities." For Asians, the effect of UVR was also in the correct direction and significant in Model 1, though it was not significant in Model 3. Similarly, latitude was not consistently in the predicted direction for any group. Overall, our results suggested either no notable role for the geoclimatic variables and UVR on cognitive ability, or, perhaps, very complex, heterogeneous causal paths of an unpredicted nature in the case of temperature, and overall insignificant effects in the case of UVR.

3.4 Gap Analysis

León [21] argued that the association between racial composition and cognitive ability was due to the higher distribution of Whites in states with low UVR. To evaluate this conjecture, we computed the average within-county Black/White, Hispanic/White, and Asian/White gaps, and then compared them to the national cognitive gaps in NAEP for the same years. To do this, county *d* values were weighted by the inverse of the standard error of the achievement gaps and then averaged. The SEDA did not include national averages, so we computed these ourselves using the NAEP explorer. Specifically, we computed effect sizes for each grade for the years 2009 to 2017. These years corresponded to those used in the SEDA database when mapping county achievement scores to state ones using NAEP math and reading results.

When computing effect sizes for the national differences, we used the White standard deviation, since this was the largest group and since sample sizes were not reported. In total there were 13 effect sizes (5 for Grade 4, 5 for Grade 8, and 3 for Grade 12) for each subject (math and reading). Following the method used in SEDA, we averaged across grades and years within subjects and then averaged across them. The average *d* values within counties and on the national level were given in Table 8 alongside the percentage of the national differences within counties. As seen, 64-73% of the gaps were within counties, supporting McDaniel's [4] proposition.

Table 8. Average within-county gaps versus national-level gaps

	Within-county *d*	National *d*	% (Within-county/national)
B/W	0.60	0.87	69%
H/W	0.44	0.69	64%
A/W	-0.16	-0.22	73%

Note:
The effects sizes are Cohen's ds. The within county ds are weighted by the inverse S.E. of the county-level ds.
Another way to approach the issue is to examine the predictors of the SIRE gaps.

Since ancestry groups are differentially adapted to climate ([28-29], [43]), if contemporaneous climatic factors affect cognitive ability and socioeconomic status they should have a differential effect across SIRE groups. For example, León and Hassall [34] conjectured that the greater melanin levels of Blacks and Hispanics "by absorbing

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and dissipating light, prevent the occurrence of radiation's cognitive effects among these populations at U.S. latitudes." If White but not Black and Hispanic Americans are affected by UVR, the magnitude of the Black/White and Hispanic/White differences should be smaller at higher UVR levels. Table 9 shows the correlation matrix for UVR, SIRE cognitive differences, SES differences, and county average cognitive ability and socioeconomic status. As seen in Table 9, there is no nontrivial negative association between higher UVR and the Black/White or Hispanic/White cognitive or SES gaps. The county-level cognitive gaps, instead, were better predicted by SIRE-specific socioeconomic status gaps and overall county-level socioeconomic status. Other geographic variables (average temperature, latitude) likewise showed trivial correlations with SIRE gap sizes.

Finally, we directly assessed whether SIRE composition was contributing to the differences between counties using the method detailed by Fuerst and Kirkegaard [69]. This method involved correlating the percentage of students of a SIRE group and difference scores across counties. These difference scores were the differences between the actual county average scores and what the county scores would have been in the absence of a specific SIRE group. Since the overall county scores were the weighted sum of the SIRE scores, it was readily determinable if a higher proportion of one group was leading to higher or lower cognitive ability scores, so long as one had both SIRE percentages and scores by SIRE groups. Since this method relied on within-county differences it was not confounded by unmeasured factors which varied between counties. The Pearson correlations for counties were: $r_{\text{Asian \%}} = .63$ (N = 1,473), $r_{\text{White \%}} = .25$ (N = 3,102), $r_{\text{Hispanic \%}} = -.87$ (N = 2,637), and $r_{\text{Black \%}} = -.94$ (N = 2,125). For school districts, which are nested within counties, the correlations were: $r_{\text{Asian \%}} = .87$ (N = 4,683), $r_{\text{White \%}} = .37$ (N = 12,762), $r_{\text{Hispanic \%}} = -.71$ (N = 8,832), and $r_{\text{Black \%}} = -.87$ (N = 6,197). Here, a positive correlation indicated that the

Table 9. Correlation matrix of group gaps and other variables

	CA	CA Black	CA Hisp	CA White	CA d bw	CA d hw	SES all	SES Black	SES Hisp	SES White	SES d bw	SES d hw	UV
CA	1.00	.65	.61	.69	.13	.15	.75	.42	.34	.40	-.24	-.04	-.37
CA Black	.67	1.00	.59	.40	-.46	-.09	.43	.55	.27	.21	-.53	-.11	-.17
CA Hisp	.60	.54	1.00	.35	-.16	-.48	.25	.24	.35	.08	-.25	-.32	-.16
CA White	.76	.47	.42	1.00	.63	.65	.60	.41	.33	.76	.00	.28	-.10
CA d bw	.17	-.46	-.09	.57	1.00	.71	.24	-.07	.08	.57	.46	.37	.02
CA d hw	.19	-.02	-.50	.57	.61	1.00	.36	.19	.02	.65	.20	.52	.01
SES	.73	.46	.24	.58	.22	.35	1.00	.65	.56	.73	-.33	-.06	-.20
SES Black	.43	.50	.24	.40	-.06	.18	.65	1.00	.55	.56	-.84	-.15	.12
SES Hisp	.28	.22	.28	.28	.09	.02	.50	.50	1.00	.50	-.35	-.69	.10
SES White	.37	.20	.10	.65	.49	.54	.73	.49	.46	1.00	-.06	.22	.06
SES d bw	-.27	-.45	-.22	-.07	.35	.13	-.36	-.87	-.31	-.05	1.00	.35	-.15
SES d hw	-.02	-.08	-.22	.20	.27	.39	-.06	-.16	-.72	.16	.31	1.00	-.11
UVR	-.33	-.25	-.17	-.10	.05	.01	-.19	-.02	.05	.08	-.02	-.05	1.00

Note:
CA = overall county cognitive ability, CA Black = Black county-level cognitive ability, CA hisp = Hispanic county-level cognitive ability, CA White = White county-level cognitive ability, SES = overall county SES, SES Black = Black county-level socioeconomic status, SES Hisp = Hispanic county-level socioeconomic status, SES White = White county-level socioeconomic status, CA d bw = county Black/White cognitive gap, CA d hw = county Hispanic/White cognitive gap, SES d bw = county Black/White SES gap, SES d hw = county Hispanic/White SES gap. Correlations above the diagonal are weighted by the square root of population size. N = 1981 to 3132 (Ns in notebook).

SIRE group's presence was raising the county or school district scores relative to what it would have been without that group. Thus, McDaniel's [4] conjecture was consistently supported.

4. Discussion

We analyzed a large dataset of U.S. counties to test whether UVR levels and other geoclimatic variables could account for geographic variation in cognitive ability. We found that although UVR, temperature, and latitude correlated with cognitive ability, these relationships were generally neither robust nor consistent. In contrast, variation in cognitive ability across U.S. counties were strongly and robustly related to variation in the demographic composition of the counties. While it has been found that low Vitamin D levels are associated with cognitive deficiencies on the individual level [31] there appears to be no such association on the regional level. Indeed, if UVR can be taken as an index of Vitamin D levels, then these results would suggest a slightly, though inconsistently so, negative association between Vitamin D levels and cognitive ability.

Results from analysis of county-level data conflicted with results from the state level reported in the literature. This suggests an aggregation effect or modifiable unit area problem (MUAP; [70]). We found that when we simulated random pseudo-states roughly similar to the actual ones to test for a MUAP this level discrepancy was often replicated (i.e., a variable which was unimportant when analyzed at the county level turned out to be important when analyzed at state level and vice versa).

We found that all variables showed substantial SAC. Some of this was also seen in model residuals. SAC in the residuals suggested either causal variables that themselves are spatially autocorrelated were omitted from the models or that the variables were measured with considerable error. As expected, the addition of a spatial lag variable removed the evidence for SAC in the residuals.

SAC in residuals is regarded as a problem because it can result in spurious associations and it can lead to overestimated precision of model estimates because the data points are not fully independent. Thus, in line with previous studies ([37-38]), we recommend that researchers employ spatial statistics in their regressions when using aggregated data. The supplement includes spatial lag variables computed for this study (for counties and states) which can be used by others.

Globally and within nations there is substantial and persistent geographic variation in cognitive ability (Lynn et al. [11]. While intelligence researchers generally attribute little variance (1-3%) to current climate and geography [12], geoclimatic models of human behavioral variation have resurged in interest (for a brief history of these models, see [15]). For example, 80 authors replied to Van Lange et al.'s [19] target article on the Climate, Aggression, and Self-control in Humans model. Moreover, there has been increased interest in light of possible effects of climate change (e.g., [16], [18]). Despite this, most research with cognitive ability as the criterion has used global or national samples where evolutionary history and geography are strongly confounded. Moreover, these analyses, by focusing on nations or states as units, limit analytic sample sizes and the ability to discriminate between predictors.

We addressed these issues by examining U.S. county differences (N = 3100), which allowed for multiple means of controlling for demographic confounding. The results did not provide consistent evidence for any geoclimatic model. It would be worthwhile repeating this analysis for other countries for which post-1500 migration waves may have attenuated associations between evolutionary history and geography (e.g., Australia, Canada, and Brazil). That said, geoclimatic variables could still be useful scientific tools for understanding geographic variation in cognitive ability. If they are not proxies for contemporaneous environmental factors, they could have had evolutionary impacts ([28], [43]) which might be evident in countries with mostly indigenous populations.

5. Conclusion

The present study is limited by several factors. First, while the sample size is large, the models used here are only cross-sectional. Although cognitive ability and demographic data have existed at the county level for multiple years (2009-2016), UVR levels do not change quickly and thus frustrate the use of a fixed effects (panel) design. Second, we reported data from only a single country. It is possible that relative wealth or some other characteristic of the U.S. obscure the putative geographical effects of the variables examined here. Further studies will need to be done for other countries to support or disconfirm this suggestion. Third, we did not have access to individual level data. It is possible that our county-level results are different from results discovered at the individual level and one cannot draw a definite conclusion that they are or are not (i.e., the ecological fallacy; [40]) with the present data or results.

An additional potential limitation is range restriction in the geoclimatic variables. The range of temperature and UVR in the U.S. is less than the level of variation across the globe. That said, the geoclimatic range in the U.S. is greater than in most other countries, including those for which associations have been reported. As such, if the

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range is too restricted for the U.S. then the variables may be of limited general use when it comes to intra-country associations. Moreover, the effects found were in directions inconsistent with typical hypotheses or were not consistently significant (e.g., Table 7), evincing no clear pattern to the geoclimatic results. For this reason we did not attempt to correct effects for range restriction relative to global UVR variance. Finally, it should be reiterated that the analyses conducted here were correlational. That said, as noted in the introduction, geoclimatic research is generally limited to correlational designs. Since previous research, showing an apparently robust relationship between geoclimatic variables and regional outcomes, has also been correlational, our conclusion-that there is no robust association-is relatively uncompromised.

In sum, large, geographically distributed differences in cognitive ability exist. These differences need to be accounted for. Several models have been proposed which have attempted to explain these differences in terms of contemporaneous geoclimatic ones. However, our present results agree with the majority opinion of intelligence researchers, that contemporaneous geoclimatic factors are not major determinants of variation in cognitive ability [12], at least for regions with geoclimatic variation similar to that in the U.S. Nonetheless, examining data in regions other than the U.S. would help to better evaluate these issues, as it may be that warmer climates or more intense UVR are needed to trigger the proposed physiological mechanisms through which these variables might affect cognitive ability.

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