Food Desert Impacts on Society

BROWN Computer Science

by: Kiana Kelii, Isaias Reyes, Michael Lu, Nya Haseley-Ayende

Background

Food deserts—areas with limited access to affordable and nutritious food—are a growing public health concern in the United States. Prior research has explored the link between nutrition and cognitive development, suggesting that limited access to healthy food may also influence academic performance in children. This project investigates the relationship between food accessibility, sleep deprivation, and educational outcomes by analyzing academic performance and health data across counties classified as urban food deserts, rural food deserts, and non-food deserts.

Hypotheses

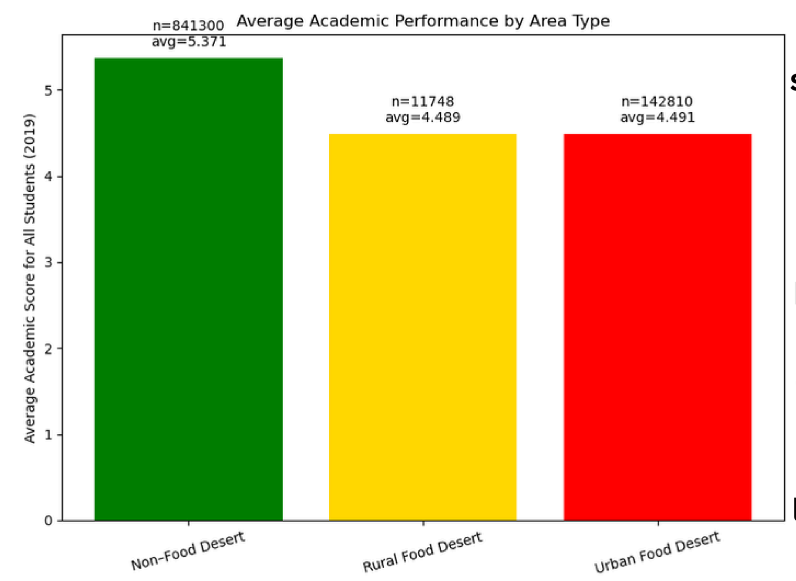
Our **(H1) major null hypothesis** was that there exists **no significant difference** in **academic performance between** students in **food deserts** and those in **non-food desert** areas. In addition to this, we also ran statistical tests for four other null hypothesis: **(H2)** There is **no statistically significant difference** in the **academic performance across race groups, (H3)** There is **no statistically significant difference** in **sleep deprivation** among individuals **in urban food deserts, rural food deserts, and non–food desert areas, (H4 & H5)** There is **no significant difference** in **education scores** between the **two racial groups** in **high/low sleep deprived** communities.

Data

Our datasets included:

1. **Food Access Research Atlas**, with census tract data including rural/urban location and whether or not it is considered a food desert
2. **Stanford Education Data Archive**, with academic achievement scores across all US counties
3. **NCES Geographic Relationship** dataset, which maps from counties to census tract numbers to standardize academic performance data
4. **CDC PLACES** dataset, with local data on the health status across census tracts

Hypothesis Testing/Results



Comparison	T-Statistic	P-Value
Urban Food Desert vs. Non-Food Desert	-172.606	0E+00
Rural Food Desert vs. Non-Food Desert	-47.711	0E+00

p-values truncated to 0 due to extreme significance (true values fall between 0 < p < 5e-324

To determine whether these differences were **statistically significant,** we conducted **one-sample t-tests** comparing **each food desert group's mean** against the **non-food desert baseline.**

The bar chart on the **left illustrates average** academic across **three community types: Non-Food Deserts, Rural Food Deserts, and Urban Food** Deserts. The average **score** in **non-food desert** communities was **5.371**, compared to **4.489** in **rural food deserts** and **4.491** in **urban food deserts**.

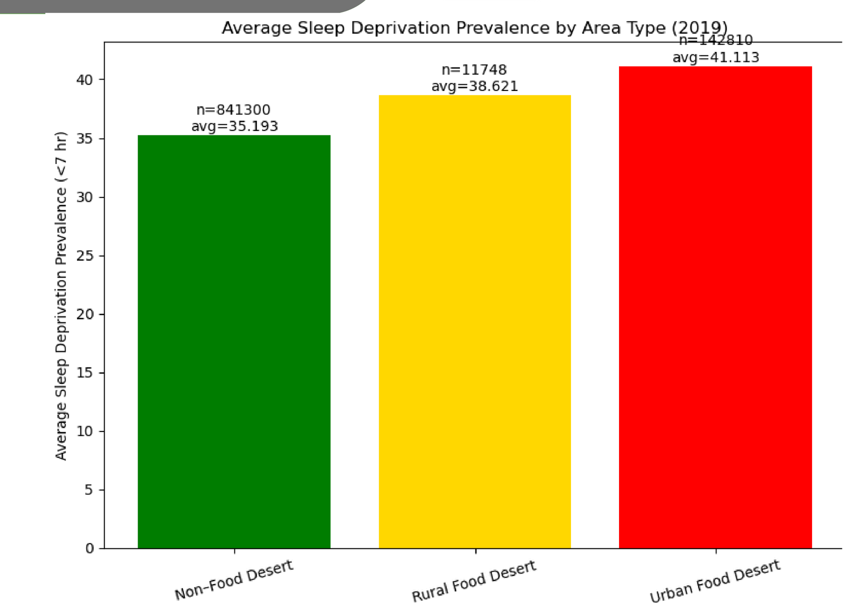
The extremely **low p-values** (effectively zero) and **large negative t-values** provide **strong evidence** that these gaps are **not** due to **random** chance.

Therefore we can **reject** the **null hypothesis**, **confirming** that **both urban and rural food desert** communities have **significantly lower academic performance** than **non-food desert communities**

Racial Pairing	T-Stat (High Sleep Dep)	P-Value (High Sleep Dep)	T-Stat (Low Sleep Dep)	P-Value (Low Sleep Dep)
White vs Asian	-36.306	1.0324E-286	-22.686	1.1605E-113
White vs Black	239.147	0E+00	276.96	0E+00
White vs Hispanic	194.038	0E+00	229.291	0E+00
White vs Native American	158.128	0E+00	187.958	0E+00
Asian vs Black	253.055	0E+00	261.92	0E+00
Asian vs Hispanic	212.198	0E+00	220.333	0E+00
Asian vs Native American	179.544	0E+00	186.981	0E+00
Hispanic vs Black	51.211	0E+00	52.539	0E+00
Hispanic vs Native American	-23.701	7.7218E-124	-21.038	4.6414E-98
Black vs Native American	-70.91	0E+00	-68.372	0E+00

The table above displays **t-statistics and p-values** from two-sample t-tests comparing academic performance between racial groups across communities with **(H4)high and (H5)low levels of sleep deprivation**. Each row represents a racial pairing, with corresponding test statistics for both conditions

All comparisons yielded statistically significant differences (p < 0.05), with several p-values truncated to 0 due to extreme significance (true values fall between 0 < p < 5e-324). **Analysis revealed a consistent trend**: racial disparities in education scores were **greater** in **low sleep-deprivation** communities. For instance, the White vs. Black t-statistic increased from **239.147** (high sleep dep) to **276.960** (low sleep dep), **displaying** a **widening academic gap**. These findings suggest that sleep deprivation may act as an equalizing stressor, with **performance gaps** between **racial groups** becoming greater in environments **where** such **stressors are reduced.**



The chart above illustrates average sleep deprivation prevalence across different area types. **Urban** food deserts show the **highest prevalence (41.113%)**, followed by **rural food deserts (38.621%)** and **non–food deserts (35.193%)**

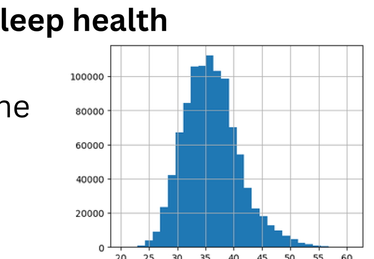
Performed **two-sample t-tests** to **determine** whether these differences are **statistically significant**

Comparison	T-Statistic	P-Value
Urban Food Desert vs. Non–Food Desert	426.85	0E+00
Rural Food Desert vs. Non–Food Desert	100.032	0E+00

Both tests produced **very large t-statistics and extremely small p-values** (between 0 < p < 5e-324), indicating **strong statistical evidence that urban and rural food deserts** experience **higher sleep deprivation than non–food desert areas**

These findings **support the idea** that **environmental** and **systemic conditions in food deserts correlate** with **reduced sleep health**

Graph on the right shows the distribution of the sleep deprivation percentages



Methodology

When processing the data, we aggregated our four data sets into a DB file. Then we use SQL queries to generate a single CSV file with rows containing joined values from all four datasets. Following this step we read our CSV file into a Panda Data Frame. Using Panda Data Frames we dropped rows that did not contain academic performance for all student racial groups.

After the clean up process for our data, we conducted analysis using the following libraries and packages:

- **ML: numpy, pandas, xgboost, seaborn, matplotlin, sklearn**
- **Stats: matplotlib, scipy, nump, pandas, one-sample ttest, two-sample ttest**
  - **Decided to set a significance threshold of .05, for all statistical tests and**

Conclusion

Based on our **analysis** and **data** we concluded there **exists** a **significant** and **predictive relationship between academic performance, health,** and **food desert status**. Specifically our analysis revealed that communities in **non-food deserts scored** on **average better** than **both rural and urban food deserts.** Analysis results proves that **regardless** of your **community type**, a **food desert serves as a determining factor** towards your **academic performance.**

We also investigated the health effects food deserts have on communities. **Analysis results** discovered **non-food desert** were **less sleep deprived** compared **to rural food deserts and urban food deserts**. We also **initially believed** the **increase** in **sleep deprivation** would be a **determining factor** towards **negative school performance**. Research shows less sleep leads to a lower ability to concentrate, problem solve, and retain information. However our **analysis results revealed** a **widening T-stat between racial groups** in communities with **low sleep deprivation**. We interpret this to mean **certain racial groups** may **have additional resources** to help them **capitalize on better conditions**

Overall these **findings reveal** that **food deserts** are **more** than just **zones** of **limited food access**, they are **structural barriers that deepen both educational and health inequities**. The combined **impact of poor nutrition, sleep deprivation, and racial disparities** emphasizes the need for interventions. Lastly our results also show there is a need to solve root causes of food deserts to address systemic inequality

Limitations / Next Steps

- **Better feature selection for the academic dataset**
- **Find more related data sources for our analysis**

Machine Learning

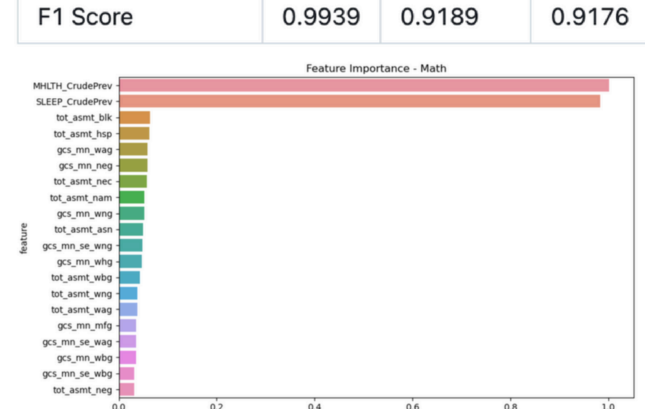
We trained two models: 1) **XGBoost classifier** and 2) **K-Nearest Neighbors clustering**. For both of our models, we used the pairwise combinations of the **Urban** and **LATracts_half** binary categorical columns. After dropping rows with nan values in the relevant feature columns we were left with 3 distinct classes in our dataset: **11** (urban and food desert), **10** (urban and not food desert), and **00** (not urban and not food desert). There were **no 01 class** data points after filtering out rows with nan values. While we were left with over **90,000** rows, the was still a significant imbalance in our dataset (roughly 84:11:5)

We used **all the academic performance** data as well as the **SLEEP_CrudePrev** and **MHLTH_CrudePrev** columns from the health dataset. We used a greedy search to remove the minimum number of features to remove any pairwise Pearson Correlation coefficients above 0.95 to drop any potentially unnecessary/collinear columns. The dataset was then split and used for K-fold cross validation with stratification. We also split the dataset by academic subject and trained each of our models on each.

We hypothesized that our feature data is sufficiently predictive of our target class. Given the large class imbalance (83.54% and 83.31% majority classes in the Math and RLA datasets) we analyzed our performance both in terms of **raw accuracy** and **equally weighted balanced accuracy**.

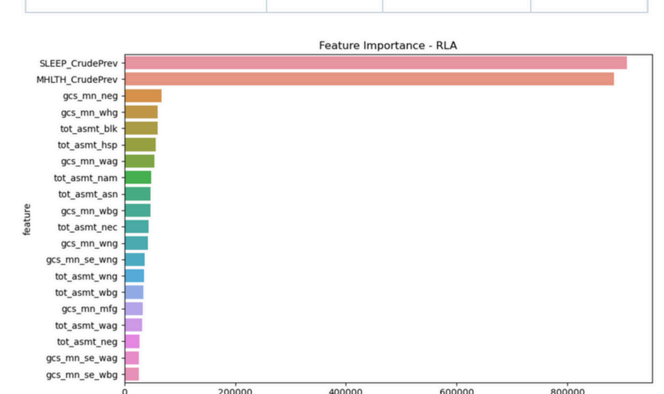
XGBoost (MATH)

Metric	Train	Validation	Test
Accuracy	0.9939	0.9190	0.9180
Balanced Accuracy	0.9974	0.8165	0.8132
Precision	0.9941	0.9189	0.9172
Recall	0.9939	0.9190	0.9180
F1 Score	0.9939	0.9189	0.9176



XGBoost (RLA)

Metric	Train	Validation	Test
Accuracy	0.9944	0.9315	0.9301
Balanced Accuracy	0.9972	0.8335	0.8366
Precision	0.9946	0.9310	0.9301
Recall	0.9944	0.9315	0.9301
F1 Score	0.9945	0.9312	0.9301



As shown in the figures to the left, our XGBoost model was able to significantly **outperform baseline accuracies** with good Precision, Recall, and F1 scores in training and test sets. We also examined XGBoost's provided importance scores to evalute which input feature(s) were most predictive. Based on these results, the sleep and mental health features were **most significant**. However, this may be caused by the significant number of academic features which were all closely correlated with each other.

Our KNN didn't perform as well with **below-baseline** raw accuracy. However, our baseline accuracies were about 33.3% so our model was able to learn representative relationships. We hypothesize that this could have been caused by the lower modeling complexity of KNN compared to XGBoost.