For office use only	Team Control Number	For office use only
T1 ________________	**88457**	F1 ________________
T2 ________________		F2 ________________
T3 ________________	Problem Chosen	F3 ________________
T4 ________________	**C**	F4 ________________

2018
MCM/ICM
Summary Sheet
The "Hottest" Clean Energy States

The future of the world revolves around climate change. As climate changes exponentially, the diverse ecosystems of the world will be subjected to drastic and irreversible change. It is pivotal that policy changes are made in order to decelerate such climate change. The toxic effect non-renewable energy sources have on global warming is innumerable. In order to potentially decelerate global warming, renewable energy usage must increase and non-renewable energy usage must decrease.

We were given a dataset of 583 variables describing consumption, production, and cost of energy in four Southwest states. We identified the eight primary energy sources that contribute to total energy consumption – Coal, Natural Gas, Petroleum Products, Fuel Ethanol, Geothermal, Hydroelectric, Solar, and Wind. The first three are non-renewable and contribute to climate change. These eight variables comprise the Energy Profile of each state. The energy profiles are visualized as bar graphs.

Using Ridge Regression, we developed models for each state to characterize how the percent of renewable energy usage changes as a function of the variables Year, resident population (TPOPP), real gross domestic product by state in million chained (2009) dollars (GDPRX), total energy consumption per real dollar of GDP (TETGR), and Electricity average price, all sectors (ESTCD). We interpreted the models and found that in all states, ESTCD is positively correlated with percent of renewable energy usage.

We determined that the "best" energy profile would be one that uses no non-renewable resources and the percent usage of each renewable is tailored to each state based on geography, climate, and community impact. We then chose ideal profiles for each state by multiplying the ideal percent vector by the total consumption in 2009. Using the technique of cosine similarity, we compared the ideal profiles to the 2009 profiles and found that California had the best profile, followed by Arizona, then Texas, then New Mexico.

To predict the 2025 and 2050 profiles for each state, we adapted the technique of principal components regression (PCR). Principal components are orthogonal linear combinations of the variables that account for the largest possible variability in the data. Instead of using the principal components to predict a response variable using ordinary least squares (OLS) regression, as in PCR, we used Year to predict Principal Component 1 (PC1). We then extracted the original variables from the single scalar PC1. This allowed us to quickly predict all 583 variables in the dataset from a single predictor variable and then extract the predicted profile variables. We validated this model by testing it against OLS regression.

We set energy profile targets for 2025 and 2050 that we believe are ambitious yet achievable. To set goals for each renewable energy resource, we identified the year that showed the most growth in BTUs consumed from the year before. We considered that Fuel Ethanol, Geothermal, Solar, and Wind technologies have the potential for growth and that the maximal growth can be replicated every year between 2009 and 2025. For 2050, we set a more ambitious goal of replicating maximal growth plus 10% for every year between 2025 and 2050. Non-renewable energy targets were set as predicted amounts minus one-third of total clean energy usage.

In order to meet these goals, we recommend four policy changes. 1. Invest in renewable energy workforce training. 2. Identify the optimal locations for clean energy technology generation and concentrate building efforts there. 3. Set higher energy efficiency standards for building codes and motor vehicles. 4. Invest in collection and analysis of energy data.

Memorandum

TO: Governors of Arizona, New Mexico, Texas, and California.

FROM: Team #88457

DATE: February 12, 2018

RE: Board of Governors' Renewable Energy Profiles (2009), Predictions, and recommended goals.

Team 88457 is pleased to transmit the state energy usage profiles for year 2009, predicted energy usage for year 2025 and 2050 if no policy changes are made, and goals for the energy compact to adopt. Energy usage profiles consist of percentage of consumption of each of eight energy sources out of total consumption. Of the energy sources in the profiles, the first three are non-renewable and the last five are renewable. The profile score is the profile's closeness to your state's ideal profile with a maximum score of one. We recommend making policy changes immediately, since our analysis of the data shows that no state is currently on track to meet the goals we have set for 2025 and 2050.[1]

Tableau 1 – Arizona:

	Coal	Natural Gas	Petroleum Products	Fuel Ethanol	Geothermal	Hydroelectric	Solar	Wind	Profile Score
2009 Profile	29.55%	26.94%	37.25%	1.39%	0.02%	4.49%	0.34%	0.02%	0.051
2025 Predicted	32.94%	19.86%	39.94%	0.46%	0.02%	6.48%	0.30%	0.00%	0.0581
2050 Predicted	32.94%	19.86%	39.94%	0.46%	0.02%	6.48%	0.30%	0.00%	0.0581
2025 Goal	17.75%	3.65%	25.30%	11.85%	10.83%	8.72%	11.06%	10.83%	0.6069
2050 Goal	4.67%	0.00%	11.60%	19.96%	19.30%	5.72%	19.45%	19.29%	0.9053

Tableau 2 – California:

	Coal	Natural Gas	Petroleum Products	Fuel Ethanol	Geothermal	Hydroelectric	Solar	Wind	Profile Score
2009 Profile	0.80%	36.67%	53.79%	1.25%	1.95%	4.17%	0.48%	0.87%	0.0598
2025 Predicted	1.13%	35.55%	54.45%	0.46%	2.10%	5.36%	0.37%	0.58%	0.0607
2050 Predicted	1.13%	35.55%	54.45%	0.46%	2.10%	5.36%	0.37%	0.58%	0.0607
2025 Goal	0.00%	19.26%	37.21%	9.12%	9.69%	7.40%	8.50%	8.82%	0.4211
2050 Goal	0.00%	4.38%	20.10%	17.54%	17.97%	5.62%	17.07%	17.31%	0.8249

Tableau 3 – New Mexico:

	Coal	Natural Gas	Petroleum Products	Fuel Ethanol	Geothermal	Hydroelectric	Solar	Wind	Profile Score
2009 Profile	37.20%	30.02%	30.05%	0.50%	0.04%	0.32%	0.03%	1.83%	0.0216
2025 Predicted	37.43%	30.34%	31.18%	0.18%	0.05%	0.31%	0.06%	0.46%	0.0082
2050 Predicted	37.43%	30.34%	31.18%	0.18%	0.05%	0.31%	0.06%	0.46%	0.0082
2025 Goal	33.83%	26.66%	27.51%	2.84%	2.45%	0.31%	2.45%	3.95%	0.1043
2050 Goal	30.00%	22.84%	23.68%	5.73%	5.42%	0.26%	5.41%	6.65%	0.2281

Tableau 4 – Texas:

	Coal	Natural Gas	Petroleum Products	Fuel Ethanol	Geothermal	Hydroelectric	Solar	Wind	Profile Score
2009 Profile	14.02%	32.42%	50.99%	0.62%	0.02%	0.09%	0.01%	1.83%	0.0186
2025 Predicted	13.79%	36.84%	48.80%	0.12%	0.01%	0.13%	0.00%	0.30%	0.004
2050 Predicted	13.79%	36.84%	48.80%	0.12%	0.01%	0.13%	0.00%	0.30%	0.004
2025 Goal	6.93%	30.11%	42.14%	5.15%	4.64%	0.22%	4.63%	6.18%	0.1748
2050 Goal	0.00%	21.29%	33.14%	11.35%	10.90%	0.19%	10.89%	12.24%	0.4482

[1] *Comap image*. (2018). Retrieved February 12, 2018, from http://www.isdde.org/isdde/prize/prize15.htm

Part I: Analyzing the State Energy Data System Reports

A. State Energy Profiles

The U. S. Energy Information Administration (EIA)[1] defines total energy consumption as the sum of eleven energy sources (four non-renewable and seven renewable), eight of which are included in the dataset (see figure 1.1). For the energy profiles, we selected total consumption of all energy-consuming sectors for each of the eight energy sources in BTUs (British Thermal Units). This profile reduces the 583 variable dataset to an easy to interpret eight variables. The energy profiles in 2009 for Arizona, California, New Mexico, and Texas are depicted in Figure 1.2. We chose to visualize the energy profiles as bar graphs rather than pie charts since relative lengths of bars are more easily judged than volumes of slices of a pie. A chart of percent of renewable energy sources consumed in each state is depicted in Table 1.

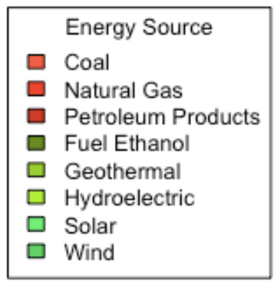

Figure 1.1 - Legend. The energy sources included in the energy profile. Non-renewable resources are in red and renewable resources are in green.

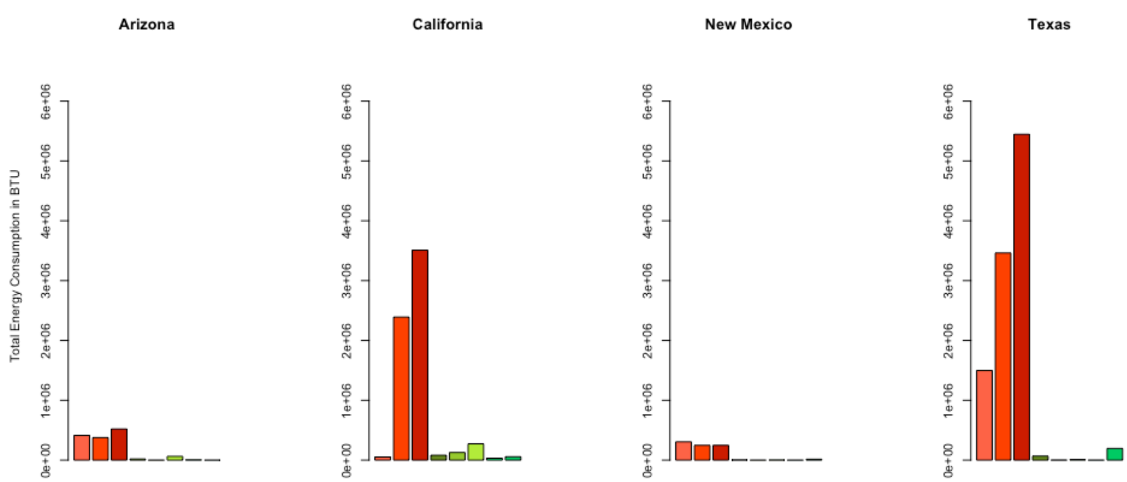

Figure 1.2 - The relative energy profiles of each state. The order of the bars from left to right matches the order of the

California	8.74%
Arizona	6.26%
New Mexico	2.73%
Texas	0.82%

Table 1 – Percentage of renewable energy consumed by state.

B. Modeling the Evolution of Energy Profiles Over Time

For each of the four states, we developed a model to characterize how the energy profile has evolved during the period studied. We predicted the percentage of renewable energy use using ridge regression, the formula for which is given below.

$$\hat{\beta}^{\text{ridge}} = \underset{\beta}{\operatorname{argmin}} \left\{ \sum_{i=1}^{N} \left(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j \right)^2 + \lambda \sum_{j=1}^{p} \beta_j^2 \right\}.$$

Ridge regression penalizes the β coefficients of the linear model subject to a penalty term lambda. Larger values for λ shrink the coefficients more, with the coefficients for predictors with the smallest variance being shrunk the most. The value for lambda is chosen using cross-validation. When many of the predictor variables are highly intercorrelated, this technique yields a model whose coefficients are generally more interpretable than those of an Ordinary Least Squares regression, since the sign of the coefficient matches the sign of the correlation of the predictor variable and the response.[2]

The variables selected to predict percentage of renewable energy use were Year, resident population (TPOPP), real gross domestic product by state in million chained (2009) dollars (GDPRX), total energy consumption per real dollar of GDP (TETGR), and Electricity average price, all sectors (ESTCD). Figure 2 shows how the β coefficients shrink from right to left as the L1 norm penalty is decreased.

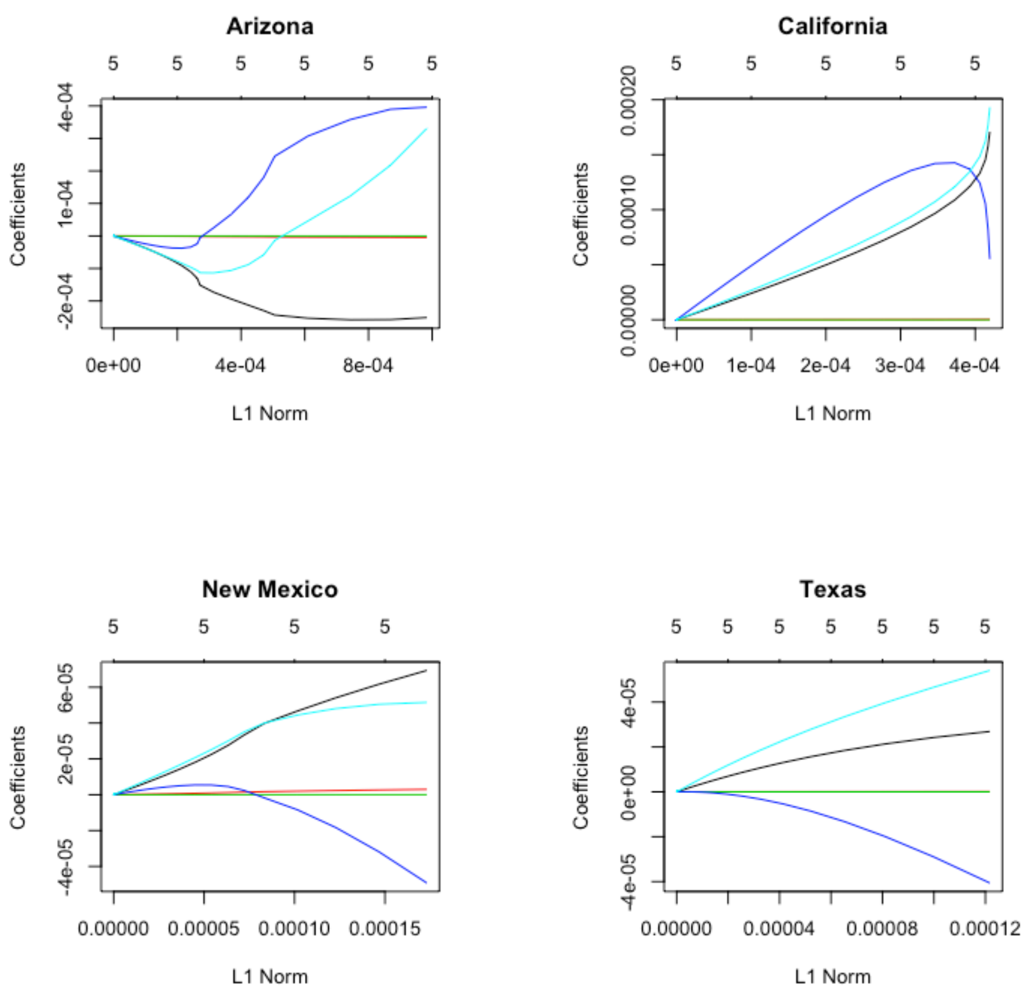

Figure 2 - Change in β coefficients as the L1 Norm penalty penalty changes

Table 2 gives the R-Squared for each of the four models. Figure 3 plots the predicted value for percent of clean energy versus the actual value for each of the four states along with the line y=x. The model in which every prediction is exactly equal to the true value would have every point exactly on the line.

State	Rsq
Arizona	0.401
California	0.242
New Mexico	0.519
Texas	0.300

Table 2 - R squared value for each of the energy profile evolution models

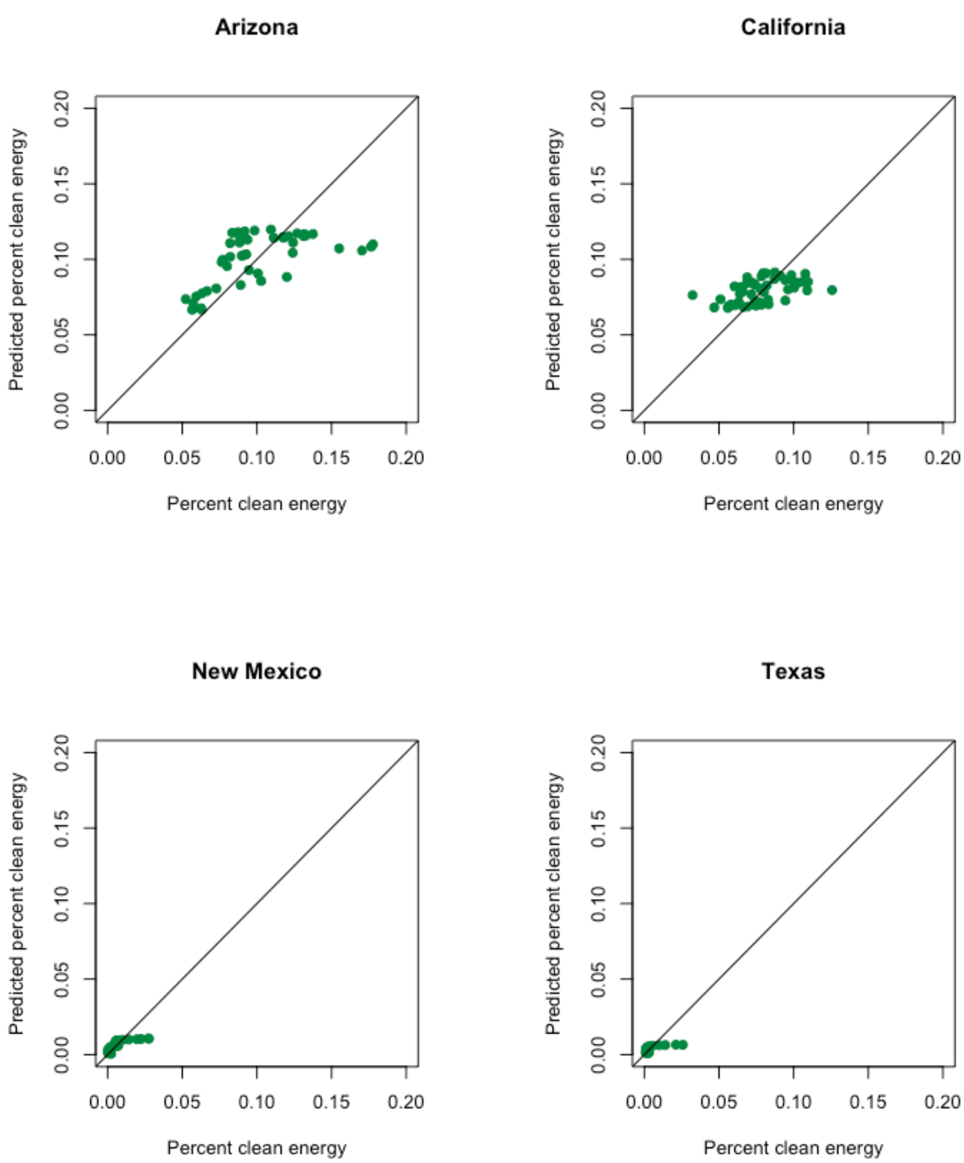

Figure 3 - Performance of each of the four reduced OLS models

The positive or negative sign of the β coefficients allows us to interpret the correlations of the variables in the model with the response variable. In Arizona, the variables that are positively correlated with percent clean energy (that is, as they increase, percent of clean energy increases) are TETGR and ESTCD. The variables that are negatively correlated with percent clean energy (that is, as they increase, percent clean energy decreases) are Year, TPOPP, and GDPRX. In California, all the variables positively correlated with percent clean energy. In New Mexico, all the variables except for TETGR are positively correlated with percent clean energy. In Texas, all the variables except for TETGR are positively correlated with percent clean energy. The model coefficients are given in Appendix A.

New Mexico and Texas have the most similar models since their model coefficients all have the same signs. Possible influential factors for the increase in similarity are due to geographic factors. The states are adjacent to each other. This suggests that the two states have similar weather patterns as well as geography.

C. Scoring 2009 Profiles Based on Renewable Energy Usage

The best profile utilizes 100% clean renewable resources. Although a renewable resource is preferable to a nonrenewable resource, some renewable resources are "better" than others. Additional data is required in order to rank renewable resources. The ranking of the "best" renewable resources would be determined by the geography, environmental costs, and impact the resource has on the surrounding community (both positive and negative). From this ranking, the optimal percentage of each resource would be determined. A vector of resource percentages would be created for each state where non-renewable resources are 0% and renewable resources are the optimal percent. Multiplying the total consumption for 2009 in BTU by the optimal percent vector would yield the "best" energy profile for each state. Since geographic, environmental costs, and community impact data are not provided, the current optimal percent vector consists of 0% for all non-renewable energy sources and 20% for each of the five renewable energy sources.

We then compared each "best" energy profile vector to the 2009 energy profile vector using the technique of cosine similarity which yields a score between -1 and 1. Since our vectors are limited in positive space, the similarity score is bounded by [0,1]. The formula for cosine similarity is given by:

$$Sim(\vec{q},\vec{d}) = \frac{\vec{q}.\vec{d}}{|\vec{q}||\vec{d}|}$$

This is defined to be the cosine of the angle between the two vectors.[3] The cosine similarity scores for the four states analyzed are given in Table 3. This allows us to rank states by how closely they match their "best" profile.

State	Similarity
Arizona	0.051
California	0.060
New Mexico	0.016
Texas	0.019

Table 3. Similarity Scores for each state's 2009 energy profile to its ideal energy profile

The state that is most similar to the "best" profile has the smallest angle where the state that is least similar to the "best" profile has the largest angle. Since the cosine(0°) = 1, the state in Table 3 that is closest to 1 is the most similar to the "best" profile. This means that California is the "best" profile, followed by Arizona, Texas and New Mexico .

D. Predicting Energy Profiles in 2025 and 2050

The technique of Principal Component Analysis (PCA) constructs orthogonal linear combinations of variables (principal components) that account for the largest possible variability in the data.[4] The principal components are given in descending order from most variance explained to least. The original data matrix is converted into the principal components matrix by multiplying the original data matrix by a matrix of "loadings," which consists of the coefficients for each of the original variables used to construct each of the principal components. Thus, we can obtain the original data matrix by multiplying the matrix of principal components by the pseudoinverse of the matrix of loadings.

Principal Component regression (PCR) uses Ordinary Least Squares (OLS) regression to predict a response variable using the principal components of the original X matrix as the predictor variables.[2] It can be used as a dimensionality reduction technique since the first three principal components often explain more than 95% of the variance in the original data.[5] In this analysis, instead of using the principal components to predict a response variable, we attempt to reverse this technique and use Year to predict Principal Component 1 (PC1). After predicting PC1, we can then extract the original X variables using the pseudoinverse of the loadings matrix.

Examination of the data revealed that for the four states analyzed, little clean energy was consumed before 1989. It is difficult to identify trends in clean energy usage before 1989 since in most cases there were none. The greenhouse effect conversation began with The National Energy Policy Act of 1988.[6] Although the bill was not enacted, it forced the government to begin thinking of potential solutions to the Greenhouse Effect. This is most likely why the data shows initial renewable energy efforts beginning in 1989. Since the focus of this investigation is clean energy usage, we chose to use only the last 21 years of data (1989-2009) to predict future energy profiles.

To begin our analysis, data matrices are created for each of the four states consisting of the years 1989 to 2009 and the 583 variables included in the dataset. Next, a Principal Component Analysis is conducted on each individual data matrix. Figure 4 shows plots for each PCA of the fraction of variance explained by each of the first ten principal components. Table 4 shows the fraction of variance explained by PC1 for each state's analysis. Because the fraction of variance explained by PC1 was over 0.99 for each state, we continued with our plan to predict PC1 from Year.

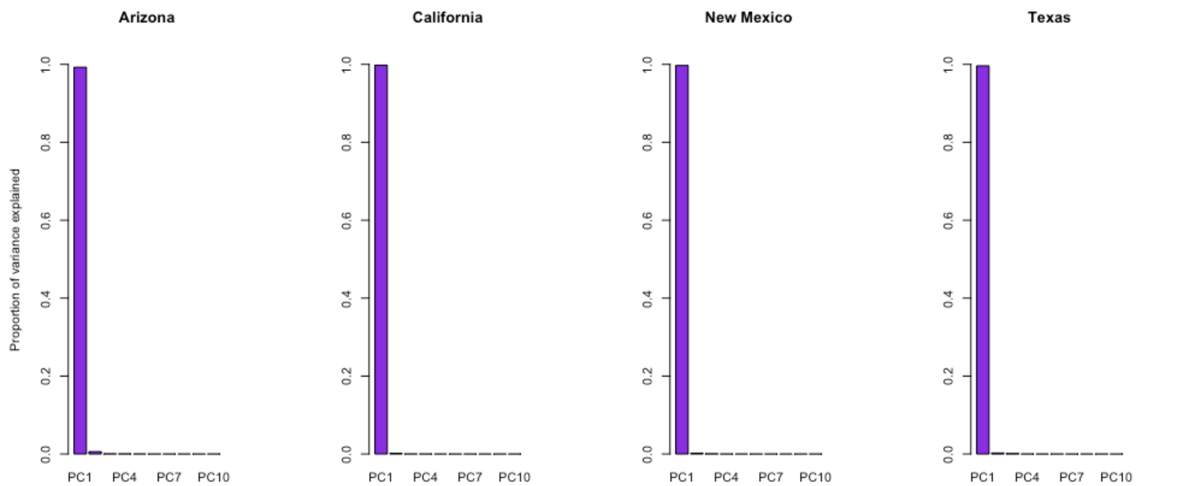

Figure 4 - Fraction of variance explained by each of the first ten principal components for each state's analysis

Arizona	California	New Mexico	Texas
0.993	0.998	0.997	0.996

Table 4 - Fraction of variance explained by PC1 for each state's analysis. Each fraction is over 0.99.

For each state, we used OLS regression to predict PC1 from Year. The results for Arizona, California, New Mexico, and Texas are given in Figures 5, 6, 7, and 8, respectively.

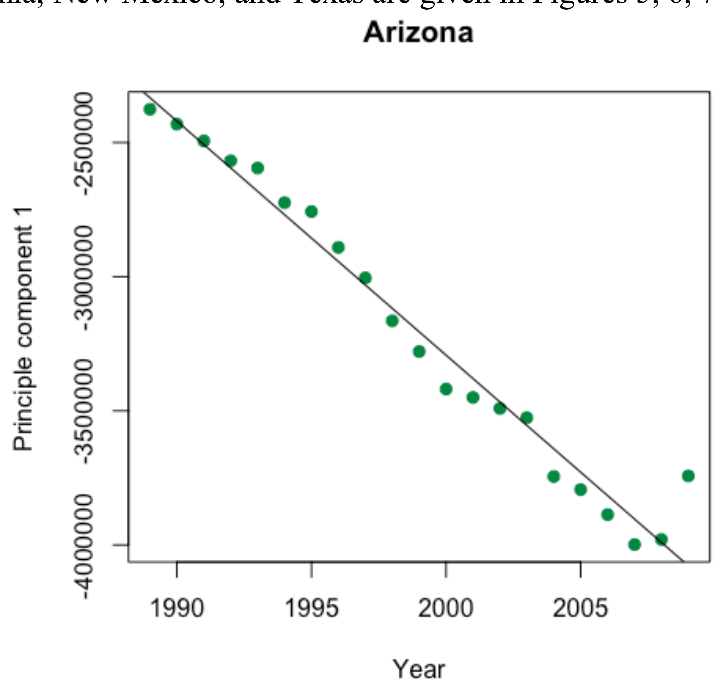

Figure 5 - Arizona PC1 ~ Year. Multiple R-squared: 0.9675, Adjusted R-squared: 0.9658, p-value: 1.33e-15

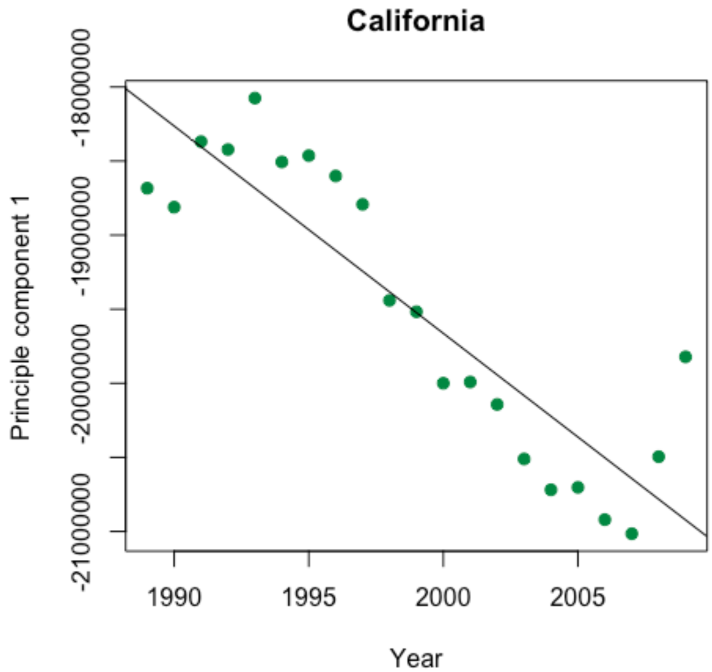

Figure 6 - California PC1 ~ Year. Multiple R-squared: 0.7843, Adjusted R-squared: 0.773, p-value: 9.436e-08

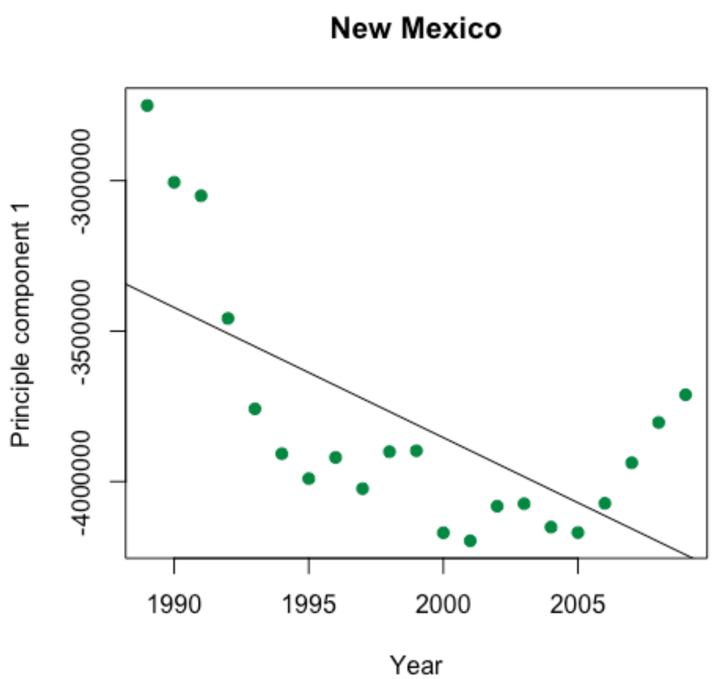

Figure 7 - New Mexico PC1 ~ Year. Multiple R-squared: 0.4299, Adjusted R-squared: 0.3999, p-value: 0.001251

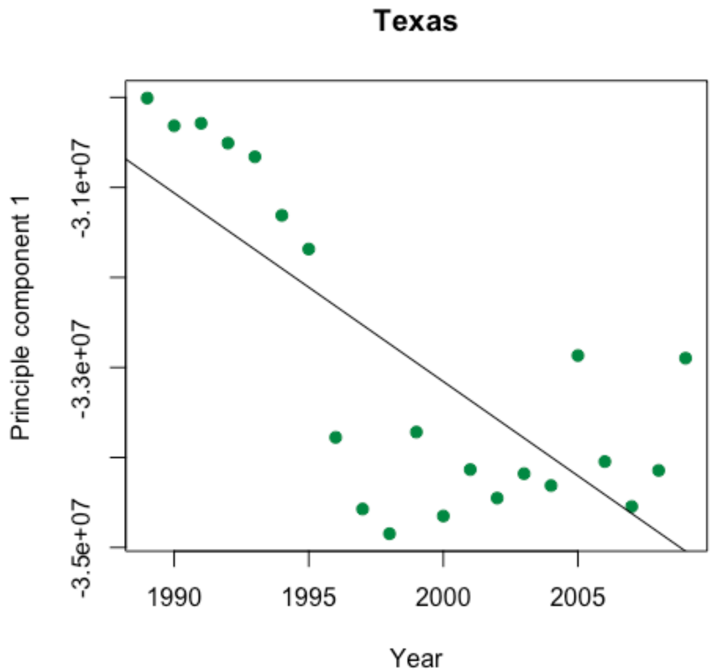

Figure 8 - Texas PC1 ~ Year. Multiple R-squared: 0.5563, Adjusted R-squared: 0.5563, p-value: 0.0001038

The linear models vary greatly in how accurately Year predicts PC1. Adding additional data to the original X matrix might improve the fit. Since climate influences the potential capacity for generating clean energy, additional variables include inches of rain in a year, number and strength of sunny days in year, and wind magnitude. Energy policy is also influenced by politics. Additional variables include relative proportion of Republicans and Democrats in the state legislative bodies, and the political party of the governor of the state. We experimented with adding exponential terms for Year to the linear model since there appears to be a parabolic relationship between PC1 and Year for particular states. However, it overfit the 1989-2009 data and had poor predictions for 2025 and 2050.

We then used the OLS models to predict PC1 for 2025 and 2050 and multiplied predicted PC1 by the pseudoinverse of the first column of the loadings matrix to obtain the predicted values of the 583 variables. The eight profile variables were then extracted and visualized as bar plots. The predicted profiles for 2025 and 2050, along with the 2009 profile for comparison, are shown in Figures 9 through 12.

Arizona

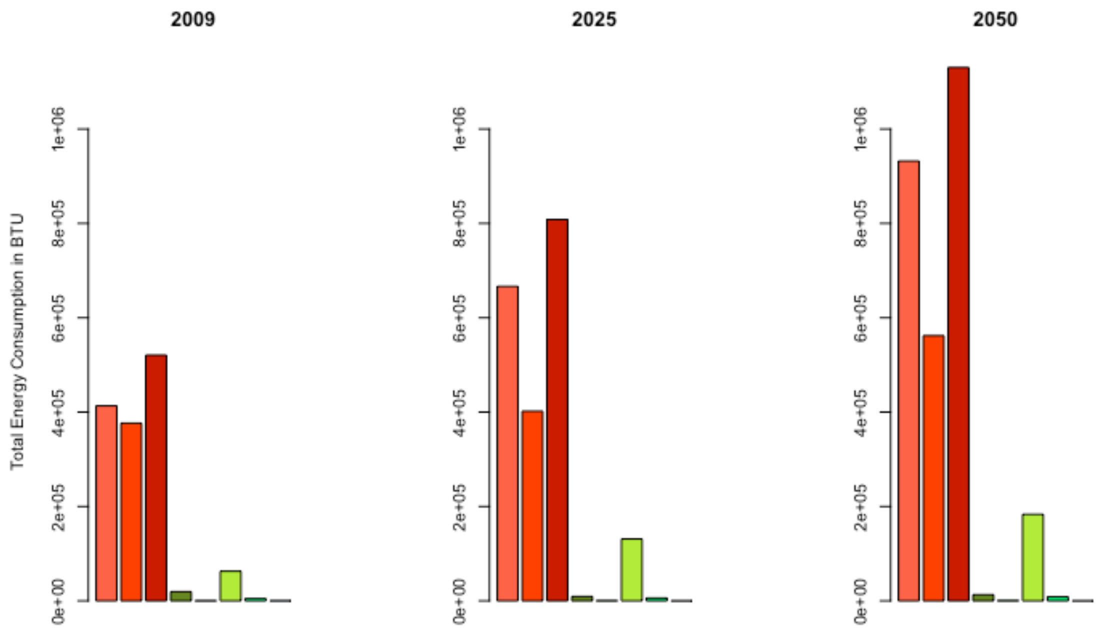

Figure 9 - Arizona Energy profile for 2009 and predicted profiles for 2025 and 2050

California

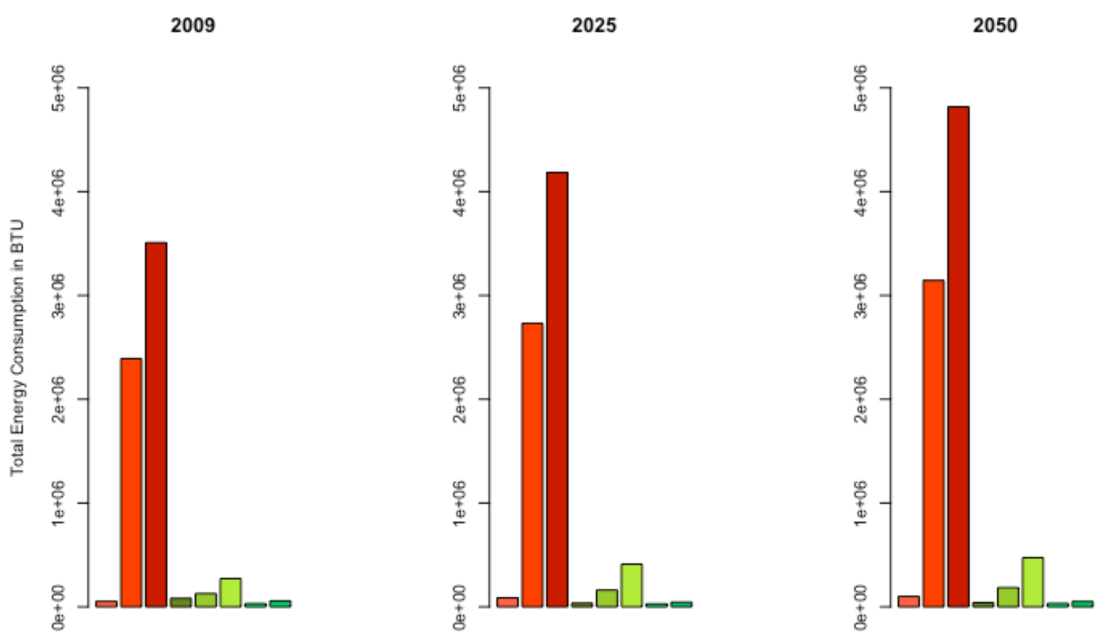

Figure 10 - California Energy profile for 2009 and predicted profiles for 2025 and 2050

New Mexico

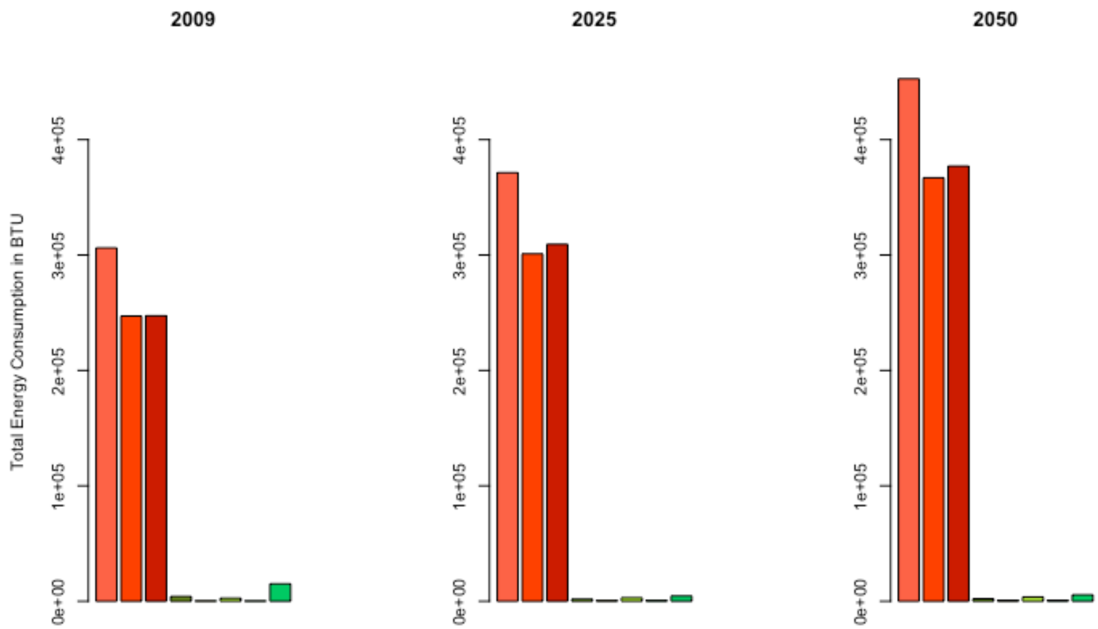

Figure 11 - New Mexico Energy profile for 2009 and predicted profiles for 2025 and 2050

Texas

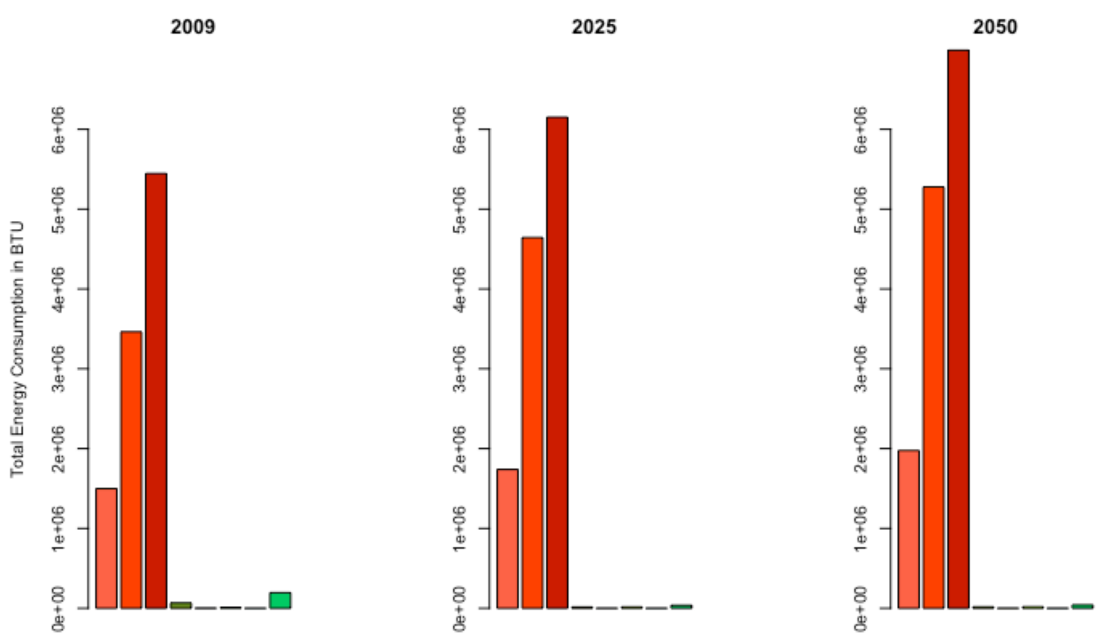

Figure 12 - Texas Energy profile for 2009 and predicted profiles for 2025 and 2050

It was more difficult to predict future clean energy usage accurately because some states have not been using these technologies for long periods of time. For example, the data shows Arizona only began using solar energy in 2009 and Texas doubled its wind usage between 2007 and 2008. The analysis we used, which expects a linear relationship between the variables, makes these patterns difficult to detect. In a future analysis we could add variables such as predicted climate measures and national goals for emissions standards to the OLS regression of PC1 to improve predictive accuracy.

We validated our model by comparing some of the predicted values from our models to the predicted values from a simple linear regression of energy sources on Year. For Arizona, we conducted a simple linear regression of total coal consumption on year and of total consumption of solar on year. The percent difference between predicted coal consumption in 2025 for our model and the simple linear model was 3.195612%. For 2050, it was 3.404888%. The percent difference between 2050 solar consumption for our model and the simple linear model was 3.48439%. For 2050, it was 0.5313149%. We also computed the cosine similarity between the actual 583 values of the variables in 2009 and the values predicted by the model for 2009. The result was 0.3827341.

In the absence of policy change in these states, fossil fuel usage is predicted to grow in every state by much more than clean energy usage. Thus, climate change will worsen. Policy change interventions are needed immediately to prevent a catastrophic future.

Part II: Goals for the new Four-State Energy Compact

A. Setting Goals for Individual States

On February 26, 2009, the United States House of Representatives held a hearing before the Subcommittee on Energy and Environment of the Committee on Energy and Commerce. Representatives called for "swift and well-thought-out action on climate change" and stated that renewable energy technologies are "engine[s] of job creation[7]." Because of this, we chose to set ambitious but achievable goals for each individual state.

For the renewable energy sources Fuel Ethanol, Geothermal, Solar, and Wind, there is great potential for growth, while for Hydroelectric there are already dams in many of the most ideal locations. For every state, for the four sources with potential for growth, we identified the year that showed the most growth in BTUs consumed from the year before. This maximal growth achieved has therefore been demonstrated to be possible and can be replicated in every year from 2009 to 2025. We set our 2025 goal consumption for each state for each of the four sources with potential for growth to be equal to the 2009 consumption plus 16 times the maximal rate of change. We set the hydroelectric consumption equal to the maximum from the years 1960-2009. We then reduced the non-renewable energy consumption from their predicted amounts by one-third of the total amount of clean energy goal.

For 2050, we set a more ambitious goal. As clean energy technologies improve, the rate of change should increase. For the four renewable resources, we set the goal to the 2025 goal consumption plus 25 times 1.1 times the maximal rate of change. The other energy goals were set in the same way. Table 5 gives the goal profiles for each state for both years and their similarity scores with the ideal profile. The goal profiles along with the 2009 profiles for each state are visualized in figures 13 through 16.

State and Year	Coal	Natural Gas	Petroleum Products	Fuel Ethanol	Geothermal	Hydroelectric	Solar	Wind	Profile Score
Arizona 2025	333116	68499	474853	222358	203236	163692	207639	203196	0.6069
Arizona 2050	133712	0	331929	571105	551983	163692	556387	551943	0.9053
California 2025	0	1557868	3010202	738198	783941	598435	687876	713476	0.4211
California 2050	0	466220	2138003	1866522	1912265	598435	1816201	1841800	0.8249
New Mexico 2025	332052	261744	270026	27840	24042	3077	24008	38821	0.1043
New Mexico 2050	359050	273335	283432	68618	64820	3077	64785	79599	0.2281
Texas 2025	868677	3773686	5281183	645903	581229	27284	579992	774627	0.1748
Texas 2050	0	3079922	4793090	1641355	1576681	27284	1575444	1770079	0.4482

Table 5 – Goal profiles in BTUs consumed for each state for 2025 and 2050. Similarity scores between goal profiles and "best" profile are given as "Profile Score."

Arizona

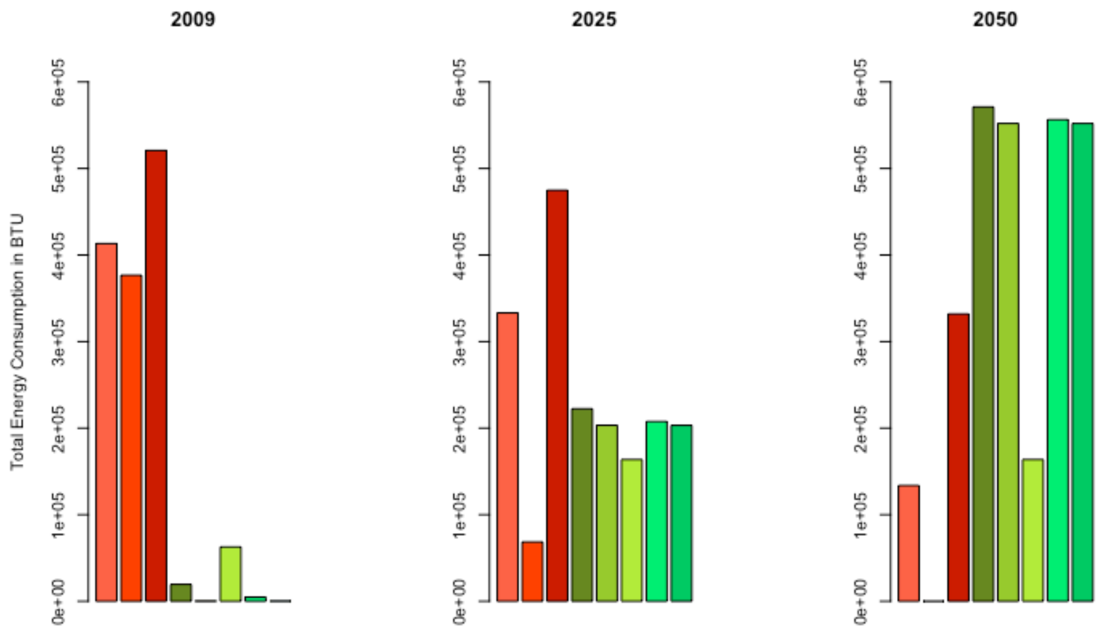

Figure 13 - Arizona Energy profile for 2009 and goal profiles for 2025 and 2050

California

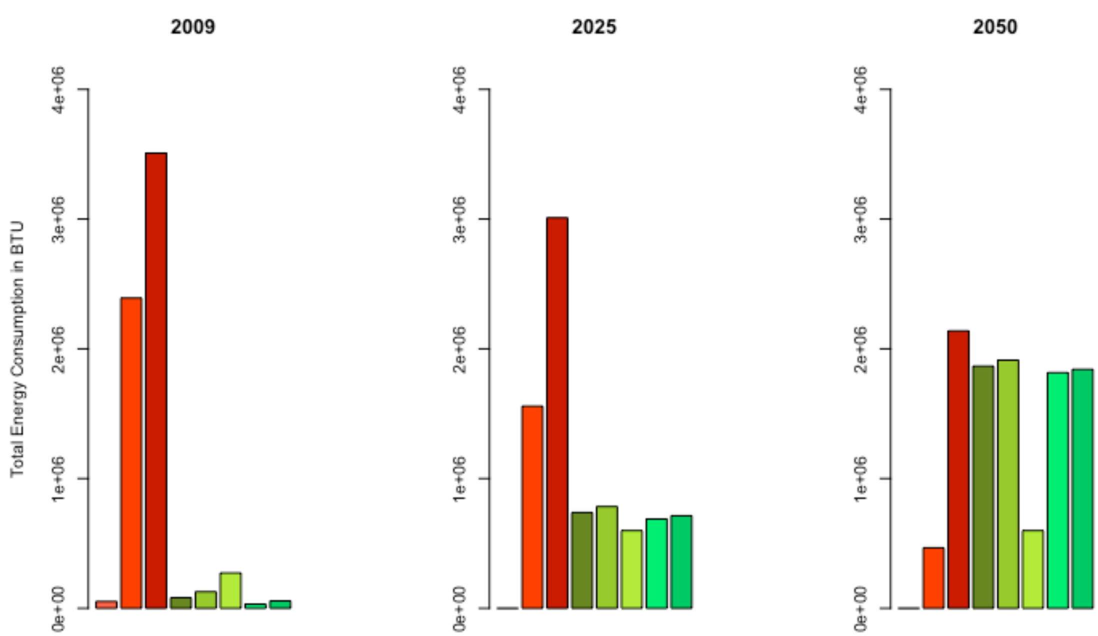

Figure 14 - California Energy profile for 2009 and goal profiles for 2025 and 2050

New Mexico

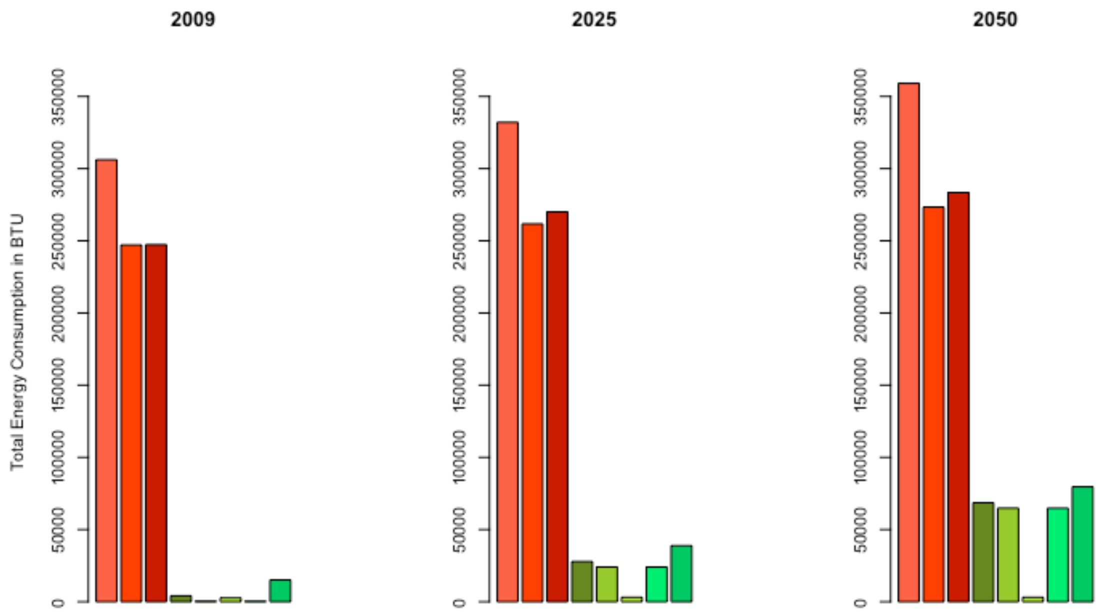

Figure 15 - New Mexico Energy profile for 2009 and goal profiles for 2025 and 2050

Texas

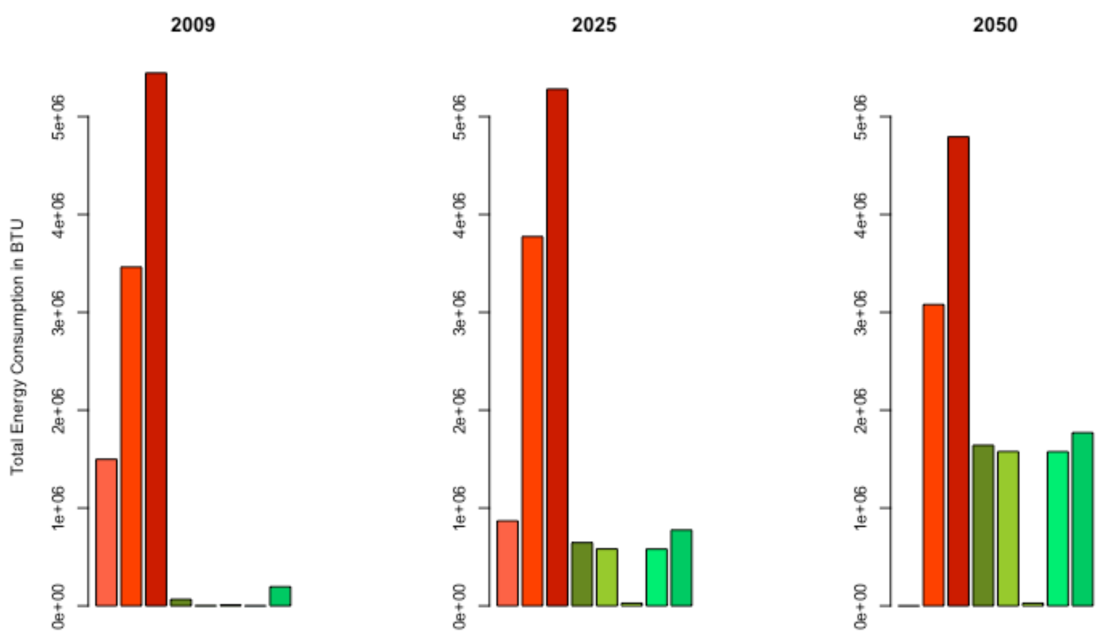

Figure 16 - Texas Energy profile for 2009 and goal profiles for 2025 and 2050

B. Necessary Actions to Meet Energy Goals

State governments and utilities must act now if they want to be on track to meet these goals by 2025. We suggest four concrete actions that they might take in order to achieve these targets.

1. Invest in the renewable energy workforce. As the energy economy is disrupted by rapid change, incoming and current employees of state utility companies will need training in order to work with renewable energy technologies. Create programs within the state technical college systems to train new job seekers and those who may lose their jobs in

the non-renewable energy field. For example, there are already 22 Wind Energy Education and Training Programs in these four states[8]. These programs and programs like them will need to expand if these goals are to be met.

2. Identify the optimal locations for clean energy technology generation and concentrate building efforts there. For example, locations vary in average daily total solar resource. This resource varies by region and is particularly highly concentrated in the American Southwest, but varies even at the zip code level. [9] States can maximize their clean energy generation by building solar, wind, and geothermal farms in the most optimal locations, making it easier to achieve the goals.
3. Set higher energy efficiency standards for building codes and motor vehicles. If less energy is required by the end consumer, utilities will have to generate less energy, and that reduction can come from non-renewable sources. The four states in the new energy compact each have Energy Efficiency Resource Standards (EERS) that "[establish] specific, long-term targets for energy savings that utilities or non-utility program administrators must meet through customer energy efficiency programs."[10] Of the states under consideration, Arizona has the strictest goals, followed by California, then New Mexico, then Texas. If each of these states were to increase their EERS to match those of Arizona, they might find it easier to reach their goals.
4. Invest in collection and analysis of energy data. Every goal and policy change requires analysis of data to back up the decision. Throughout this project, we have imagined different models that could be built if only we had more data to analyze. Ideally, the compact would create a centralized, publicly available database with data on climate patterns, energy production, energy consumption, energy cost, population statistics, and economic indicators. The data granularity needs to be as deep as the zip code and hour (instead of state and year). This could lead to fascinating and actionable insights.

References

1. *State Energy Data System 2015 Consumption Technical Notes*[PDF]. U.S. Energy Information Administration.
2. Hastie, T. J., Tibshirani, R. J., & Friedman, J. H. (n.d.). *The elements of statistical learning: data mining, inference, and prediction*.
3. Rahutomo, F., Kitasuka, T., & Aritsugi, M. (2012). Semantic Cosine Similarity. In *The 7th International Student Conference on Advanced Science and Technology ICAST*.
4. Garniwa, I. (2017, March). Principal Component Analysis and Cluster Analysis in Profile of Electrical System. In *IOP Conference Series: Materials Science and Engineering* (Vol. 180, No. 1, p. 012103). IOP Publishing.
5. Young, J. (11-4-2017). Linear Models Lecture.
6. National Energy Policy Act of 1988 and Global Warming. (n.d.). Retrieved February 12, 2018, from http://web.mit.edu/12.000/www/m2006/teams/wingheit/Text_1021.html
7. Renewable energy. [electronic resource] : complementary policies for climate legislation : hearing before the Subcommittee on Energy and Environment of the Committee on Energy and Commerce, House of Representatives, one Hundred Eleventh Congress, first session, February 26, 2009. (2011). Washington : U.S. G.P.O., 2011.
8. Wind Energy Education and Training Programs. (n.d.). Retrieved February 12, 2018, from https://windexchange.energy.gov/training-programs
9. Solar Maps. (n.d.). Retrieved February 12, 2018, from https://www.nrel.gov/gis/solar.html
10. Energy Efficiency Resource Standard (EERS). (2017, January 09). Retrieved February 12, 2018, from https://aceee.org/topics/energy-efficiency-resource-standard-eers

Appendix A: Ridge Model Coefficients

Arizona

```
(Intercept)  6.206154e-01
Year        -2.523483e-04
TPOPP       -4.777742e-06
GDPRX       -1.142379e-07
TETGR        3.975616e-04
ESTCD        3.306939e-04
```

California

```
(Intercept) -2.226363e-01
Year         1.456848e-04
TPOPP        3.073037e-07
GDPRX        1.813956e-09
TETGR        1.052063e-04
ESTCD        1.623873e-04
```

New Mexico

```
(Intercept) -1.382466e-01
Year         6.938737e-05
TPOPP        2.981882e-06
GDPRX        4.070445e-08
TETGR       -4.928554e-05
ESTCD        5.148580e-05
```

Texas

```
Year         2.689914e-05
TPOPP        1.106658e-07
GDPRX        1.115023e-09
TETGR       -4.062872e-05
ESTCD        5.408549e-05
```