Prediction of the immigrant location choices under the lack of sufficient water for the entire U.S.

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Abstract

We are living in a critical part of time that human beings are threatened by the environment. Under the critical situations, humans either decide to stay, resist and adapt to the new environment or decide to move to another location where there is a better situation. If they decide to immigrant to the new location, the possible destinations can be predicted using of assessing the two groups of factors including pushing factors and polling factors. For example, the existence of sufficient water is a pulling factor and consequently the lack of that is a pushing factor. Therefore it is important to find a way for quantifying and for examining our environment based on these factors. This study assesses the trend of water storage changes for each state using the GRACE satellite data during 2004-2016 and provides a prediction of the location choices for people who will be faced with the lack of sufficient water and decided to migrate from their state to another state. Because the decision of people would depend on other pushing and pulling factors such as cost of living, education level and etc., we employed a multi-criteria decision-making techniques called TOPSIS and defined three different scenarios based the weight of water value (25%, 50%, and 75%) in this decision. Results indicates that States of Alaska, Texas, California, Arizona, New Mexico, Oklahoma, Utah, Nevada, Louisiana, Colorado, Arkansas, Mississippi, Kansa, and Alabama have the negative slope in terms of water storage changes and if this situation continues there is a migration wave from these States to other States. Moreover, the most possible destination for people who are living in these States are estimated using the TOPSIS model.

Introduction

Nowadays, in the blue planet, sometimes humans forced to move from current locations to another for a short or long time. According to the recent studies, people would decide to migrate for many different reasons. These reasons can be classified into four categories. The first reason is originated from the economic situation. For example, some people may decide to migrate because there is no proper job in their living space. They may migrate to find a job, earn money and provide the necessary needs for their family. The second is related to the social migration. These people are seeking to enjoy a high-quality of education, high-quality of services in their environment. Generally, they are moving to have a better quality of life. The third category is because of political migration. For example, some people may migrate for escaping the war. When war happens, because of unexpected consequences, one of the most important issue is to move to the safe place. And finally, the fourth category is migration because of the environmental situation. Such as moving to escape drought, to access to fresh water and to find foods.

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To sum up, we can conclude that the final destination of immigrants depends on the push factors and pull factors. Push factors are the factors that force people to move from their location such as war, high rate of unemployment, famine or natural disasters and pull factors are the interesting factors that make a place attractive for immigrants such as safety, job opportunity, better health care and high quality of education. Therefore, if we evaluate and quantify the potential of possible destination locations based on these factors, we can predict the final destination for immigrants.

One of the most important factors that have a high value in a decision of immigrants who are suffering from famine, drought, lack of food or even the high rate of unemployment is originated from "the availability of water". As our water resources includes saltwater (97%) and fresh water (3%) whose 68.7% is ice and permanent snow, 31% is groundwater and 0.3% is lakes and rivers, the population growth from 1.65 billion to 6 billion during the 20^{th} century, and also affecting the climate change and global warming, we can expect that the crisis of lack of sufficient water will happen in future. Dow et al. (2005) tried to find the connection between water shortage and population movement. Black et al., (2011) conducted a research on the effect of climate change on migration pattern. Selby (2012) characterized the relations between water shortage and migration pattern. Therefore, water shortage will be a critical issue and may a good reason for people to change their location.

The main object of this study is to answer these question: (1) which state will be faced with water shortage? (2) Which state would be the destination of people who want to change their location because of water shortage? What would be the rate of decreasing water storage and increasing water storage for each state? For answering these questions, the monthly water usage for each state is extracted using the water equivalent anomaly (WEA) products of Gravity Recovery and Climate Experiment (GRACE) satellite for a 12 year period (2004-2016). Afterward, the times series of this dataset and the trend line for each of them is drawn. The slope of the trend line is considered as the current situation of water storage changes corresponding to each state. Therefore, if a state has a negative value in the trend line of time series, it is expected that the people who are living in this State will be faced with the lack of sufficient water and some of them will force to immigrate assuming that these trends continue. In contrast, if a State has a positive value, it can be a possible destination for people who are suffering from the lack of sufficient water. However, because choosing the destination, inherently, is a multi-criteria problem and it is needed to consider other factors, the technique for an order of preference by similarity to ideal solution (TOPSIS) is used as multi-criteria decision-making technique to determine and rank the possible destinations under three scenarios. These scenarios are defined based on the importance of water storage changes weights in choosing the destination (25%, 50%, and 75%). It should be noted that, in this study, immigrants are the US people who will decide to move from their State to another because of lack of water availability and the scale of moving State to State not city to city or country to country.

Methodology

In this section, a brief description of the source of data used in this study, the concept of TOPSIS, and the process of extraction of the current situation of water storage changes for each State are discussed.

Data sources

In this study, for extracting the time series of water storage changes corresponding to each State, the WEA products produced using the measurements of GRACE satellite is used. As it is mentioned before, choosing the final destination under the lack of sufficient water may depend on other factors such as employment rate and safety. Therefore, the current situation of each State in terms of these factors are extracted from a reliable report of CNBC called "America's Top States for Business" that have been yearly released from 2007 to 2016.

GRACE

GRACE is a twin satellite launched in March 2002 with a five-year lifespan. The measurements of this satellite will result in obtaining precise measurements of changing in gravity over the surface of Earth. Although the products of this satellite are coarse-resolution, the accuracy of them is acceptable and helps researchers have better interpret of natural processes. One of the most important products of this satellite is WEA. The logic of producing this product is related to the water movement. In other words, GRACE can measures the gravity changes and gravity changes is related to mass changes. Also, the main portion of mass changes has resulted from water movement or water depletion. As a result, GRACE can provide a product that shows the water storage changes in time and in space. Therefore, by measuring gravity anomalies, GRACE satellite is able to produce a product called WEA and shows how water is distributed and how it changes over time.

America's Top States for Business

"America's Top States for Business" report is a reliable that has been presented for each year from 2007-2016. Not only does this report rely on opinion survey, but also it depends upon 40- 60 factors that its data is publicly available. These factors are combined to 10 groups and all 50 State are scored based on the points that each State received. These 10 groups are the cost of business, workforce, quality of life, economy transportation and technology, education, Business friendly, Access to capital, and cost of living. More information about the methodology and public database used in presenting "America's Top States for Business" report can be found in http://www.cnbc.com/2015/05/27/americas-top-states-for-business-2015-our-methodology.html

TOPSIS

When there are several options that each of them has several features, choosing the best option or ranking them is not easy as it seems. These problems are classified into a Multiple Criteria Decision Making (MCDM) problems and there are unique methods for solving them. TOPSIS as one of this technique proposed by Hwang et al. (1995) has the capability of ranking the possible alternatives based on their attributes. In this study, the alternatives are the name of State and the attributes are the features of State such as water availability, employment, and crime rate (pushing and pulling factors). The concept of TOPSIS is based on ranking the alternatives using the calculation of Euclidian distance from each alternative to the positive ideal solution. Therefore, TOPSIS ranks the possible alternatives based on this distance. The first step of the TOPSIS method is the construction of a decision matrix. In this matrix, each row is related to the each possible alternatives and each column are related to each attribute. Therefore, the size of the decision matrix is equal to the number of alternatives x the number of attributes. In the second step, the normalized decision matrix is generated. Each member of this matrix is calculated using the Eq. (1).

$$\boldsymbol{R_{ij}} = \frac{\boldsymbol{x_{ij}}}{\sqrt{\sum_{i=1}^{m} \boldsymbol{x_{ij}}^2}} \tag{1}$$

in which, the i and j stand for attributes index and alternative index, respectively. $\boldsymbol{R_{ij}}$ stands for the member ith (row) and jth (column) in the normalized decision matrix and $\boldsymbol{x_{ij}}$ is the member ith (row) and jth (column) in the decision matrix. In the third step, the importance of each attribute is determined as the weighted value (W_j) such that the summation of them is equal to 100. In the fourth step, the weighting decision matrix is calculated using the Eq. (2)

$$\boldsymbol{V_{ij}} = \boldsymbol{W_j} \times \boldsymbol{R_{ij}} \tag{2}$$

$\boldsymbol{V_{ij}}$ stands for the member ith (row) and jth (column) in the weighting decision matrix.

In the fifth step, the best ($\boldsymbol{V_j^+}$) and worst ($\boldsymbol{V_j^-}$) alternatives in terms of each attribute are chosen. In the next step, the Euclidian distance between each member of the weighting decision matrix and the best alternatives and the worst alternatives are calculated using the Eq. (3, 4)

$$\boldsymbol{D_i^+} = \sqrt{\sum_{j=1}^{n} (\boldsymbol{V_j^+} - \boldsymbol{V_{ij}})^2} \tag{3}$$

$$\boldsymbol{D_i^-} = \sqrt{\sum_{j=1}^{n} (\boldsymbol{V_j^-} - \boldsymbol{V_{ij}})^2} \tag{4}$$

In the final step, the closeness ratio is computed using the Eq. (5)

$$\boldsymbol{C_i} = \frac{\boldsymbol{D_i^-}}{\boldsymbol{D_i^-} + \boldsymbol{D_i^+}} \tag{5}$$

According to the values of $\boldsymbol{C_i}$, the alternatives are sorted from the highest value to lowest value. Therefore, the alternative that has the highest value is a most desirable alternative.

Main Process:

The first main part of the process of the methodology has been shown in Fig 1.

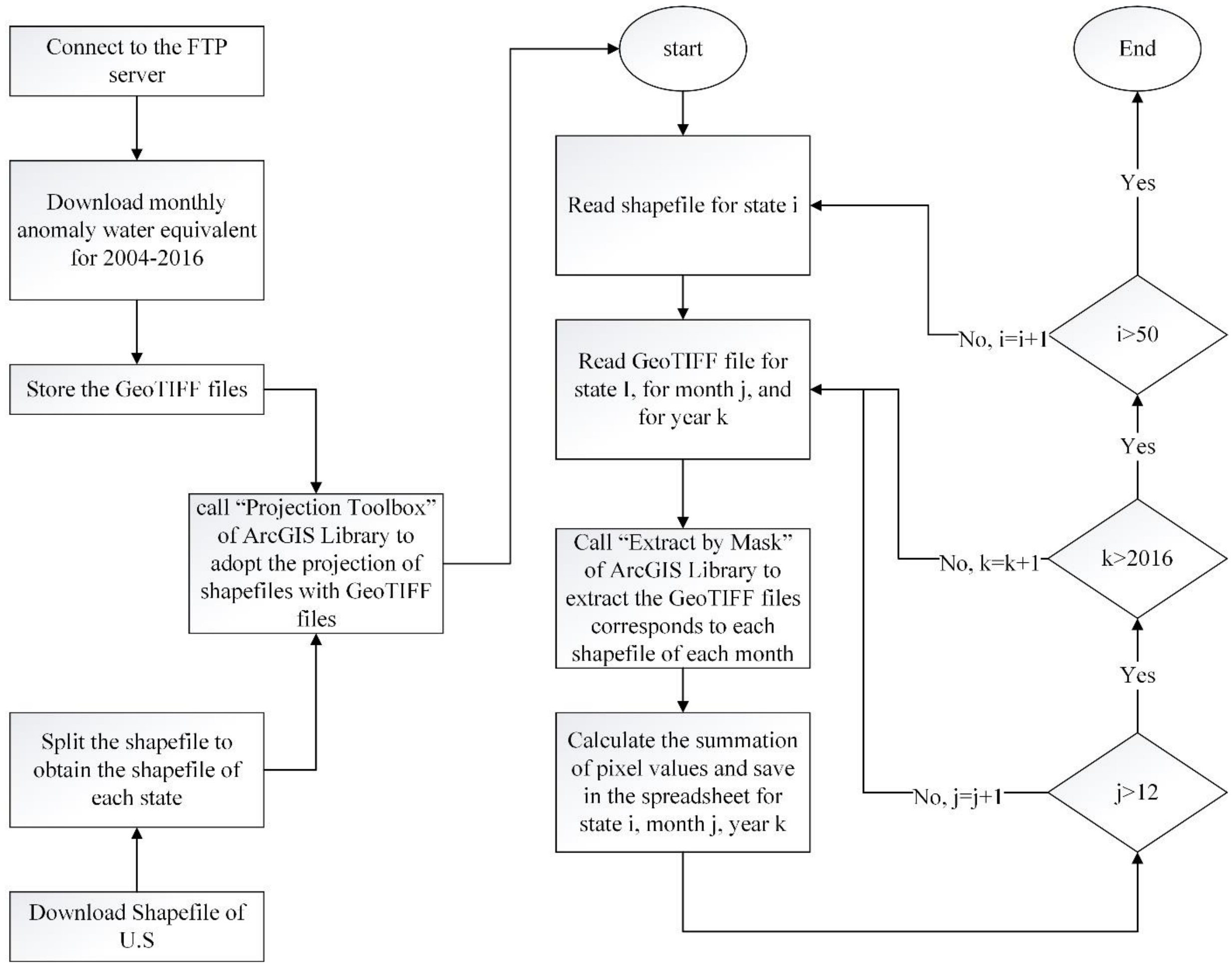


Fig 1. The first part of main process

As it is shown in Fig 1, the first step is to obtain the monthly data of total water storage changes ($\Delta W_{\text{storage}}$) and store them for each State during 2004-2016. In this research, WEA product of GRACE satellite is used as estimations of water storage. Therefore, this dataset is obtained by connecting to the FTP data server and stored in a specific directory. In the second step, the shapefiles of the United States are downloaded and split to shapefiles corresponding to each State. In the third step, the projection of GeoTIFF files and shapefiles are matched using the "Define Projection toolbox" called in the Python Programming. Afterward, all GeoTIFF files downloaded from FTP server and matched their projection with the shapefiles are clipped using "extract by mask toolbox" of ArcGIS Pro GIS, regarding each State shapefile. Finally, the summation pixels values located in each State's shapefile are stored in a spreadsheet format and time series of water storage, their trend lines and the slope values of each trend line is drawn, is calculated and stored in an excel format. As it is mentioned before, the slope values of the trend line of these time series, measure how much the value of water storage changes in each year and show the situation of each State in terms of water availability rate. In this step, States are classified into two groups. One group includes States that have Negative Slopes (SNS) and another includes States that have Positive Slopes (SPS). Assuming these trends continues, we expected that there is gradually immigrant wave from SNS to SPS. However, more detailed information of these movements is needed. In other words, which SPS is the most possible destinations for the people who are living in the SNS? These details are provided by TOPSIS model. Therefore, after calculating slopes and storing them in spreadsheet file, it turns to the second main part of the process shown in Fig 2.

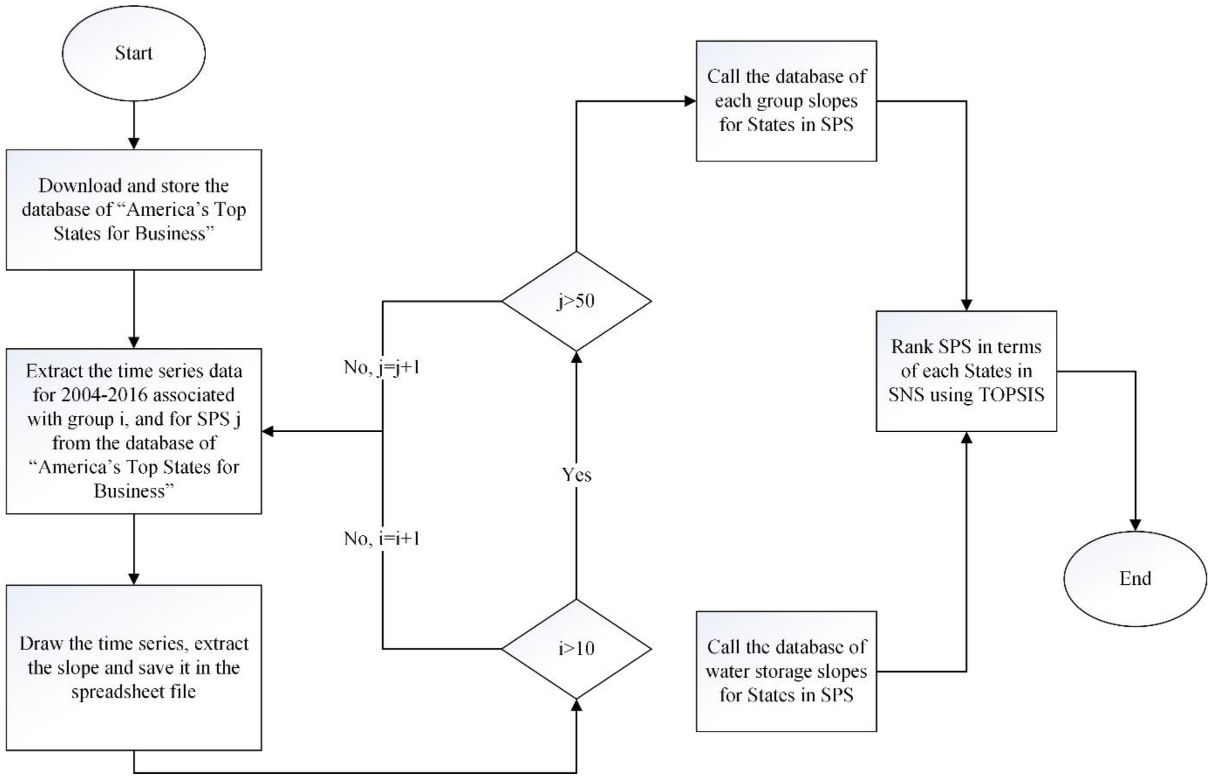


Fig 2. The second part of main process

As it is shown in Fig 2, in the second main part, the database is downloaded for each year (2004-2016) and the time series of each group mentioned in the methodology part for each of States categorized in the SPS category is extracted. Afterwards, the slope of each time series is calculated and stored in the spreadsheet file. After doing the same procedure for all groups and all SPS and constructing the database, it turns to run the TOPSIS model. To execute the TOPSIS both database, slopes of time series for each ranking groups and the slopes of water storage, are required. However, because the amount of difference between the slopes of states in SPS and a state in SNS should be considered in the decision matrix of TOPSIS, each member of decision matrix is replaced by the ratio values using Eq. (6).

$$x'_{ij} = \frac{y_{ij} - x_{ij}}{abs(x_{ij})} \quad (6)$$

in which y_{ij} stands for the slope of each attributes of SPS alternatives.

As mentioned in the TOPSIS segment, in executing TOPSIS, the decision matrix, the normalized decision matrix, and the weighting decision matrix are constructed, respectively. The alternatives are the names of States and the attributes are the (slope values as the water storage situation, other factors calculated by CNBC). It should be noted that the weights in the weighting decision matrix, are considered based on three deferent scenarios. These scenarios are defined based on the different importance of water changes rate (weighting values = 25%, 50% and 75%). The weighting values for other factors are equal to [1- water weighting values]/10. Then, the Euclidian distance for each member of the weighting decision matrix from the best State and the worst State are calculated. After executing the TOPSIS model and computing the closeness ratio, a sorted list of SPS in terms of each State in SNS is provided. Therefore, we can estimate which SPS can be most possible immigrant choices in terms of each State in SNS category. In other words, we can predict the immigrant location choices for people who live in a specific State that will be faced with the lack of water.

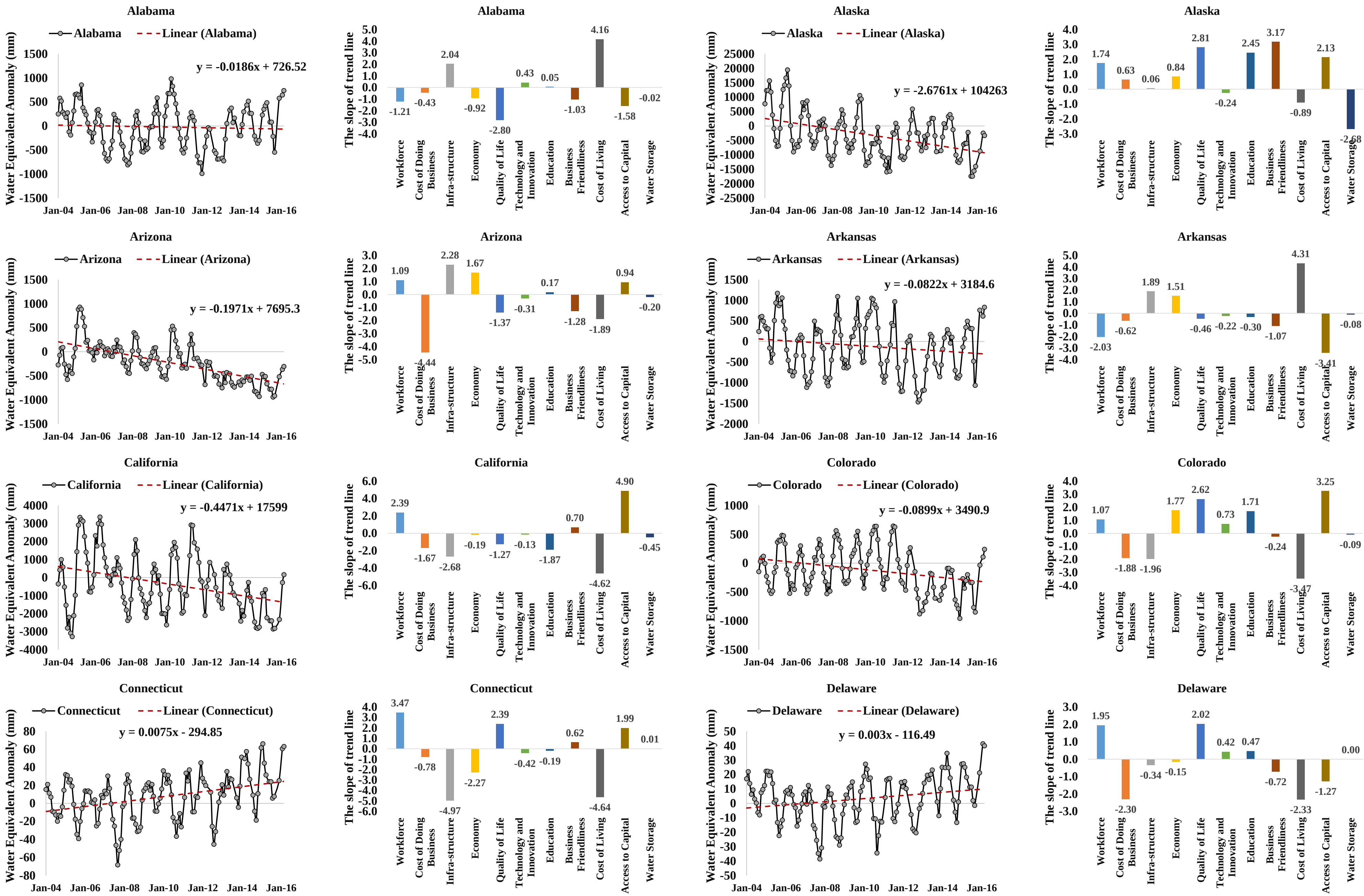
It is worth to mention that the main reason for using Python programing is that there were a numerous GeoTIFF files (144 for 12 years) and downloading these numbers of data cannot be manually possible. Moreover, these GeoTIFF files should be clipped for each State and stored as a time series for each State. Therefore, an automated procedure to avoid repetition is employed using Python environment.

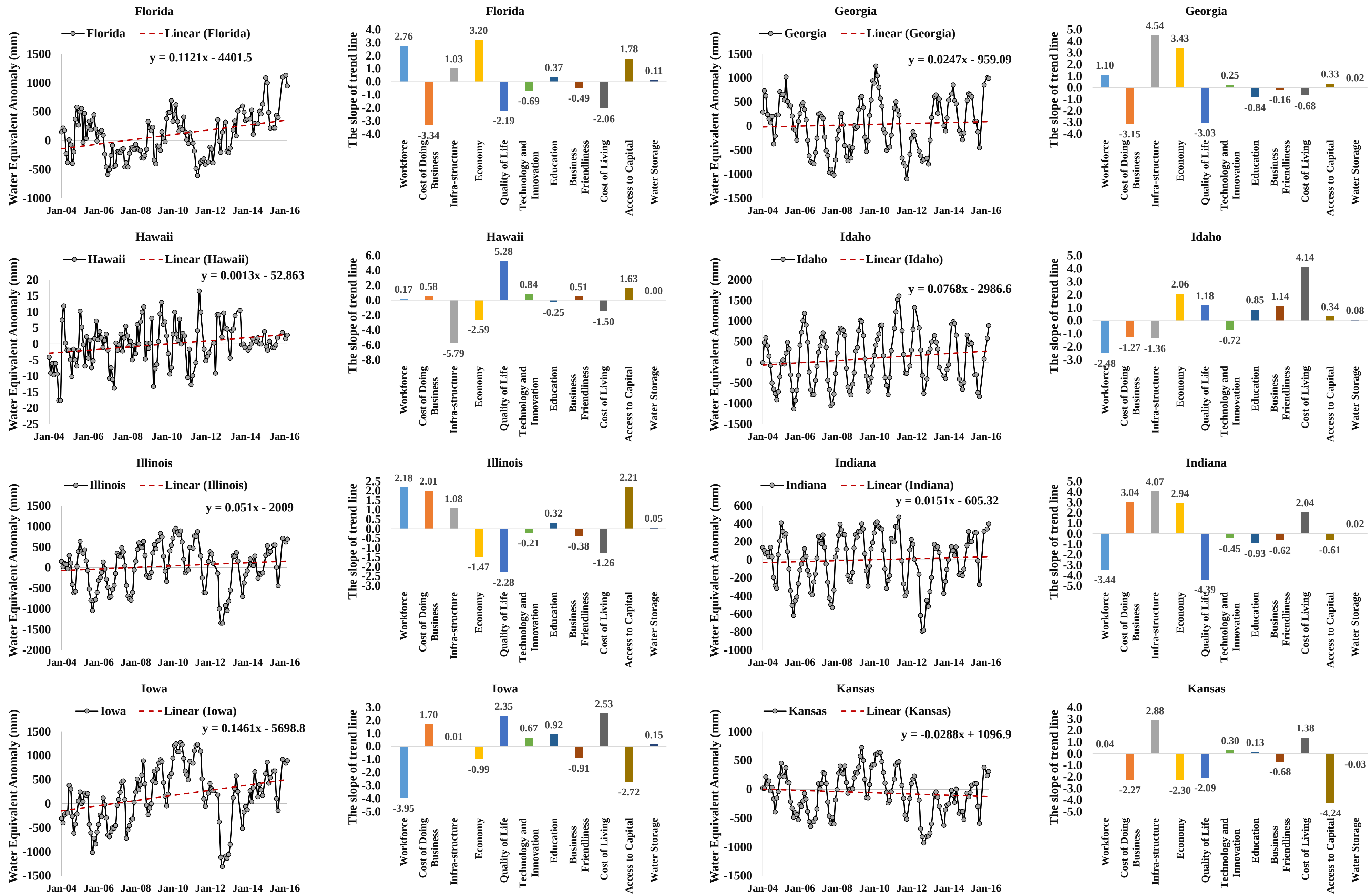
Case study

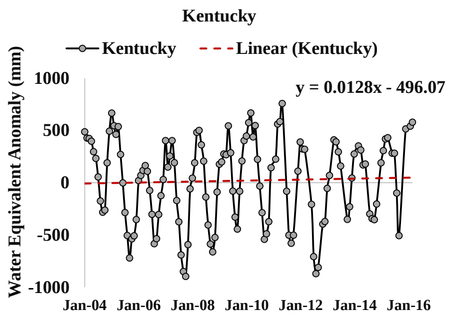
As it is discussed before, in this study, all 50 States are considered as the case studies for the period of 2004-2016.

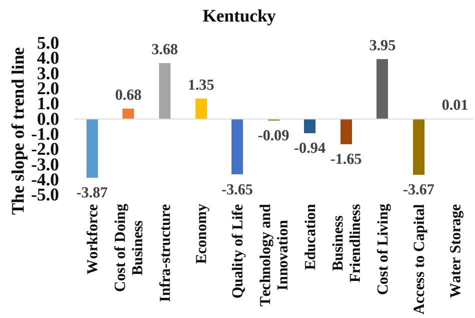
Results

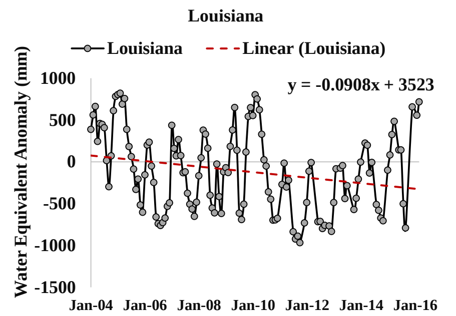
The time series of WEA for each State for 2004-2016 with the trend lines and also the slope of trend lines for 11 factors (10 for overall scoring of CNBC for 2007-2016 and one for WEA) are shown in Fig 3 using the scatter plot and bar plot, respectively.

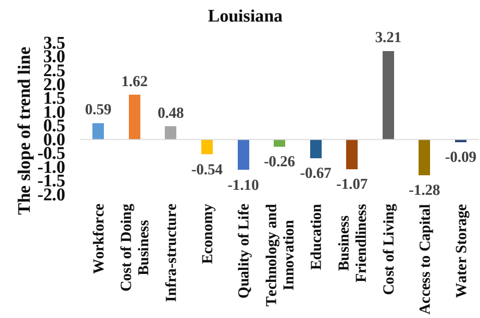

Alabama
Alabama
Linear (Alabama)
y = -0.0186x + 726.52
Water Equivalent Anomaly (mm)
Alabama
The slope of trend line
-1.21 -0.43 2.04 -0.92 -2.80 0.43 0.05 -1.03 4.16 -1.58 -0.02
Workforce
Cost of Doing Business
Infra-structure
Economy
Quality of Life
Technology and Innovation
Education
Business Friendliness
Cost of Living
Access to Capital
Water Storage
Alaska
Alaska
Linear (Alaska)
y = -2.6761x + 104263
Alaska
1.74 0.63 0.06 0.84 2.81 -0.24 2.45 3.17 -0.89 2.13 -2.68
Arizona
Arizona
Linear (Arizona)
y = -0.1971x + 7695.3
Arizona
1.09 -4.44 2.28 1.67 -1.37 -0.31 0.17 -1.28 -1.89 0.94 -0.20
Arkansas
Arkansas
Linear (Arkansas)
y = -0.0822x + 3184.6
Arkansas
-2.03 -0.62 1.89 1.51 -0.46 -0.22 -0.30 -1.07 4.31 -3.41 -0.08
California
California
Linear (California)
y = -0.4471x + 17599
California
2.39 -1.67 -2.68 -0.19 -1.27 -0.13 -1.87 0.70 -4.62 4.90 -0.45
Colorado
Colorado
Linear (Colorado)
y = -0.0899x + 3490.9
Colorado
1.07 -1.88 -1.96 1.77 2.62 0.73 1.71 -0.24 -3.47 3.25 -0.09
Connecticut
Connecticut
Linear (Connecticut)
y = 0.0075x - 294.85
Connecticut
3.47 -0.78 -4.97 -2.27 2.39 -0.42 -0.19 0.62 -4.64 1.99 0.01
Delaware
Delaware
Linear (Delaware)
y = 0.003x - 116.49
Delaware
1.95 -2.30 -0.34 -0.15 2.02 0.42 0.47 -0.72 -2.33 -1.27 0.00
Jan-04 Jan-06 Jan-08 Jan-10 Jan-12 Jan-14 Jan-16

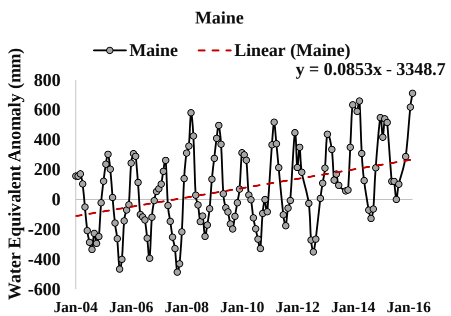

Florida
Florida
Linear (Florida)
y = 0.1121x - 4401.5
Water Equivalent Anomaly (mm)
Jan-04 Jan-06 Jan-08 Jan-10 Jan-12 Jan-14 Jan-16
Florida
The slope of trend line
2.76 -3.34 1.03 3.20 -2.19 -0.69 0.37 -0.49 -2.06 1.78 0.11
Workforce
Cost of Doing Business
Infra-structure
Economy
Quality of Life
Technology and Innovation
Education
Business Friendliness
Cost of Living
Access to Capital
Water Storage
Georgia
Georgia
Linear (Georgia)
y = 0.0247x - 959.09
Georgia
1.10 -3.15 4.54 3.43 -3.03 0.25 -0.84 -0.16 -0.68 0.33 0.02
Hawaii
Hawaii
Linear (Hawaii)
y = 0.0013x - 52.863
Hawaii
0.17 0.58 -5.79 -2.59 5.28 0.84 -0.25 0.51 -1.50 1.63 0.00
Idaho
Idaho
Linear (Idaho)
y = 0.0768x - 2986.6
Idaho
-2.48 -1.27 -1.36 2.06 1.18 -0.72 0.85 1.14 4.14 0.34 0.08
Illinois
Illinois
Linear (Illinois)
y = 0.051x - 2009
Illinois
2.18 2.01 1.08 -1.47 -2.28 -0.21 0.32 -0.38 -1.26 2.21 0.05
Indiana
Indiana
Linear (Indiana)
y = 0.0151x - 605.32
Indiana
-3.44 3.04 4.07 2.94 -4.39 -0.45 -0.93 -0.62 2.04 -0.61 0.02
Iowa
Iowa
Linear (Iowa)
y = 0.1461x - 5698.8
Iowa
-3.95 1.70 0.01 -0.99 2.35 0.67 0.92 -0.91 2.53 -2.72 0.15
Kansas
Kansas
Linear (Kansas)
y = -0.0288x + 1096.9
Kansas
0.04 -2.27 2.88 -2.30 -2.09 0.30 0.13 -0.68 1.38 -4.24 -0.03

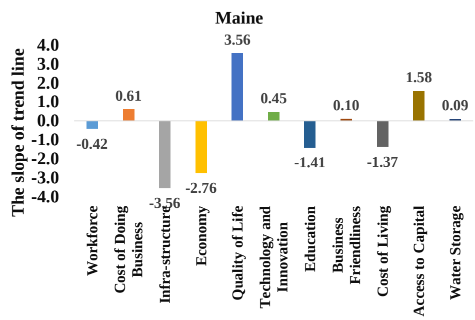

Kentucky
Kentucky
Linear (Kentucky)
y = 0.0128x - 496.07
Water Equivalent Anomaly (mm)

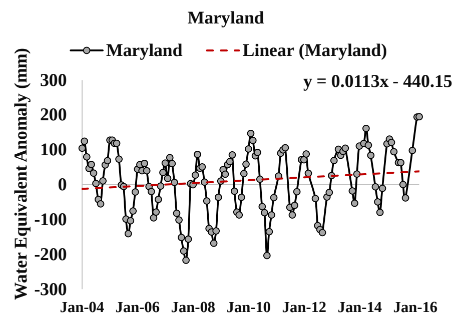

Kentucky
The slope of trend line
-3.87
0.68
3.68
1.35
-3.65
-0.09
-0.94
-1.65
3.95
-3.67
0.01
Workforce
Cost of Doing Business
Infra-structure
Economy
Quality of Life
Technology and Innovation
Education
Business Friendliness
Cost of Living
Access to Capital
Water Storage

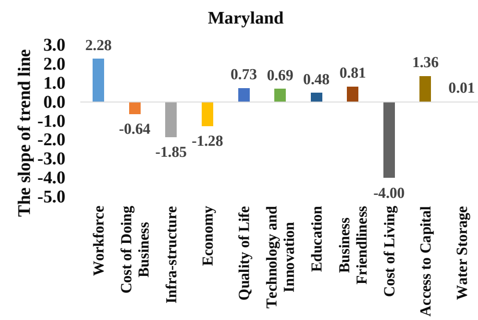

Louisiana
Louisiana
Linear (Louisiana)
y = -0.0908x + 3523
Water Equivalent Anomaly (mm)

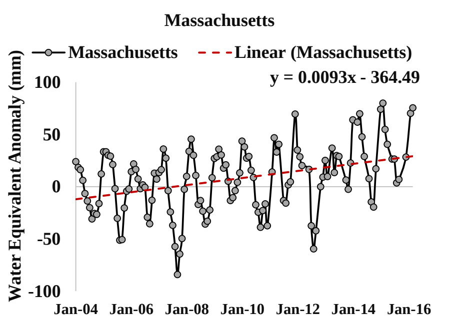

Louisiana
The slope of trend line
0.59
1.62
0.48
-0.54
-1.10
-0.26
-0.67
-1.07
3.21
-1.28
-0.09
Workforce
Cost of Doing Business
Infra-structure
Economy
Quality of Life
Technology and Innovation
Education
Business Friendliness
Cost of Living
Access to Capital
Water Storage

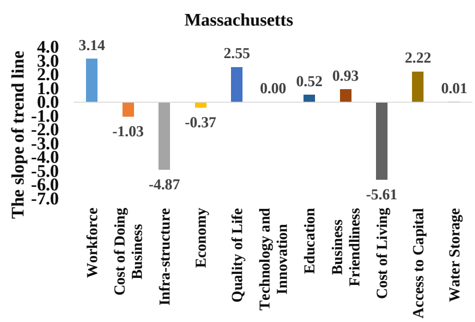

Maine
Maine
Linear (Maine)
y = 0.0853x - 3348.7
Water Equivalent Anomaly (mm)

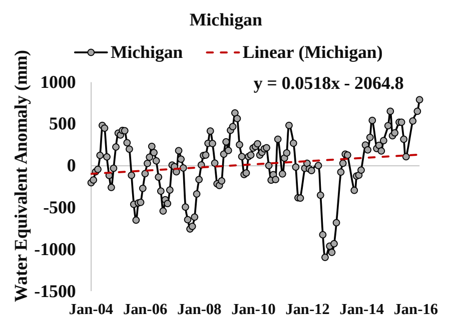

Maine
The slope of trend line
-0.42
0.61
-3.56
-2.76
3.56
0.45
-1.41
0.10
-1.37
1.58
0.09
Workforce
Cost of Doing Business
Infra-structure
Economy
Quality of Life
Technology and Innovation
Education
Business Friendliness
Cost of Living
Access to Capital
Water Storage

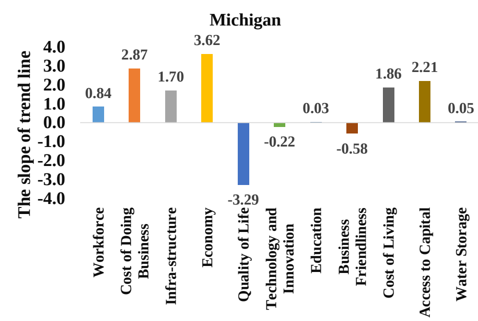

Maryland
Maryland
Linear (Maryland)
y = 0.0113x - 440.15
Water Equivalent Anomaly (mm)

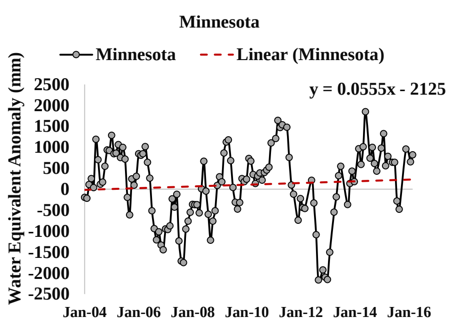

Maryland
The slope of trend line
2.28
-0.64
-1.85
-1.28
0.73
0.69
0.48
0.81
-4.00
1.36
0.01
Workforce
Cost of Doing Business
Infra-structure
Economy
Quality of Life
Technology and Innovation
Education
Business Friendliness
Cost of Living
Access to Capital
Water Storage

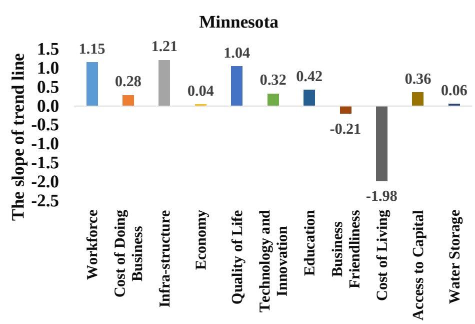

Massachusetts
Massachusetts
Linear (Massachusetts)
y = 0.0093x - 364.49
Water Equivalent Anomaly (mm)

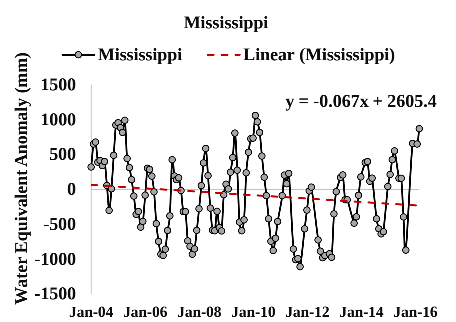

Massachusetts
The slope of trend line
3.14
-1.03
-4.87
-0.37
2.55
0.00
0.52
0.93
-5.61
2.22
0.01
Workforce
Cost of Doing Business
Infra-structure
Economy
Quality of Life
Technology and Innovation
Education
Business Friendliness
Cost of Living
Access to Capital
Water Storage

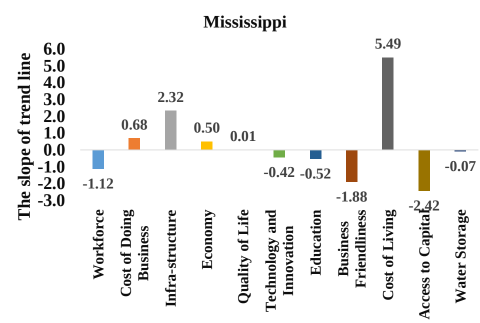

Michigan
Michigan
Linear (Michigan)
y = 0.0518x - 2064.8
Water Equivalent Anomaly (mm)

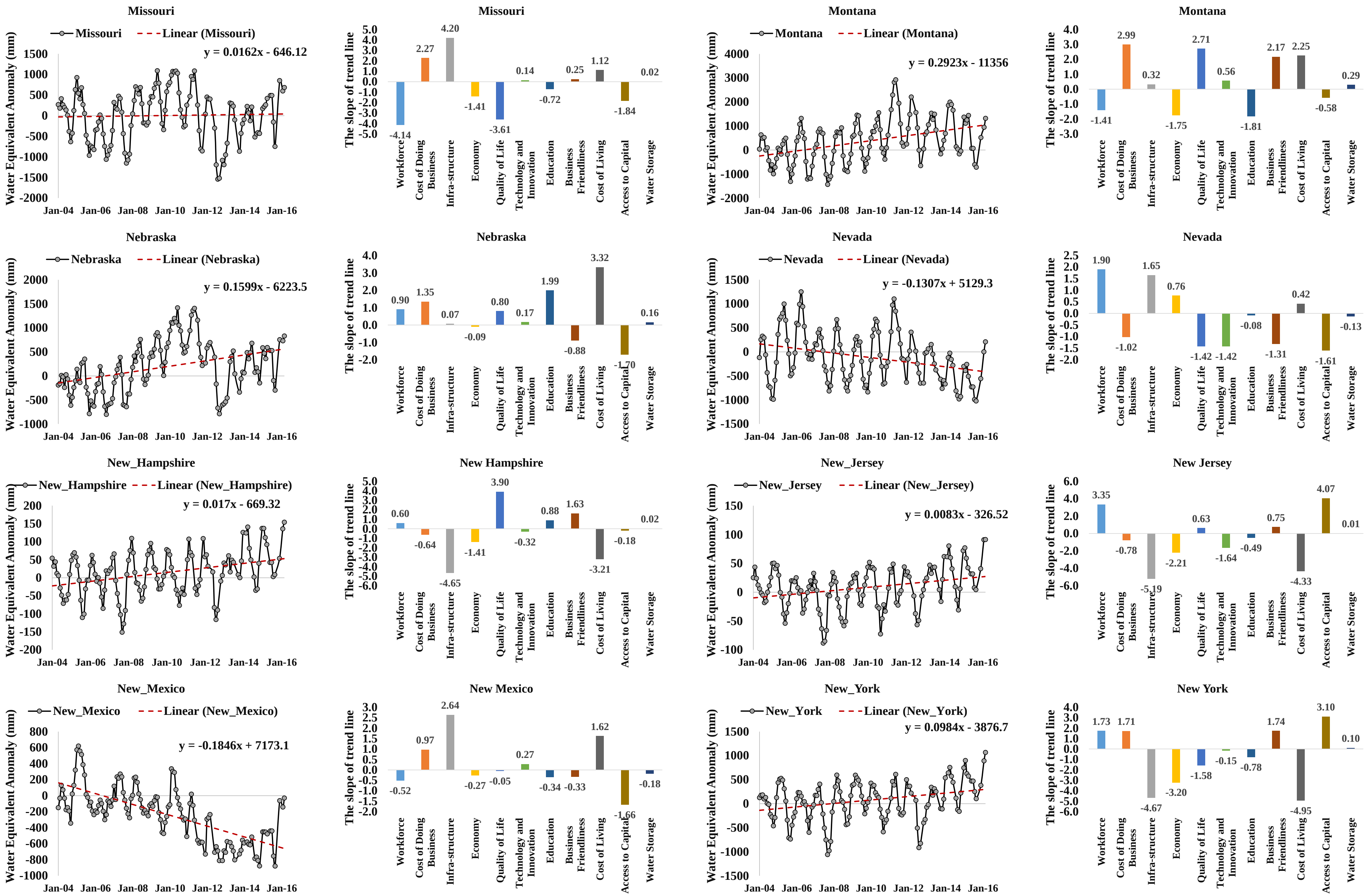

Michigan
The slope of trend line
0.84
2.87
1.70
3.62
-3.29
-0.22
0.03
-0.58
1.86
2.21
0.05
Workforce
Cost of Doing Business
Infra-structure
Economy
Quality of Life
Technology and Innovation
Education
Business Friendliness
Cost of Living
Access to Capital
Water Storage

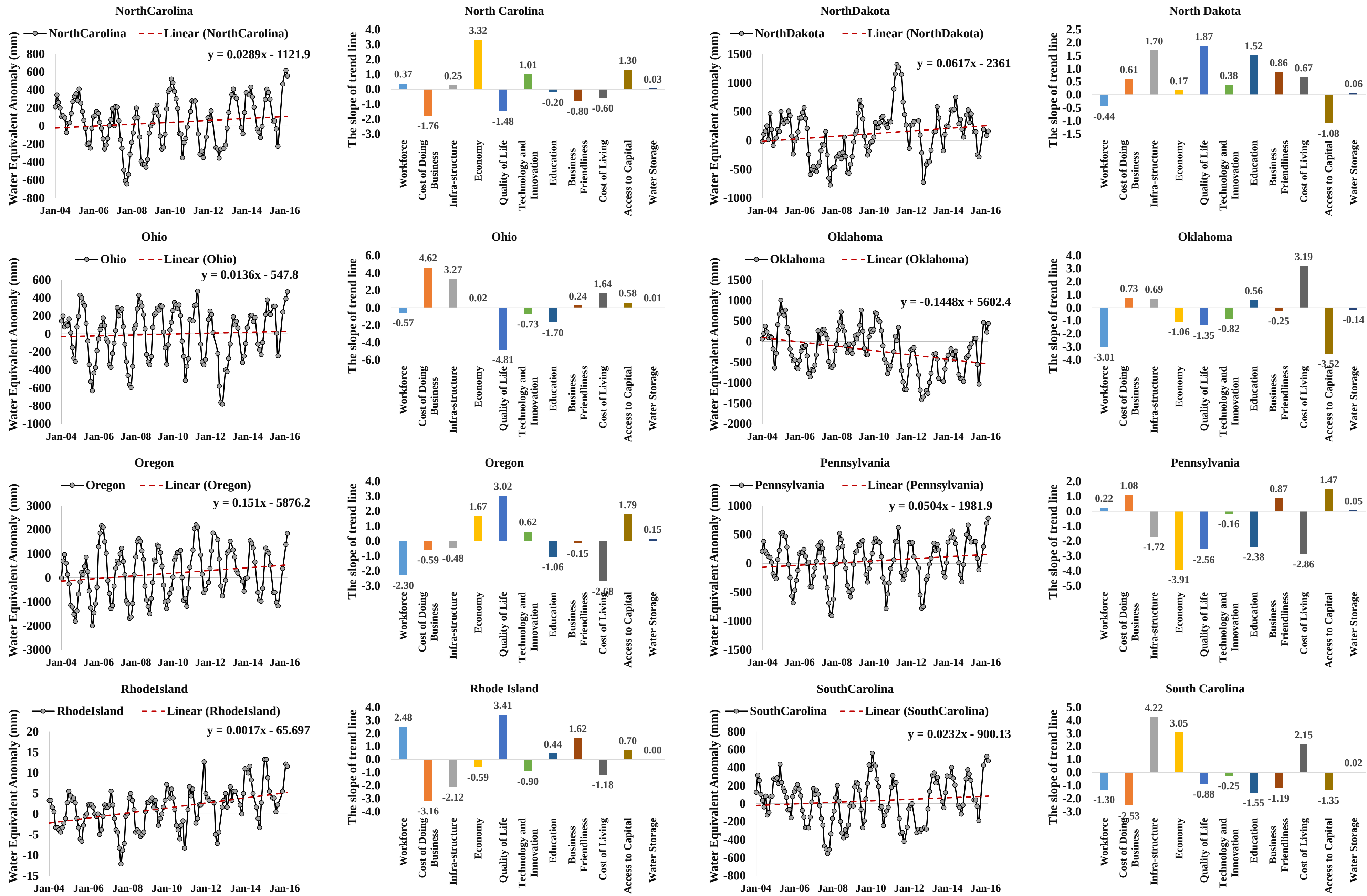

Minnesota
Minnesota
Linear (Minnesota)
y = 0.0555x - 2125
Water Equivalent Anomaly (mm)

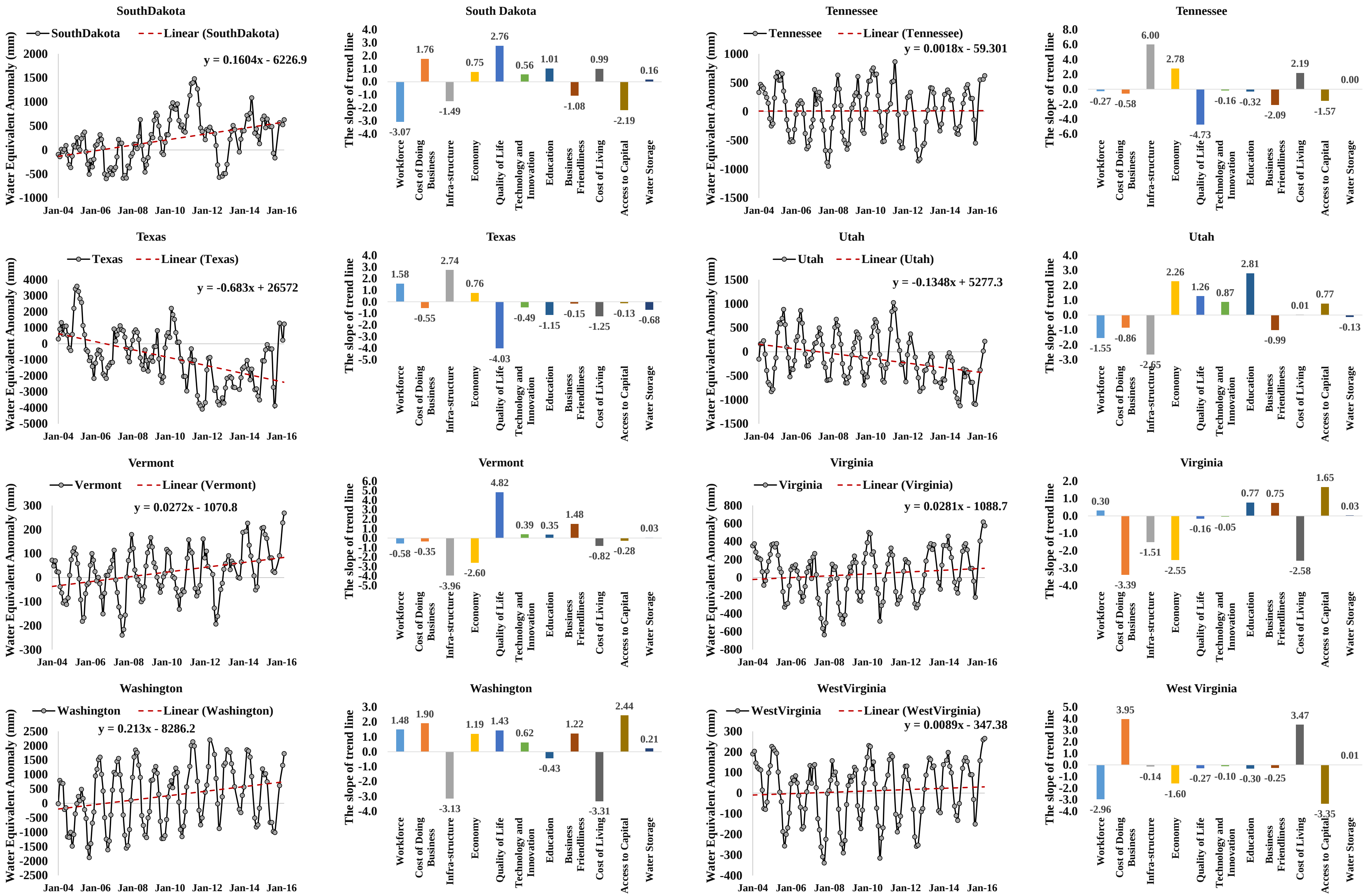

Minnesota
The slope of trend line
1.15
0.28
1.21
0.04
1.04
0.32
0.42
-0.21
-1.98
0.36
0.06
Workforce
Cost of Doing Business
Infra-structure
Economy
Quality of Life
Technology and Innovation
Education
Business Friendliness
Cost of Living
Access to Capital
Water Storage


Mississippi
Mississippi
Linear (Mississippi)
y = -0.067x + 2605.4
Water Equivalent Anomaly (mm)


Mississippi
The slope of trend line
-1.12
0.68
2.32
0.50
0.01
-0.42
-0.52
-1.88
5.49
-2.42
-0.07
Workforce
Cost of Doing Business
Infra-structure
Economy
Quality of Life
Technology and Innovation
Education
Business Friendliness
Cost of Living
Access to Capital
Water Storage


Missouri
Missouri
Linear (Missouri)
y = 0.0162x - 646.12
Water Equivalent Anomaly (mm)
Missouri
The slope of trend line
-4.14
2.27
4.20
-1.41
-3.61
0.14
-0.72
0.25
1.12
-1.84
0.02
Montana
Montana
Linear (Montana)
y = 0.2923x - 11356
Montana
-1.41
2.99
0.32
-1.75
2.71
0.56
-1.81
2.17
2.25
-0.58
0.29
Nebraska
Nebraska
Linear (Nebraska)
y = 0.1599x - 6223.5
Nebraska
0.90
1.35
0.07
-0.09
0.80
0.17
1.99
-0.88
3.32
-1.70
0.16
Nevada
Nevada
Linear (Nevada)
y = -0.1307x + 5129.3
Nevada
1.90
-1.02
1.65
0.76
-1.42
-1.42
-0.08
-1.31
0.42
-1.61
-0.13
New_Hampshire
New_Hampshire
Linear (New_Hampshire)
y = 0.017x - 669.32
New Hampshire
0.60
-0.64
-4.65
-1.41
3.90
-0.32
0.88
1.63
-3.21
-0.18
0.02
New_Jersey
New_Jersey
Linear (New_Jersey)
y = 0.0083x - 326.52
New Jersey
3.35
-0.78
-5.19
-2.21
0.63
-1.64
-0.49
0.75
-4.33
4.07
0.01
New_Mexico
New_Mexico
Linear (New_Mexico)
y = -0.1846x + 7173.1
New Mexico
-0.52
0.97
2.64
-0.27
-0.05
0.27
-0.34
-0.33
1.62
-1.66
-0.18
New_York
New_York
Linear (New_York)
y = 0.0984x - 3876.7
New York
1.73
1.71
-4.67
-3.20
-1.58
-0.15
-0.78
1.74
-4.95
3.10
0.10
Jan-04
Jan-06
Jan-08
Jan-10
Jan-12
Jan-14
Jan-16
Workforce
Cost of Doing Business
Infra-structure
Economy
Quality of Life
Technology and Innovation
Education
Business Friendliness
Cost of Living
Access to Capital
Water Storage


NorthCarolina
NorthCarolina
Linear (NorthCarolina)
y = 0.0289x - 1121.9
Water Equivalent Anomaly (mm)
North Carolina
The slope of trend line
0.37
-1.76
0.25
3.32
-1.48
1.01
-0.20
-0.80
-0.60
1.30
0.03
NorthDakota
NorthDakota
Linear (NorthDakota)
y = 0.0617x - 2361
North Dakota
-0.44
0.61
1.70
0.17
1.87
0.38
1.52
0.86
0.67
-1.08
0.06
Ohio
Ohio
Linear (Ohio)
y = 0.0136x - 547.8
Ohio
-0.57
4.62
3.27
0.02
-4.81
-0.73
-1.70
0.24
1.64
0.58
0.01
Oklahoma
Oklahoma
Linear (Oklahoma)
y = -0.1448x + 5602.4
Oklahoma
-3.01
0.73
0.69
-1.06
-1.35
-0.82
0.56
-0.25
3.19
-3.52
-0.14
Oregon
Oregon
Linear (Oregon)
y = 0.151x - 5876.2
Oregon
-2.30
-0.59
-0.48
1.67
3.02
0.62
-1.06
-0.15
-2.68
1.79
0.15
Pennsylvania
Pennsylvania
Linear (Pennsylvania)
y = 0.0504x - 1981.9
Pennsylvania
0.22
1.08
-1.72
-3.91
-2.56
-0.16
-2.38
0.87
-2.86
1.47
0.05
RhodeIsland
RhodeIsland
Linear (RhodeIsland)
y = 0.0017x - 65.697
Rhode Island
2.48
-3.16
-2.12
-0.59
3.41
-0.90
0.44
1.62
-1.18
0.70
0.00
SouthCarolina
SouthCarolina
Linear (SouthCarolina)
y = 0.0232x - 900.13
South Carolina
-1.30
-2.53
4.22
3.05
-0.88
-0.25
-1.55
-1.19
2.15
-1.35
0.02
Jan-04
Jan-06
Jan-08
Jan-10
Jan-12
Jan-14
Jan-16
Workforce
Cost of Doing Business
Infra-structure
Economy
Quality of Life
Technology and Innovation
Education
Business Friendliness
Cost of Living
Access to Capital
Water Storage


SouthDakota
SouthDakota
Linear (SouthDakota)
y = 0.1604x - 6226.9
Water Equivalent Anomaly (mm)
South Dakota
The slope of trend line
-3.07 1.76 -1.49 0.75 2.76 0.56 1.01 -1.08 0.99 -2.19 0.16
Tennessee
Tennessee
Linear (Tennessee)
y = 0.0018x - 59.301
Tennessee
-0.27 -0.58 6.00 2.78 -4.73 -0.16 -0.32 -2.09 2.19 -1.57 0.00
Texas
Texas
Linear (Texas)
y = -0.683x + 26572
Texas
1.58 -0.55 2.74 0.76 -4.03 -0.49 -1.15 -0.15 -1.25 -0.13 -0.68
Utah
Utah
Linear (Utah)
y = -0.1348x + 5277.3
Utah
-1.55 -0.86 -2.65 2.26 1.26 0.87 2.81 -0.99 0.01 0.77 -0.13
Vermont
Vermont
Linear (Vermont)
y = 0.0272x - 1070.8
Vermont
-0.58 -0.35 -3.96 -2.60 4.82 0.39 0.35 1.48 -0.82 -0.28 0.03
Virginia
Virginia
Linear (Virginia)
y = 0.0281x - 1088.7
Virginia
0.30 -3.39 -1.51 -2.55 -0.16 -0.05 0.77 0.75 -2.58 1.65 0.03
Washington
Washington
Linear (Washington)
y = 0.213x - 8286.2
Washington
1.48 1.90 -3.13 1.19 1.43 0.62 -0.43 1.22 -3.31 2.44 0.21
WestVirginia
WestVirginia
Linear (WestVirginia)
y = 0.0089x - 347.38
West Virginia
-2.96 3.95 -0.14 -1.60 -0.27 -0.10 -0.30 -0.25 3.47 -3.35 0.01
Jan-04 Jan-06 Jan-08 Jan-10 Jan-12 Jan-14 Jan-16
Workforce
Cost of Doing Business
Infra-structure
Economy
Quality of Life
Technology and Innovation
Education
Business Friendliness
Cost of Living
Access to Capital
Water Storage

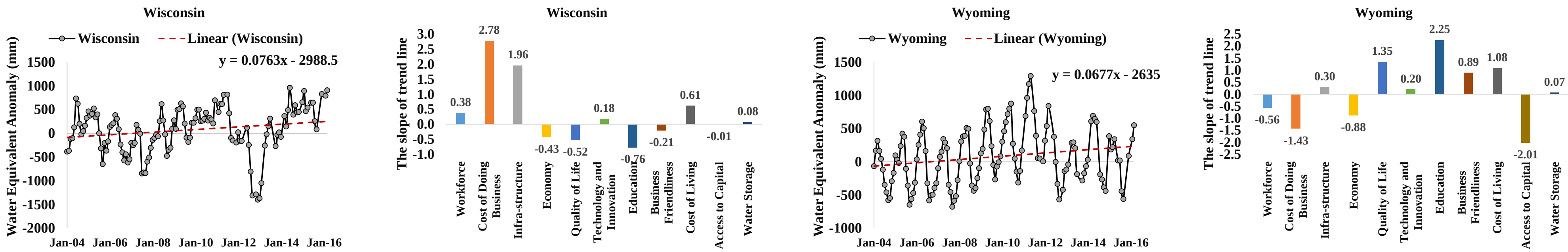
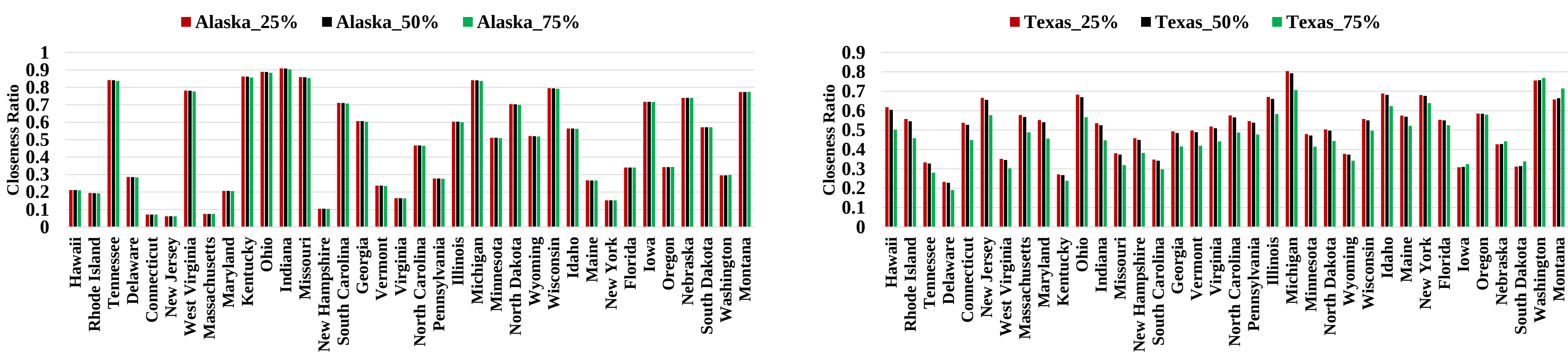
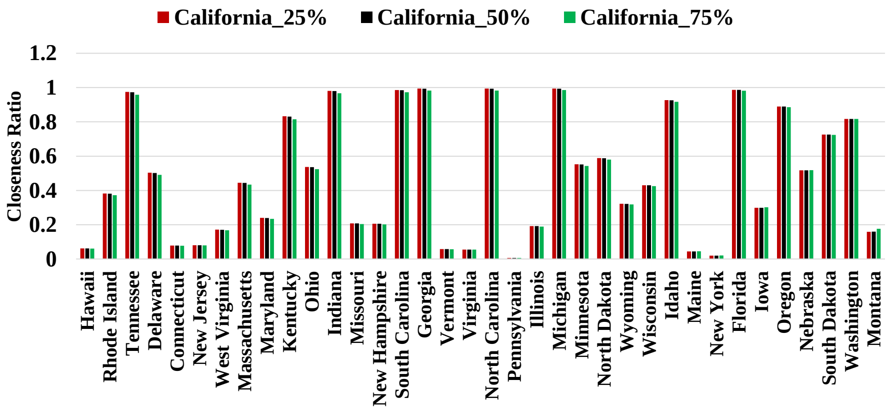
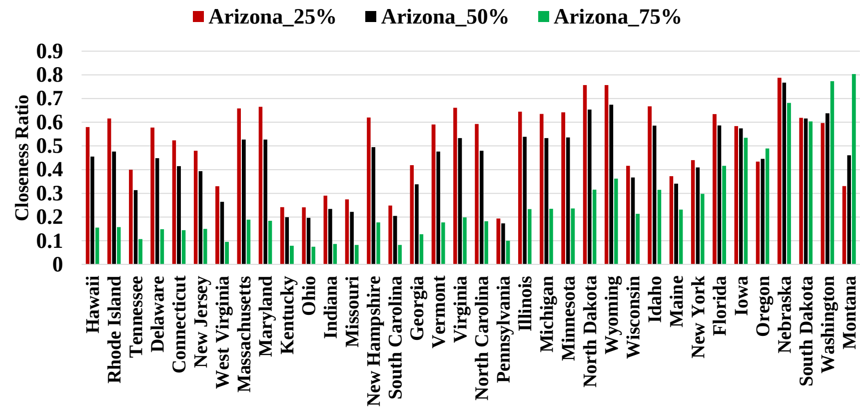


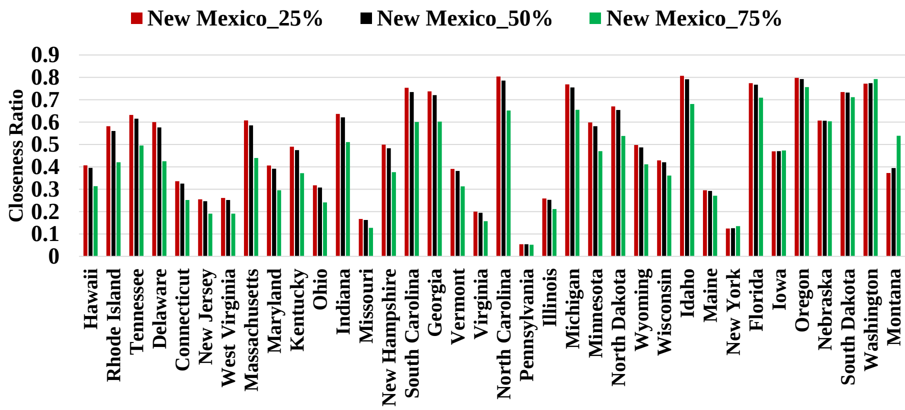
Fig 3. The time series of WEA for each State for 2004-2016 with the trend lines and the bar chart of trend line slopes in terms of 11 factors

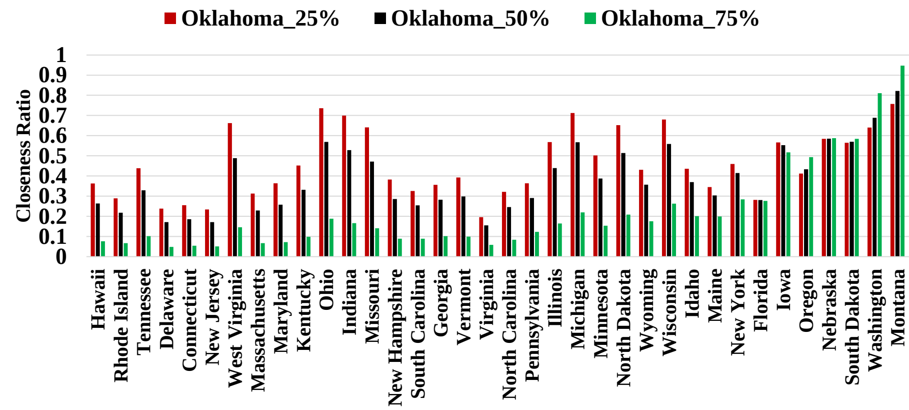
As it is shown in Fig 3, 14 States from 50 States have the negative slope in the trend lines of WEA including Alaska, Texas, California, Arizona, New Mexico, Oklahoma, Utah, Nevada, Louisiana, Colorado, Arkansas, Mississippi, Kansa, and Alabama, respectively. Therefore, assuming these trends continues, we expected that these States will be faced with the lack of sufficient water and a part of the population will be moved from these States to other States. Also, the slope of the trend line of 11 factors discussed before for 2007-2016 are extracted and shown in the Fig 3. The negative values indicate that a State moves to worse situation in terms of each factors and the positive values shows that a State has an improvement in terms of each factors. These slopes provide useful information about each State. For example, Mississippi has the best improvement in terms of "Cost of Living" among the other States between 2007 and 2016. In contrast, Massachusetts has the worst situation regarding "Cost of Living". These information is necessary for ranking the destinations (States that have a positive slope means SPS) in terms of people who are living in the States with the negative slope means SNS and will move to other States because of lacking the sufficient water. Therefore, TOPSIS model executed for ranking SPS that have a better situation of water storage changes (36 States) in terms of people who are living in each of SNS (14 States). The results of TOPSIS model for three scenarios are shown in Fig 4.

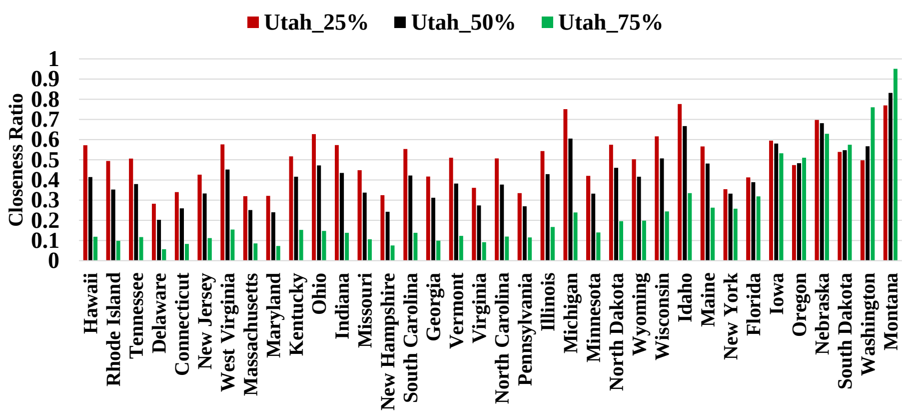


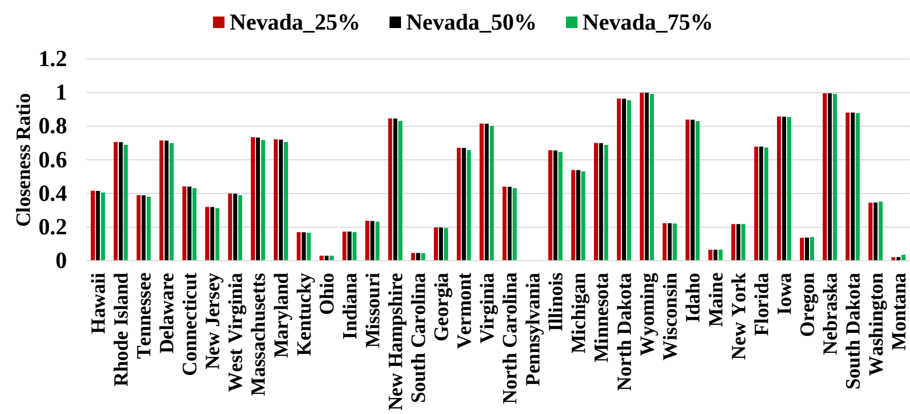

California_25%
California_50%
California_75%
Closeness Ratio
1.2
1
0.8
0.6
0.4
0.2
0
Hawaii
Rhode Island
Tennessee
Delaware
Connecticut
New Jersey
West Virginia
Massachusetts
Maryland
Kentucky
Ohio
Indiana
Missouri
New Hampshire
South Carolina
Georgia
Vermont
Virginia
North Carolina
Pennsylvania
Illinois
Michigan
Minnesota
North Dakota
Wyoming
Wisconsin
Idaho
Maine
New York
Florida
Iowa
Oregon
Nebraska
South Dakota
Washington
Montana


Arizona_25%
Arizona_50%
Arizona_75%
Closeness Ratio
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Hawaii
Rhode Island
Tennessee
Delaware
Connecticut
New Jersey
West Virginia
Massachusetts
Maryland
Kentucky
Ohio
Indiana
Missouri
New Hampshire
South Carolina
Georgia
Vermont
Virginia
North Carolina
Pennsylvania
Illinois
Michigan
Minnesota
North Dakota
Wyoming
Wisconsin
Idaho
Maine
New York
Florida
Iowa
Oregon
Nebraska
South Dakota
Washington
Montana


New Mexico_25%
New Mexico_50%
New Mexico_75%
Closeness Ratio
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Hawaii
Rhode Island
Tennessee
Delaware
Connecticut
New Jersey
West Virginia
Massachusetts
Maryland
Kentucky
Ohio
Indiana
Missouri
New Hampshire
South Carolina
Georgia
Vermont
Virginia
North Carolina
Pennsylvania
Illinois
Michigan
Minnesota
North Dakota
Wyoming
Wisconsin
Idaho
Maine
New York
Florida
Iowa
Oregon
Nebraska
South Dakota
Washington
Montana


Oklahoma_25%
Oklahoma_50%
Oklahoma_75%
Closeness Ratio
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Hawaii
Rhode Island
Tennessee
Delaware
Connecticut
New Jersey
West Virginia
Massachusetts
Maryland
Kentucky
Ohio
Indiana
Missouri
New Hampshire
South Carolina
Georgia
Vermont
Virginia
North Carolina
Pennsylvania
Illinois
Michigan
Minnesota
North Dakota
Wyoming
Wisconsin
Idaho
Maine
New York
Florida
Iowa
Oregon
Nebraska
South Dakota
Washington
Montana


Utah_25%
Utah_50%
Utah_75%
Closeness Ratio
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Hawaii
Rhode Island
Tennessee
Delaware
Connecticut
New Jersey
West Virginia
Massachusetts
Maryland
Kentucky
Ohio
Indiana
Missouri
New Hampshire
South Carolina
Georgia
Vermont
Virginia
North Carolina
Pennsylvania
Illinois
Michigan
Minnesota
North Dakota
Wyoming
Wisconsin
Idaho
Maine
New York
Florida
Iowa
Oregon
Nebraska
South Dakota
Washington
Montana


Nevada_25%
Nevada_50%
Nevada_75%
Closeness Ratio
1.2
1
0.8
0.6
0.4
0.2
0
Hawaii
Rhode Island
Tennessee
Delaware
Connecticut
New Jersey
West Virginia
Massachusetts
Maryland
Kentucky
Ohio
Indiana
Missouri
New Hampshire
South Carolina
Georgia
Vermont
Virginia
North Carolina
Pennsylvania
Illinois
Michigan
Minnesota
North Dakota
Wyoming
Wisconsin
Idaho
Maine
New York
Florida
Iowa
Oregon
Nebraska
South Dakota
Washington
Montana

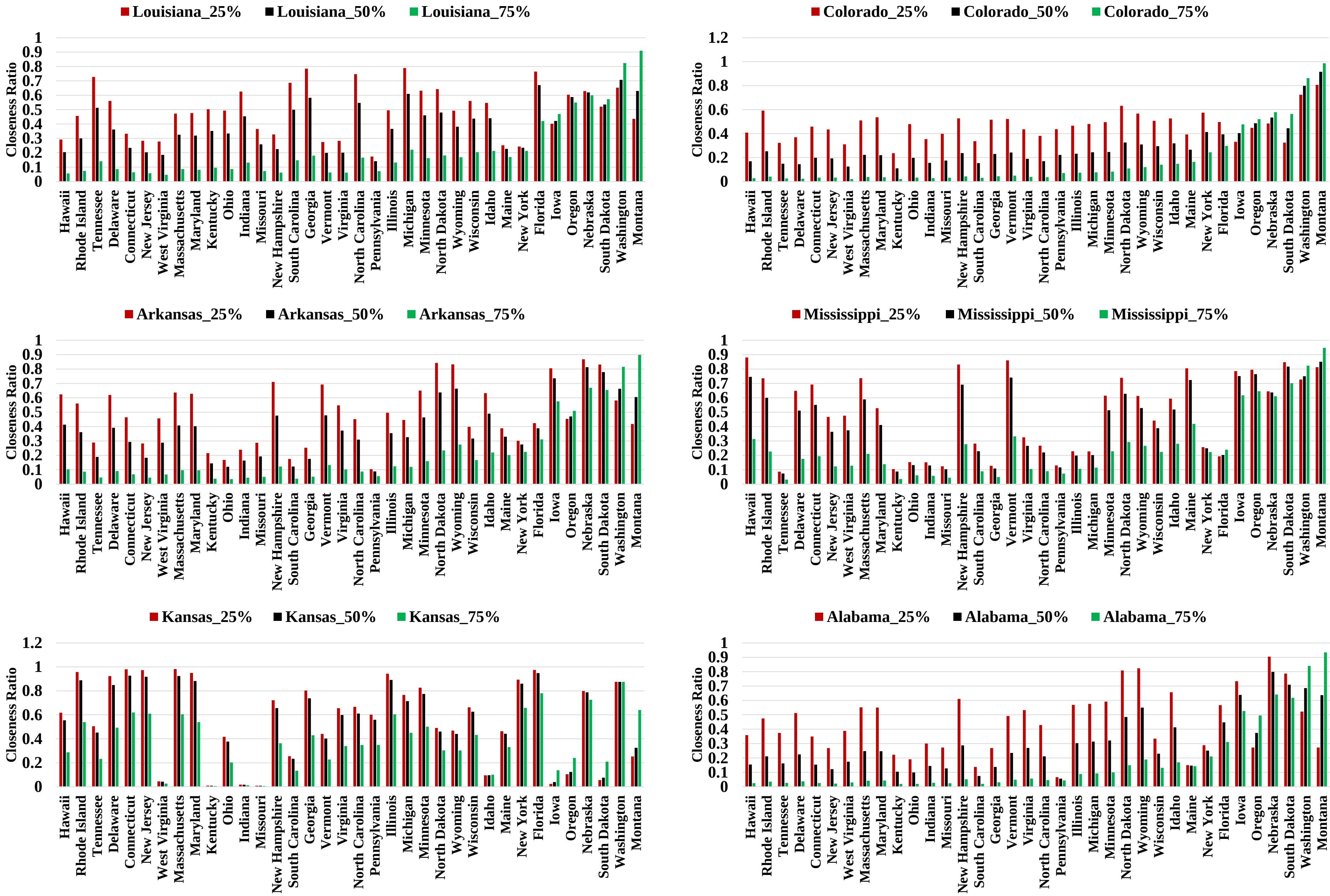


Fig 4. The results of TOPSIS model for three scenarios

As it is shown in Fig 4, the sorted list of SPS in terms of each State located in SNS for three deferent scenarios are drawn. For Alaska, Indiana (all three scenarios); for Texas, Michigan for 1st and 2nd scenarios and Washington for the 3rd scenarios; for California, Gorgias (all three scenarios); for Arizona, Montana (1st and 2nd scenarios) and Nebraska for 3rd scenario; for New Mexico, both Idaho and Oregon (1st and 2nd scenarios) and Washington for 3rd scenario; for Oklahoma, Montana (all three scenarios); for Utah, Idaho for 1st and Montana (2nd and 3rd scenarios); for Nevada, Wyoming and Nebraska (all three scenarios); for Louisiana, Michigan for 1st, Washington for 2nd, and Montana for 3rd scenarios; for Colorado, Montana (all three scenarios); for Arkansas, Nebraska for 1st and 2nd scenarios and Montana for 3rd scenario; for Mississippi, Hawaii for 1st Montana (2nd and 3rd scenarios); for Kansas, Florida for 1st and Washington for 2nd and 3rd scenarios; and for Alabama, Nebraska for 1st and Montana (2nd and 3rd scenarios) are the most possible destinations.

Conclusion

To sum up, this project shows the trend of water storage situation of all 50 States using satellite data derived from 2004-2016. The WEA product of GRACE is extracted for all 50 States using Python Programming and the time series of this product with its trend line are shown. This information shows 14 States from 50 States may face with the lack of sufficient water if the current and previous situation continues. Using the combination of this information and also the trend line slopes of other factors which are really important in making a decision to move from location, possible location choices for people who are living in the mentioned 14 States are ranked. For ranking these locations, a multi-criteria decision techniques called TOPSIS is used. The outputs of this model are shown in the bar charts.

Reference

Black, R., Bennett, S.R., Thomas, S.M., Beddington, J.R. (2011) “Climate change: Migration as adaptation”. Nature 478:447–449

Dow, K., Carr, E. R., with Douma, A., Han, G., and Hallding, K. (2005). “Linking water scarcity to population movements: From global models to local experiences”. SEI Poverty and Vulnerability Program Report. Stockholm. Stockholm Environment Institute.

Selby, J., Hoffman, C. (2012). “Water scarcity, conflict, and migration: A comparative analysis and reappraisal”. Environ. Plan. C Gov., 30, 997–1014

Yoon, K.P., Hwang, C.L., “Multiple Attribute Decision Making: An Introduction”, Sage Pub., Thousand Oaks, CA, 1995

Appendix (1): Python Codes

```
from ftplib import FTP

import os.path

import sys

ftp = FTP('neoftp.sci.gsfc.nasa.gov')

ftp.login()

ftp.cwd('geotiff.float')

ftp.cwd('GRACE_LWE_M')

filename=ftp.nlst()

n = len(filename)

ftp.quit()

for i in range (0,n-1):

    ftp = FTP('neoftp.sci.gsfc.nasa.gov')

    ftp.login()

    ftp.cwd('geotiff.float')

    ftp.cwd('GRACE_LWE_M')


    save_path = 'C:/Utah State/Utah State University/Fall_2016/Python/DataFTP_GRACE'

    completeName = os.path.join(save_path, filename[i])

    localfile = open(completeName, 'wb')

    ftp.retrbinary('RETR ' + filename[i], localfile.write)

    ftp.quit()

    localfile.close()

from ftplib import FTP

import os.path

import sys

import arcgisscripting

import os

import fnmatch

import arcpy, numpy

from xlwt import Workbook

import numpy as np

wb=Workbook()

sheet1=wb.add_sheet('Sheet 1')

sheet1.write(0,0,'State')

ftp = FTP('neoftp.sci.gsfc.nasa.gov')

ftp.login()

ftp.cwd('geotiff.float')

ftp.cwd('GRACE_LWE_M')

filename=ftp.nlst()

n = len(filename)

ftp.quit()

os.getcwd()
```

```
os.chdir('C:/Utah State/Utah State University/Fall_2016/Python/Other/SplitShapeFileOther/')
i=1;
for file in os.listdir('.'):
    if fnmatch.fnmatch(file, '*.shp'):
        ShapeName=file
        State=os.path.splitext(ShapeName)[0]
        print ShapeName
        print State

        sheet1.write(i,0,State)
        sheet1.write(i+1,0,State)
        sheet1.write(i+2,0,State)

        for j in range (0,n-1):

            save_path = 'C:/Utah State/Utah State University/Fall_2016/Python/DataFTP_GRACE'
            completeName = os.path.join(save_path, filename[j])

            save_path_Shape = 'C:/Utah State/Utah State University/Fall_2016/Python/Other/SplitShapeFileOther'
            completeName_Shape = os.path.join(save_path_Shape, ShapeName)

            save_path_Result = 'C:/Utah State/Utah State University/Fall_2016/Python/Other/ResultNewOther'
            FileName=filename[j]
            ResultName=State[0:6]+FileName[14:19]
            completeName_Result = os.path.join(save_path_Result,ResultName)
            gp = arcgisscripting.create()
            try:
            # Set local variables
                InRaster = completeName
                InMask = completeName_Shape
                OutRaster = completeName_Result
            # Check out Spatial Analyst extension license
                gp.CheckOutExtension("Spatial")
            # Process: ExtractByMask
                gp.ExtractByMask_sa(InRaster, InMask, OutRaster)
            except:
            # If an error occurred while running a tool, then print the messages.
                print gp.GetMessages()
            # Convert the raster to a numpy array
            arcpy.SetRasterProperties_management(OutRaster, "#", "#", "#", "1 -3.4028235e+03; 1 99999")
            array = arcpy.RasterToNumPyArray(OutRaster, nodata_to_value = 0)
            #print array
            #print array
            # Sum the array
```

```
            Sum_Raster=array.sum()

            #print Sum_Raster

            Sum_Raster=np.float64(Sum_Raster)

            sheet1.write(i,j+1,Sum_Raster)

            sheet1.write(i+1,j+1,FileName[12:16])

            sheet1.write(i+2,j+1,FileName[17:19])

            wb.save('xlwt exampleNewOther.xls')

        i+=3
```

Appendix (2): MATLAB Programming (TOPSIS)

```
clear;
clc;
close all;
load Slopes_States;
load State;
Ww=0.75;
Ws=(1-Ww)/10;
W=[Ws Ws Ws Ws Ws Ws Ws Ws Ws Ws Ww];
for i=1:36
Slopes_States_Ratio(i,:)=(Slopes_States(i,:)-State)./abs(State);
end
SuMM=sum(Slopes_States_Ratio);
SuMM=SuMM.^2;
for j=1:11
    for i=1:36
        R(i,j)=Slopes_States_Ratio(i,j)/sqrt(SuMM(j));
    end
end
for i=1:36
V(i,:)=W.*R(i,:);
end
BestV=max(V);
WorstV=min(V);
D_Plus=zeros(36,1);
D_Minus=zeros(36,1);
for j=1:11
 for i=1:36
  A=(BestV(j)-V(i,j))^2;
  D_Plus(i)=D_Plus(i)+A;
  B=(WorstV(j)-V(i,j))^2;
  D_Minus(i)=D_Minus(i)+B;

 end
end

C=D_Minus./(D_Plus+D_Minus);
[Result index]=max(C);
```