Towards understanding Potential Evapotranspiration across 10 African cities using Statistical Machine Learning

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Abstract

The world is rapidly evolving at an unprecedented rate largely due to human actions on the environment. The effects of this change is being noticed through variable patterns in the climate across the global which is projected to have unforeseen consequences in the near and far future. Climate change is a prevailing threat existential crisis we are facing as a human species which if not mitigated will have devastating consequences on us and our surrendering fauna and flora. Therefore, in this work, we use state-of-the-art Hierarchical Cluster Analysis (CA) and Principal Component Analysis (PCA) algorithms. We found four clusters for the 10 cities with similar Potential Evapotranspiration and using PCA (both non rotated and rotated) to identify the underlying processes that gave rise to the factors of variation int the data set wherein we identified two principal components using varimax that explain nearly 90 per cent of variability in the data.

Contents

1 Introduction

Climate change is one of the prevailing threats existential crisis we are facing as a human species which if not mitigated will have devastating consequences on us and our surrendering fauna and flora. This effect is large since the climatic condition of the atmosphere dictates the survival ability of all life forms, the civilization we take for granted is hinged on our ability to produce food on an industrial scale to cater for the soaring global population, availability of clean air and freshwater systems as well as the ozone layer of the atmosphere to shield us from ultraviolet radio from the sun. A scholarly exposition of the effect of climatic changes is crucial for especially the developing world where the effect of such changes is projected to have greater impact leading to extreme events such as droughts, flooding, hurricanes, famines, the rise of sea levels along coastal regions. These events starkly have the potential to undermine economic activities and political stability.

2 Research Problem

Understanding the effect of evapotranspiration patterns across different geographic regions across the African continent is pivotal to coordinated climate action and policy formulation. However, this process involves aggregating big data sets from locations that have varied underlying factors of variation in the processes that generated the data.

3 Research Objective

(I) The object of this research is to explore the characteristics of three Cluster Analysis (CA) algorithms using the provided climate dataset over African cities (Kamembe, Kayonza, Kigali, Koulikoro, Lagos, Lome, Maseno, Mombasa, Musanze, Nairobi) using evapotranspiration. This is done to show the sensitivity of the grouping to three Cluster Analysis algorithms (single linkage, average linkage, and Ward's algorithm) and make a comparative analysis the results as well as the physical interpretation of those findings.

(II) The second object of this work is to study the characteristics of Principal Component Analysis (PCA) algorithm and contrast it with that of CA using the data set in question from ten African cities using evapotranspiration. We seek to explore the sensitivity of PCA analysis to (i) rotated and (ii) non-rotated PCA methods and the temporal variation of the Principal Factors (PFs) over the study period. Finally, we give physical interpretations of our findings in comparison with the objective I.

4 Research Methodology

4.1 Evapotranspiration

Potential Evapotranspiration (PET) is the sum of water evaporation and transpiration from a surface area to the atmosphere. Evaporation accounts for the movement of water to the air from sources such as the soil, canopy interception, and water bodies as depicted in Figure 1.

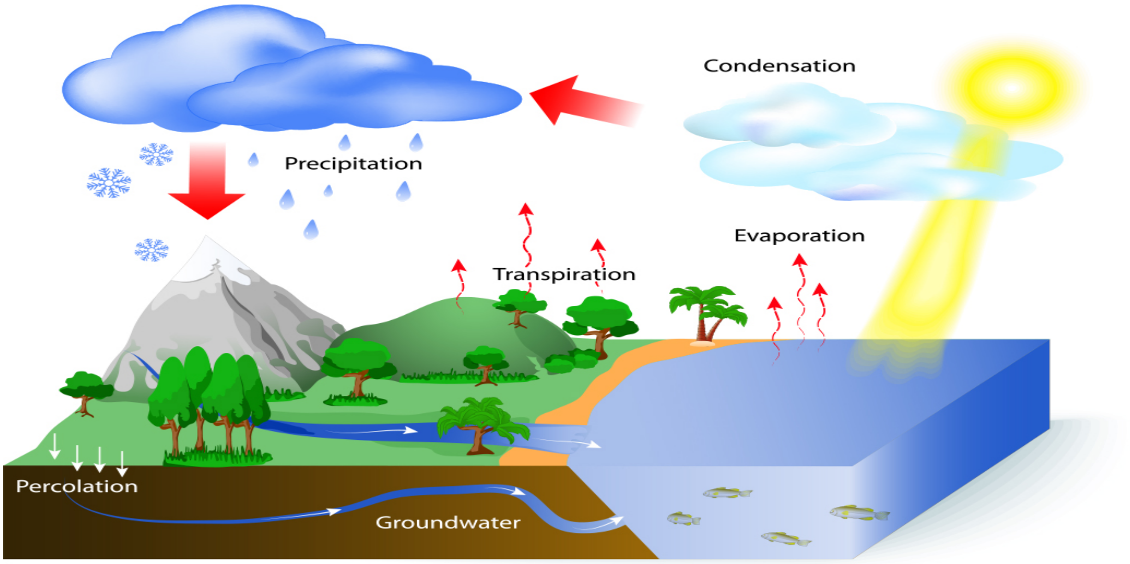


Figure 1: Illustration of Evapotranspiration

4.2 Research Instruments

In this research, we use Cluster Analysis technique to group ten African cities (Kamembe, Kayonza, Kigali, Koulikoro, Lagos, Lome, Maseno, Mombasa, Musanze, Nairobi) based on their evapotranspiration patterns. The CA algorithm explores three different linkage methods viz: single linkage, average linkage, and Ward's algorithm to investigate their effect on the cluster formation of clustering parameters.

We further subject the same dataset to PCA algorithm with a goal of understanding the principal factors of variation that impact the evapotranspiration process for the cities in being studied with sensitivity of PCA analysis to (i) rotated and (ii) non-rotated PCA.

The primary computational tool for our experiment is the R programming language primarily because it is well suited and expressive to undertake high-level rapid exploratory data analysis for scientific reporting as well as being able to automate repetitive predictive analytic processes which all aid reproducibility of research.

4.3 Data set

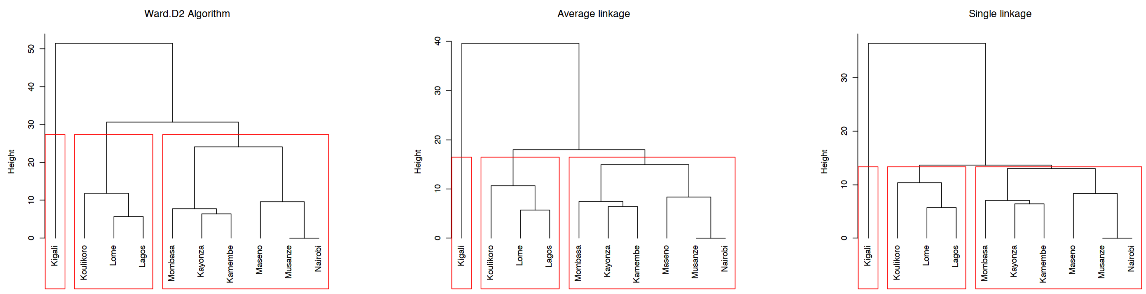
We utilise a secondary data set of evapotranspiration in this report from ten African cities (Kamembe, Kayonza, Kigali, Koulikoro, Lagos, Lome, Maseno, Mombasa, Musanze, Nairobi) with different geographic conditions. This consists of 10 parameters (i.e., evapotranspiration for each city) and 612 observations (monthly averaged evapotranspiration) from January 1960 to December 2010 (50 years).

5 Results and Discussions

5.1 Results

In this section of report, we present the empirical observations after carrying out CA and PCA on the Potential Evapotranspiration data set for the ten cities being studied.

5.1.1 Cluster Analysis



(a) (b) (c)

Figure 2: Cluster Analysis with 3 distinct linkage algorithms

The dendogram in Figure 2 presents the impact of using Ward.D2, Average and Single linkage algorithms on the data set using a cluster value (K = 4). The red rectangle in the sub figures indicate cities that belong to the same evapotranspiration grouping thereby resulting on four clusters for the 10 cities in each on the linkage algorithms.

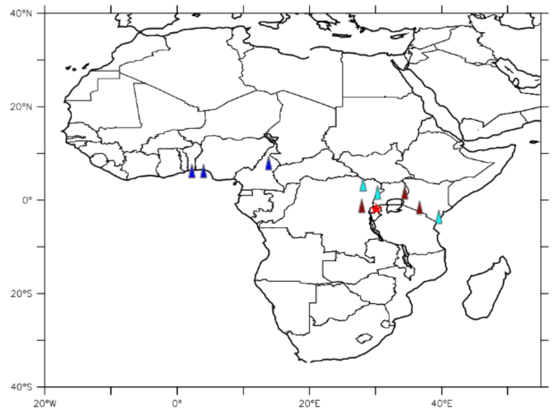
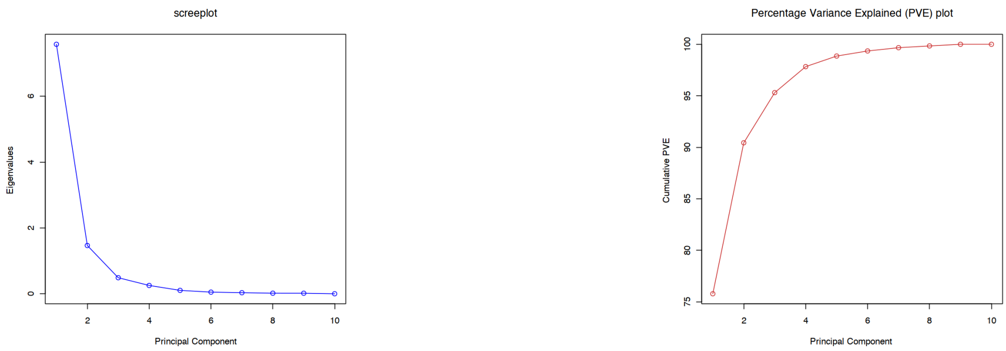


Figure 3: Map representation of the clustered cities

In Figure 3, we overlay the Ward.D2 cluster result onto the coordinates (longitude and latitude) of the 10 cities to infer physical and geographical interpretation of the results. Such visual representation of the clustered data gives rise to rich geographical interpretation for the trend of Potential Evapotranspiration in the cities being studied.

5.1.2 Principal Component Analysis

PCA is one of the popular dimensionality reduction alogrithms, it extracts fewer and independent underlying factors of variation around which the data variance is organised. This is achieved by identifying principal processes that explain the largest variability in the data set. Therefore, in this study, our principal motivation for factor analysis using PCA is to understand the underlying principal processes that drive Potential Evapotranspiration across the ten cities. The Figures (a) and (b) below indicate the screeplot of the eigenvalues and the Percentage Variance Explained (PVE) of the ten principal components using varimax rotation. From Figures (a) and (b), clearly indicate that the first and second principal components explain nearly 90 per cent of the variability in the underlying processes that generated the data. To



(a) (b)

Figure 4: Principal Component Analysis

further understand the effect of the underlying processes of the principal components, we have plotted a 10 year window time series for the two rotations in the figure below.

PCA Loadings (unrotated)

Loadings:

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
Musanze	0.912	0.309	-0.241							
Mombasa	0.899	0.211	0.348	-0.109						
Maseno	0.856	0.342	-0.333		0.143	-0.129				
Lome	0.901	-0.321		0.255						
Lagos	0.882	-0.361		0.272						
Koulikoro	0.907	-0.343			0.195	0.132				
Kigali	-0.360	0.862	0.244	0.246						
Kayonza	0.952	0.131	0.170	-0.153			-0.117			
Kamembe	0.961		0.200	-0.126				0.103		
Nairobi	0.912	0.309	-0.241							

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
SS loadings	7.578	1.466	0.487	0.252	0.103	0.050	0.032	0.017	0.016	0
Proportion Var	0.758	0.147	0.049	0.025	0.010	0.005	0.003	0.002	0.002	0
Cumulative Var	0.758	0.904	0.953	0.978	0.989	0.994	0.997	0.998	1.000	1

PCA Loadings (unrotated)

Loadings:

	RC3	RC1	RC4	RC2	RC5	RC7	RC6	RC9	RC8	RC10
Musanze	0.866	0.400	0.272			-0.110				
Mombasa	0.443	0.830	0.328							
Maseno	0.899	0.301	0.233			0.200				
Lome	0.378	0.397	0.750	0.352				0.112		
Lagos	0.333	0.380	0.777	0.358						
Koulikoro	0.389	0.481	0.534	0.478	0.323					
Kigali			-0.242	-0.970						
Kayonza	0.547	0.737	0.322	0.132			0.162			
Kamembe	0.504	0.748	0.373	0.178					0.119	
Nairobi	0.866	0.400	0.272			-0.110				

	RC3	RC1	RC4	RC2	RC5	RC7	RC6	RC9	RC8	RC10
SS loadings	3.463	2.736	2.061	1.479	0.121	0.066	0.034	0.022	0.018	0
Proportion Var	0.346	0.274	0.206	0.148	0.012	0.007	0.003	0.002	0.002	0
Cumulative Var	0.346	0.620	0.826	0.974	0.986	0.993	0.996	0.998	1.000	1

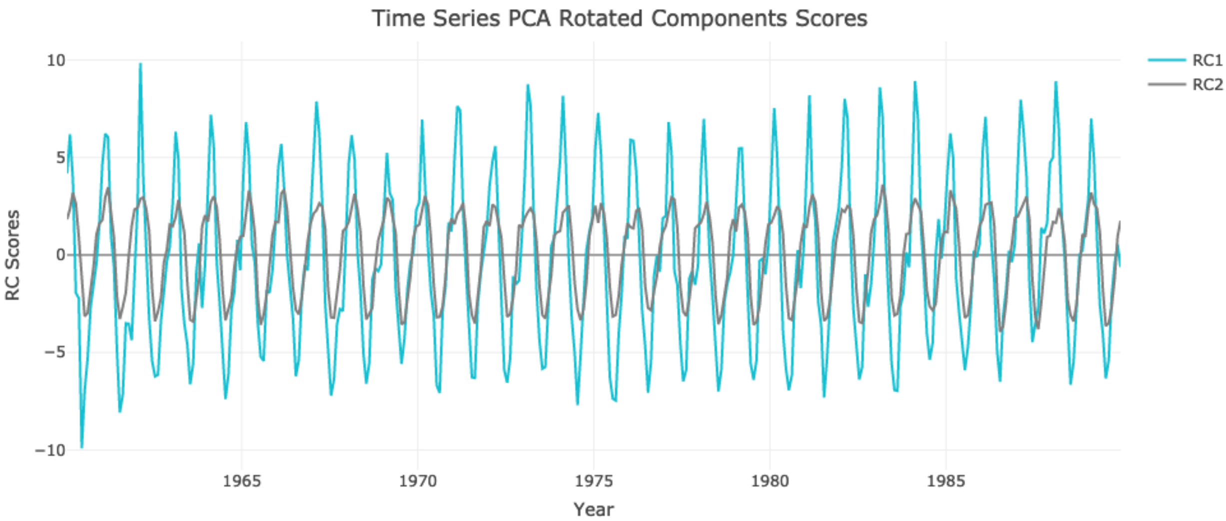
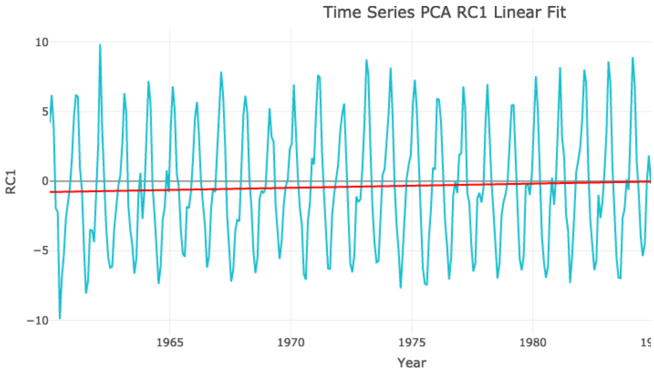


Figure 5: Timeseries of PCA Rotations

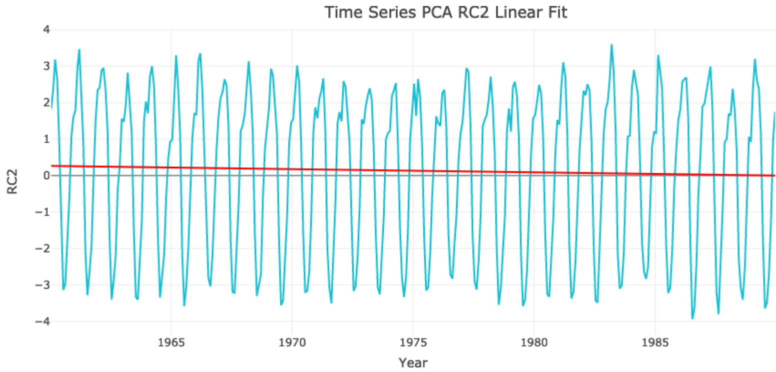
Figure 5 describes proportion of variability captured by each Principal Rotated Components (RC1 and RC2) on the original data and the component scores. The scores shows how each process varies in the time domain. RC1 most active in 2, most inactive in 1968 but was dormant in 1975. There overall trend shows that both principal components periodically have strong influence on the amount of Potential Evapotranspiration of the ten cities.

6 Conclusion

In this report, we have explored Potential Evapotranspiration phenomenon across ten geographically different African cities using CA algorithms (using 3 distinct linkage methods) find their PET groupings, and we further, used PCA to perform dimensionality reduction to identity the underlying processes that generated the data set. Using CA, we identified four distinct PET clusters as shown in Figure 2(a).

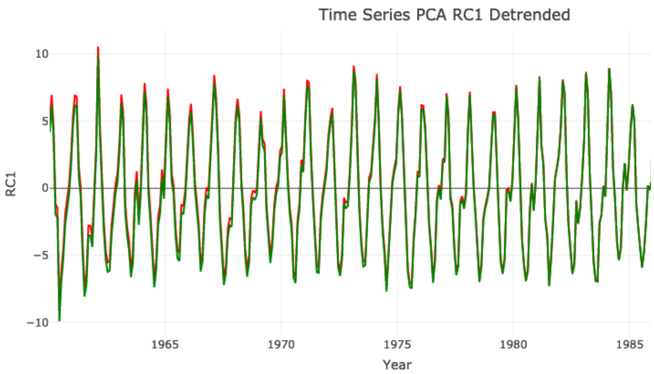


(a) Timeseries of PCA Rotation 1 and Linear Fit

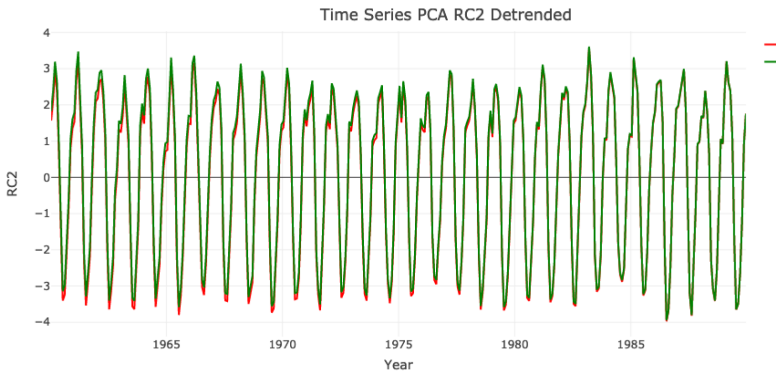


(b) Timeseries of PCA Rotation 2 and Linear Fit

Figure 6: Principal Component Analysis: Linear Fit

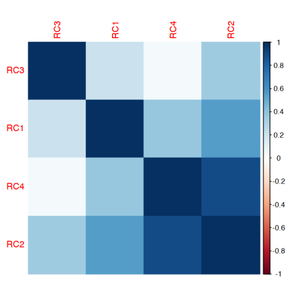


(a)

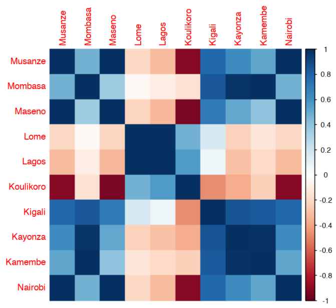


(b)

Figure 7: Principal Component Analysis: detrended



(a) Rotation Factors



(b) Cities PET

Figure 8: Principal Component Analysis: Factor Correlation

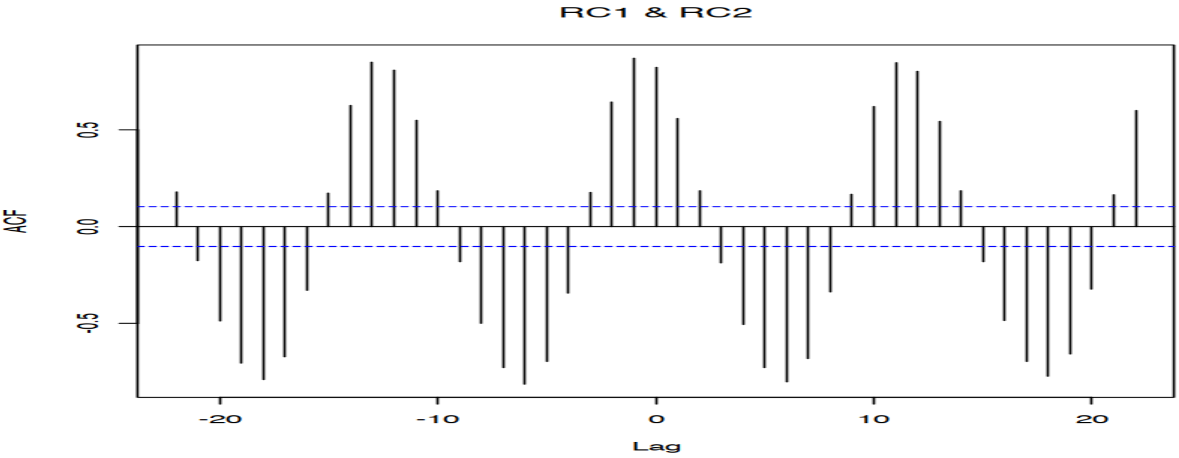
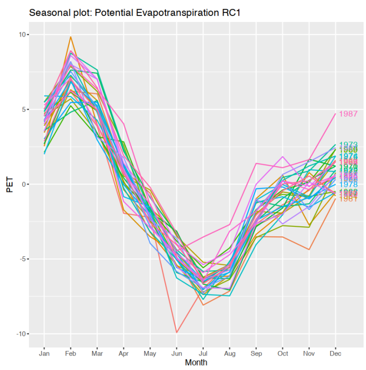
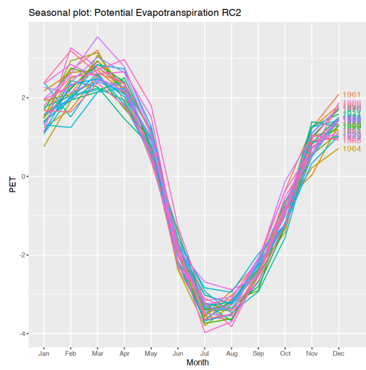


Figure 9: Timeseries of PCA Rotations: Cross-correlations

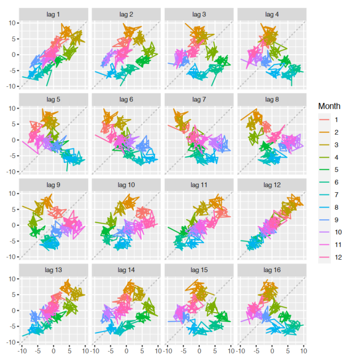


(a)

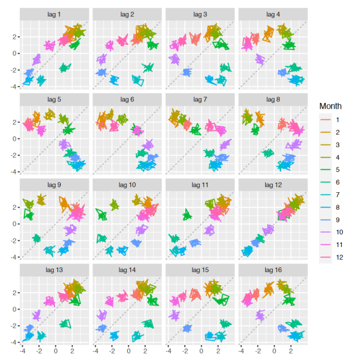


(b)

Figure 10: Principal Component Analysis: Scores Periodicity



(a)



(b)

Figure 11: Principal Component Analysis: Lagged Plots