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Statistical Modelling of Palestinian Meteorological Data Using Panel Data Techniques

A. Abuzaid[1*], S. Alshqaq[2] and M. Elbozom[3]

[1]*Department of Mathematics, Al Azhar University – Gaza, Gaza, Palestine*

[2]*Department of Mathematics, Jazan University, Jazan, Saudi Arabia.*

[3]*Department of Applied Statistics, Al Azhar University – Gaza, Gaza, Palestine*

Panel data analysis has gained much interest in different fields. This article considers modelling metrological data in Palestine using panel data models to predict the total rainfall based on temperature, pressure, relative humidity, and wind speed at five different governorates in the West Bank, Palestine. Different unit root tests have confirmed the stationarity of data. Based on Hausman's test, the fixed effect model was chosen as the best model out of all other panel data models. The fitted model shows that temperature and pressure have significant negative effects, while relative humidity and wind speed have positive effects on rainfall. Furthermore, with respect to the governorate of Nablus, Ramallah and Hebron have a positive effect on the total monthly rainfall, while Jenin and Jericho have a negative effect.

Keywords: ARIMA models; Dickey-Fuller test; KPSS test; stationary.

I. INTRODUCTION

Panel data refers to data sets that provide multiple observations of each individual in the sample. Consequently, panel data consists of two dimensions (N×T); a cross-sectional dimension (N) and a time series dimension (T) (Hsiao, 2014). Panel data allows the examination of problems that cannot be handled by cross-section data or time-series data (Biørn, 2016). Applications of panel data arise in different fields, for instance: the economy, such as income dynamics and labour statistics in the US (Baltagi, 2005); environmental context, such as the impacts of climate change on agriculture (Emediegwu *et al.*, 2022); health surveillance of SARS-CoV-2 infection rates (Oehmke *et al.*, 2022); teacher qualifications and student achievement (Collier, 2013).

Baltagi (2005) described two types of panel data based on their dimensions (macro and micro) or the existence of missing values (balanced and unbalanced).

Different authors assessed the meteorological factors that affect the amount of rainfall by using panel data techniques in different countries such as Bangladesh (Rokonuzzaman and Hossain, 2018), Ghana (Asare and Yeboah, 2022) and Ethiopia (Alem and Colmer, 2022).

Allouh (2004) explored the correlation between certain atmospheric and natural variations and the annual rainfall in the West Bank, Palestine. The meteorological factors for five west bank governorates between 1974 and 1998 are used. According to the results, there is a statistically significant positive correlation between the relative humidity and the annual rainfall, while there is a statistically significant negative correlation between the annual rainfall and the temperature. Allouh (2004) used Pearson’s correlation coefficient as a measure of association regardless of the governorate or whether autocorrelation exists in the recorded meteorological values.

As far as the authors know, no published research has used panel data to predict how much rain will fall in the West Bank, Palestine. Therefore, this article uses data from five different governorates in the West Bank, Palestine to assess the effect of different meteorological factors on the amount of monthly rainfall.

*Corresponding author’s e-mail: a.abuzaid@alazhar.edu.ps

The rest of this article is organised as follows: Section 2 reviews the main panel data models, and Section 3 discusses the stationarity tests of the panel data. The application of the meteorological data from five governorates in the West Bank, Palestine is analysed in Section 4.

II. PANEL DATA MODELS

A. Formulations of Panel Data Models

The panel data models describe individual behaviour both across time and across individuals. The basic linear panel models can be described through the restrictions of the following general model (Greene, 2018):

$$Y_{it} = \alpha_i + \beta X_{it} + \varepsilon_{it}\ , \quad i = 1, \dots, N;\ t = 1, \dots, T, \qquad (1)$$

where Y_{it} is the dependent variable, X_{it} is a K dimensional vector of explanatory variables without a constant term, α_i is the intercept (i.e. the heterogeneity and or individual effects), β is a (K×1) vector of unknown coefficients (i.e. the slopes), and ε_{it} is iid error terms, where ε_{it}~N(0 , $\sigma_\varepsilon{}^2$).

There are three models of panel data, which are the pooled regression model, the fixed effect model, and the random effect model as described in the following:

1- A pooled regression model:

The pooled regression model assumes that α_i is constant across all the individuals ($\alpha_i = \alpha, \forall_i$), and given by:

$$Y_{it} = \alpha + \beta X_{it} + \varepsilon_{it} \qquad i = 1,\dots, N;\ t = 1, \dots, T, \qquad (2)$$

2-Fixed effect (fe) model:

If α_i is correlated with the explanatory variables X_{it} (i.e., E ($\alpha_i|X_I$) ≠0) then we have the fixed effect model, which treats the individual effects α_i as fixed parameters (each individual has a different intercept term and the same slope parameters). The form of this model is:

$$Y_{it} = \alpha_i + \beta X_{it} + \varepsilon_{it} \qquad i=1,\dots,N;\ t=1,\dots,T \qquad (3)$$

3-Random effects (RE) model:

If the individual specific effects are uncorrelated with the explanatory variables X_{it}; (i.e. E ($\alpha_i|X_I$) = 0), then α_i is included in the error term u_{it}, and it is formulated as follows:

$$Y_{it} = \beta X_{it} + u_{it}, \qquad i = 1, \dots, N;\ t = 1, \dots, T, \qquad (4)$$

where the error term $u_{it} = \alpha_i + \varepsilon_{it}$, with variance $var(u_{it}) = \sigma_\alpha^2 + \sigma_\varepsilon^2$ and $cov(u_{it}, u_{is}) = \sigma_\alpha^2$.

B. Choosing between fixed and random effects models

After estimating panel data models, we must determine the best model for our data. The Hausman test (Hausman, 1978) investigates if there is a significant difference between the fixed and random effects estimators. The null and alternative hypotheses of the Hausman test are given as follows:

H_0: The RE model is preferred.
H_a: The FE model is preferred.

The Hausman test statistic follows a chi-square distribution with K degrees of freedom, where K is the number of parameters for the time-varying regressors. At a certain level of significance, if Hausman's test is insignificant, then use the random effects otherwise use the fixed effects.

III. STATIONARITY TESTS

Stationarity is the most important and common assumption in time series analysis, which means that the process properties don't vary with time. Thus, we can develop powerful and reliable techniques to forecast their future values.

A. Tests for the Unit Root of Time Series

If the time series is not stationary, then the series is said to have a unit root. The presence of unit roots in time series may cause a misinterpretation of estimated results. Testing for unit roots and stationarity in time series is now common practice among empirical studies (Brockwell and Davis, 2016). There are many unit root tests for individual time series, such as the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) and the Phillips Perron (PP) test (Phillips and Perron, 1988), which are based on the null hypothesis that there is a unit root in the time series against the alternative of stationary. Kwiatkowski *et al.* (1992) proposed an alternative test, the so-called (KPSS test), with the contrary.

B. Tests for the Unit Root of Panel Data

It is important to use panel unit root tests, which are more powerful than performing a separate unit root test for each individual series because the power of the test increases as the sample size increases (Afriyie *et al.*, 2020). The importance of a prior check of the existence of unit roots in the panel data is to avoid the effect of misinterpretation of estimated results. Two generations of panel unit root tests can be distinguished according to whether the unit root tests allow for the existence of correlation across residuals of panel units.

The first generation of panel unit root tests is based on the cross-sectional independency hypothesis and includes Levin and Lin (1993), Levin *et al.* (2002), Harris and Tzavalis (1999), Im *et al.* (1997, 2002, 2003), Maddala and Wu (1999), Choi (2001, 2002), Hadri (2000). On the contrary, the second-generation type assumes there is a correlation across sections, which includes the contributions of Bai and Ng (2004), Phillips and Sul (2003), Moon and Perron (2004), Choi (2002), and Pesaran (2003).

The second-generation tests aren't used often, and commercial software doesn't have them yet. So, we'll only go over the tests from the first generation.

The first generation of panel unit root tests, which are based on the cross-sectional independency hypothesis, is divided into two parts; the first part assumes that there is a common unit root for all individuals (homogeneous unit root). This part includes three tests: the Levin Lin Chu test, the Breitung test, the Harris-Tzavalis test, and the Hadri test. While the second part includes the tests that allow for different unit roots across individuals (heterogeneous unit root), these tests are the Im, Pesaran and Shin tests, Maddala and Wu tests, and Choi test.

1. Tests with a common unit root process (homogeneous):

The following tests treat panel data as being composed of homogeneous cross-sections (i.e. pooled data series), with the null hypothesis that each individual time series Y_{it} contains a unit root ($H_0\colon \rho = 0$) against the alternative that each time series is stationary (no unit root) ($H_a\colon \rho < 0$).

a. Levin Lin (LL) test:

Levin and Lin (1993) proposed a unit root test by considering the model:

$$Y_{it} = \rho y_{i,t-1} + \alpha_{mi} d_{mt} + \varepsilon_{it} \qquad m = 1,2,3, \qquad (5)$$
$$i = 1,\ldots, N, \text{ and } t = 1,\ldots,T,$$

where α_{mi} represents the corresponding vector of coefficients for the model and d_{mt} indicates the vector of deterministic variables. In particular $d_{1t} = \varphi$ with no individual effects, $d_{2t} = \{1\}$ in which the series y_{it} has an individual-specific mean but no time trend, and $d_3 = \{1, t\}$ in which the series y_{it} has an individual-specific mean and a linear individual-specific time trend, and $\varepsilon_{it}$is a stationary process.

b. Levin Lin Chu (LLC) test:

The LLC test (Levin *et al.*, 2002) suggests some adjustments to the LL test by considering the following model:

$$\Delta Y_{it} = \rho y_{i,t-1} + \sum_{L=1}^{P_i} \theta_{iL} \Delta Y_{i,t-L} + \alpha_{mi} d_{mt} + \varepsilon_{it}, \qquad (6)$$
$$m = 1, 2, 3.$$

The lag order P_i is the lag order and can vary across individuals. This LLC test is suggested to be used for balanced panels of moderate size with N between 10 and 250 and T between 25 and 250.

c. Harris and Tzavalis (HT) test:

Harris and Tzavalis (1999) derived a test that is similar to the LLC test but easier to use. It is designed to be applied to balanced panel data sets that are relatively short in T and relatively large in N for serially uncorrelated errors only. The test statistic is based on the OLS estimator of ρ, in the regression model:

$$y_{it} = \rho y_{i,t-1} + \alpha_{mi} d_{mt} + \varepsilon_{it}, \qquad m=1,2,3 \qquad (7)$$

Since the test, as implemented, uses y_{it} rather than Δy_{it} as the dependent variable, then the test is for $H_0\colon \rho = 1$ rather than $\rho = 0$.

d. Breitung test:

Breitung (2000) developed a pooled unit root test based on unbiased estimators rather than bias-corrected ones as in the LLC test and Im, Pesaran and Shin tests because the bias corrections imply a severe loss of power. The general model for this test is:

$$Y_{it} = \rho y_{i,t-1} + \sum_{L=1}^{p_i} \theta_{iL} \Delta Y_{i,t-L} + \alpha_{mi} d_{mt} + \varepsilon_{it} \quad , \quad m=1,2,3 \tag{8}$$

Note that the Breitung test has good power even with small datasets (N=25, T=25), but the power of the test appears to deteriorate when T is fixed and N is increased.

e. Hadri test:

For a different null hypothesis that there is no unit root in any of the series in the panel against the alternative of a unit root in the panel, and as a generalisation of the KPSS test for a single time series, Hadri (2000) proposed a residual-based Lagrange Multiplier (*LM*) test. Practically, this test is recommended for large T and moderate N.

2. Tests with individual unit root processes (heterogeneous)

a. Im, Pesaran, and Shin (IPS) test:

The IPS test (Im *et al.*, 1997, 2003) is proposed for balanced panel data to relax the LLC's strong assumption of homogeneity of ρ_i in Equation (6), where it allows for some (but not all) of the individual series to have unit roots.

The IPS test is derived based on the ADF statistics averaged across individuals as $\bar{t} = \frac{1}{N}\sum_{i=1}^{N} t_{iT}$, where t_{iT} is the t-statistic for a testing unit root in the i^{th}individual with finite mean and variance.

The IPS test is the most often used in practice because it is simple and easy to use.

b. Maddala and Wu (MW) test:

Maddala and Wu (1999) suggested using the Fisher (1932) test, which is based on adding up the p-values of the test statistics for a unit root in each cross-sectional unit and comparing them to the appropriate χ^2critical value.

There are two pros of the MW test; the first is that it does not require using the same unit-root test in each cross-section, and the last is that it does not require a balanced panel as the IPS test does. On the other hand, the main cons of the MW are that the p-values for each t statistic in a cross-section have to be derived by Monte Carlo simulation.

c. Choi test:

Choi (2000) has explored the confirmatory analysis, which combines a test under the null hypothesis of stationarity with a test under the null of unit root in panel data. This approach is expected to improve the reliability of test inferences over using either test alone when the two tests corroborate each other. Further, if under different null hypothesis, the two tests reject their respective nulls simultaneously.

IV. METEOROLOGY DATA

The data is obtained from the Palestinian Meteorological Department (PMD) at the Ministry of Transport, Palestine. The available data present meteorological factors of five stations in the West Bank in Palestine, namely Ramallah, Nablus, Jenin, Jericho, and Hebron, between the periods from January 2007 to December 2014. The factors are temperature, pressure, wind speed, relative humidity, and rainfall.

In this section, the main goal is to try to figure out how much temperature, pressure, relative humidity, and wind speed affect rainfall in the five study governorates.

Since the amount of rainfall is affected by the change of other meteorological factors, rainfall is the dependent variable represented by total monthly rainfall, and the other variables will be explanatory. This data set has no missing observations, so we have balanced panel data.

A. Descriptive Statistics

Table 1 presents the basic descriptive statistics for study variables, as well as the basic descriptive statistics of considered variables for each governorate in the study period from (Jan-2007 to Dec-2014). Each governorate has 96 observations for each variable, for a total of 480 observations for each variable. The descriptive statistics in Table 1 reveal the following characteristics.

Jericho has a drier climate compared to the other governorates, where it has the highest central tendency values of temperature and pressure, while it has the lowest central tendency values of rainfall, relative humidity, and wind speed. That's due to its occurrence in the rain shadow (Allouh, 2004) and its dropping elevation under the sea level (-260 m), (PMD, 2022).

Table 1. Descriptive statistics for variables by governorate.

Variable	Statistic	All data	Ramallah	Nablus	Jericho	Jenin	Hebron
TEMPERATURE (C)	**mean**	19.550	16.98	18.46	24.56	20.88	16.84
	median	19.950	18.05	19.50	25.1	21.65	17.7
	S.D	6.409	5.284	5.48	5.825	6.453	5.588
	minimum	5.700	6	7.20	11.8	9.4	5.7
	maximum	34.500	25.7	27.2	34.5	29.9	26.2
PRESSURE (millibar)	**mean**	960.4	917.3	950.1	1040	996.4	898.3
	median	950.4	917.2	950.4	1040	996.5	898
	S.D	52.135	1.745	3.725	3.365	5.819	4.329
	minimum	881.2	881.2	941.5	1028	989.6	881.2
	maximum	1051.6	920.8	957.4	1052	1003.9	928.9
HUMIDITY (%)	**mean**	61.97	66.85	66.07	48.74	65.86	62.35
	median	63.00	67.8	66	47	65.9	62
	S.D	10.80	9.639	7.876	5.901	8.759	9.383
	minimum	34.00	44	46	34	52	38
	maximum	85.00	85	83	68	79	83
WIND SPEED (Km/hour)	**mean**	6.969	9.671	6.049	5.207	6.248	7.668
	median	6.7	9.9	6.3	5.050	6.7	8.050
	S.D	2.775	2.655	1.619	2.144	2.052	2.821
	minimum	1.3	3.5	2.3	1.3	1.7	2
	maximum	17.7	15.4	9	9.8	12.1	17.7
RAINFALL (millimetre)	**mean**	36.15	49.58	48.52	10.77	33.63	38.25
	median	3.9	3.95	5.65	0.50	4.75	4.45
	S.D	62.605	79.293	73.886	52.860	16.796	62.775
	minimum	0.0	0.0	0.0	0.0	0.0	0.0
	maximum	430.7	430.7	327.8	73.5	258.7	311

S.D: Standard deviation

Ramallah and Hebron have a wetter climate compared to the other governorates, where they have the lowest central tendency values of temperature and pressure and the highest central tendency values of rainfall, relative humidity, and wind speed. This is due to the effect of the elevation factor above sea level of 856 m and 1005 m, respectively (PMD, 2022).

Jenin and Nablus have a moderate climate depending on their central tendency values. This is due to its middle elevation compared to the other study governates, 178 m and 570 m, respectively (PMD, 2022).

The standard deviation of the rainfall for each governorate is ranged between 16.796 millimetres and 79.293 millimetres. It may be referred to the location and other meteorological factors as will be assessed in the following subsections.

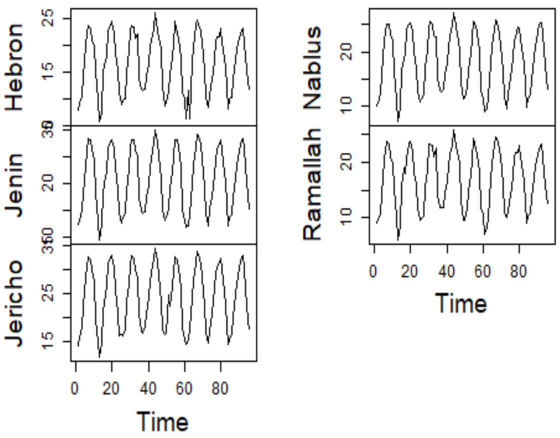
B. Time Series for Study Variables

The time series plots are used to evaluate patterns, general trends, and behaviours in data over time. Figure 1 presents the time series plots for the five considered meteorological factors with respect to the five governorates.

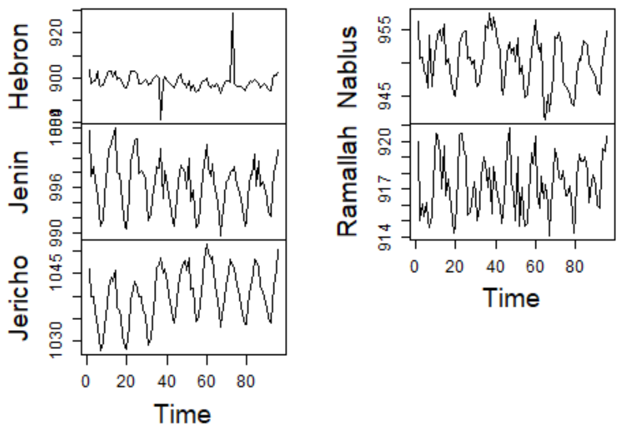
Table 2 shows the values of the KPSS test and their p-value as well as the fitted ARIMA models and its associated coefficients for the monthly average/total values of the time series factors for each of the study stations in the period (Jan 2007-Dec 2014).

Table 2. KPSS test and ARIMA models for meteorological factors time series in study stations.

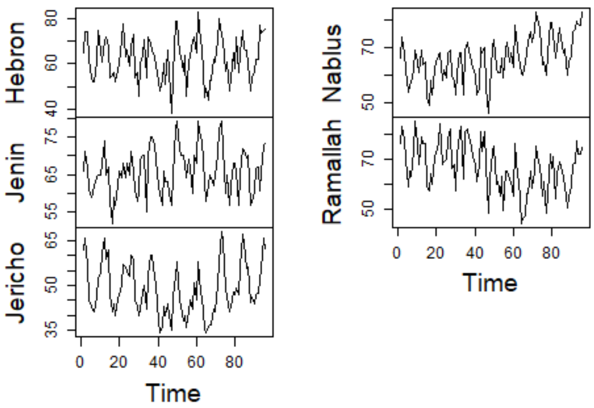
	Variable	Ramallah	Nablus	Jericho	Jenin	Hebron
Temperature	KPSS (P-value)	0.025 (0.100)	0.023(0.100)	0.027(0.100)	0.029 (0.100)	0.021 (0.100)
	ARIMA Model	ARIMA (5,0,1)	ARIMA (2,0,2)	ARIMA (5,0,0)	ARIMA (5,0,0)	ARIMA (3,0,1)
	Coefficients	AR (1) 1.146	AR (1) 1.715	AR (1) 0.774	AR (1) 0.791	AR (1) 1.186
		AR (2) -0.366	AR (2) -0.979	AR (2) 0.043	AR (2) -0.027	AR (2) -0.084
		AR (3) -0.143	MA (1) -1.039	AR (3) -0.189	AR (3) -0.108	AR (3) -0.502
		AR (4) -0.001	MA (2) 0.270	AR (4) - 0.129	AR (4) -0.157	MA (1) -0.686
		AR (5) -0.200	Constant 18.488	AR (5) -0.245	AR (5) -0.256	Constant 16.885
		MA (1) -0.512		Constant 24.571	Constant 20.894	
		Constant 17.021				
Pressure	KPSS (P-value)	0.080 (0.100)	0.248 (0.100)	0.421 (0.068)	0.119 (0.100)	0.200 (0.100)
	ARIMA Model	ARIMA (0,0,2)	ARIMA (2,0,3)	ARIMA (0,0,2)	ARIMA (3,0,1)	ARIMA (1,0,0)
	Coefficients	MA (1) 0.584	AR (1) 1.698	MA (1) 0.296	AR (1) 1.164	AR (1) 0.161
		MA (2) 0.442	AR (2) -0.964	MA (2) 0.514	AR (2) -0.134	Constant 898.295
		Constant 917.312	MA (1) -1.205		AR (3) -0.408	
			MA (2) 0.426		MA (1) -0.598	
			MA (3) 0.174		Constant 996.372	
			Constant 950.152			
Humidity	KPSS (P-value)	**0.856 (0.010)**	**1.297 (0.010)**	0.190 (0.100)	0.180 (0.100)	0.058 (0.100)
	ARIMA Model	ARIMA (1,1,1)	ARIMA (0,1,0)	ARIMA (3,0,0)	ARIMA (3,0,0)	ARIMA (2,0,2)
	Coefficients	AR (1) 0.429	White Noise	AR (1) 0.842	AR (1) 0.594	AR (1) 1.693
		MA (1) -0.926		AR (2) 0.013	AR (2) -	AR (2) -0.975
				AR (3) -0.306	0.082	MA (1) -1.565
				Constant 48.745	AR (3) -0.216	MA (2) 0.806
					Constant 65.837	Constant 62.159
Wind Speed	KPSS (P-value)	0.314 (0.100)	**1.349 (0.010)**	**1.263 (0.010)**	0.261 (0.100)	**0.663 (0.017)**
	ARIMA Model	ARIMA(1,0,0)	ARIMA(1,1,1)	ARIMA(0,1,0)	ARIMA(1,0,2)	ARIMA(0,1,1)
	Coefficients	AR(1) 0.763	AR(1) 1.164	White Noise	AR(1) 0.598	MA(1) -0.504
		Constant 9.471	AR(2) -0.134		MA(1) 0.125	
			AR(1) 0.312		MA(2) 0.368	
			MA(1) -0.864		Constant 6.067	
Rain	KPSS (P-value)	0.027 (0.100)	0.026 (0.100)	0.044 (0.100)	0.046 (0.100)	0.029 (0.100)
	ARIMA Model	ARIMA(4,0,1)	ARIMA(4,0,1)	ARIMA(2,0,2)	ARIMA(1,0,0)	ARIMA(2,0,2)
	Coefficients	AR(1) 0.945	AR(1) 0.815	AR(1) 1.584	AR(1) 0.331	AR(1) 1.7015
		AR(2) -0.189	AR(2) 0.008	AR(2) -0.818	Constant 33.544	AR(2) -0.9657
		AR(3) -0.019	AR(3) -0.090	MA(1) -1.594		MA(1) -1.8103
		AR(4) -0.229	AR(4) -0.292	MA(2) 0.628		MA(2) 0.9685
		MA(1) -0.771	MA(1) -0.768	Constant 10.118		Constant 37.2175
		Constant 49.022	Constant 48.216			



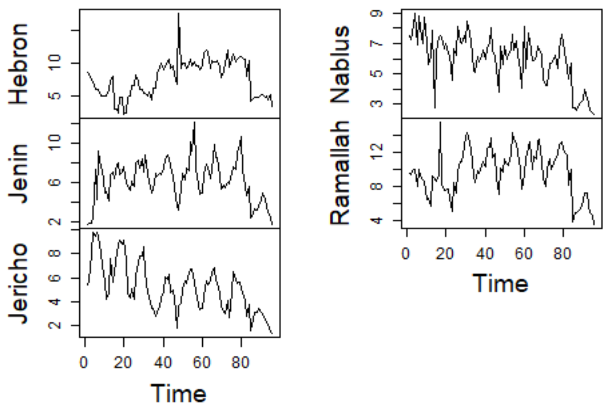
(a) Temperature



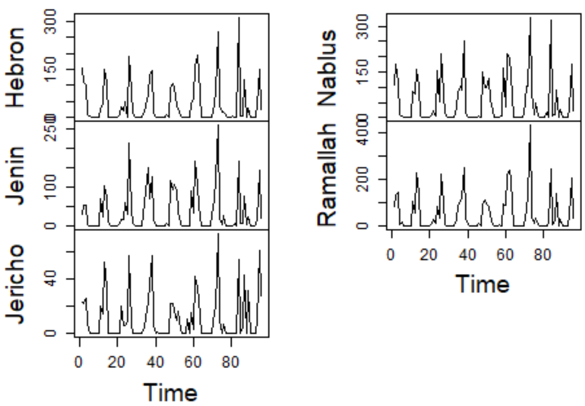
(b) Pressure



(c) Relative humidity



(d) Wind speed



(e) Rainfall

Figure 1. Time series plots of monthly average/total factors at each station (Jan 2007-Dec 2014), (a) temperature, (b) pressure, (c) relative humidity, (d) wind speed, and (e) rainfall.

The p-value of the KPSS test is greater than the significance level 0.05 for all governorates, which indicates that the series of all considered factors are stationary, except for five series (in bold), which become stationary at the first difference of series values. The series of relative humidity at Ramallah and Nablus, where Ramallah has a downward trend, while Nablus has an upward trend, and the series of wind speeds at Nablus, Jericho, and Hebron, where Hebron has an upward trend, while Nablus and Jericho have downward trends.

Since the objective of this article is to study the impact of the meteorological factors (temperature, pressure, relative humidity, and wind speed) on rainfall for the five governorates, ARIMA models could not achieve such an objective. Thus, we utilise the panel data models and their tests in the following subsection.

C. Unit Root Tests for Panel Data:

Before constructing the appropriate model for the meteorological panel data, we conducted the stationarity (unit root) tests for each variable, namely LLC, IPS, Hadri and Breitung tests.

Table 3 presents the values of panel unit root tests associated with their p-values for each factor. In general, most tests show that the study factors are stationary since the p-value is less than 0.05. Thus, we can fit the appropriate panel model for the data, as discussed in the following subsection.

Table 3. Panel unit root tests and their p-values in brackets for study factors.

Test	RAIN	TEMP	PRESS	HUMID	WIND
LLC	-5.063 (0.000)	-0.138 (0.890)	-10.182 (0.000)	-9.580 (0.000)	-5.611 (0.000)
IPS	-12.321 (0.000)	-20.045 (0.000)	-14.630 (0.000)	-11.545 (0.000)	-5.601 (0.000)
Hadri	-1.340 (0.180)	-0.859 (0.390)	2.151 (0.030)	7.878 (0.000)	30.396 (0.000)
Breitung	0.000 (0.001)	0.003 (0.020)	0.017 (0.820)	0.003 (0.026)	0.006 (0.212)

D. Panel Data Models

The considered metrological data contains 96 time periods for each governorate (i.e., $T_i = 96, \forall_i = 1, \dots, 5$), so the data is balanced since the number of time periods is large compared to the number of individuals (governorate), i.e., (N=5<<T=96) then the data is considered macro panel data.

The proposed model uses the total monthly rainfall as the dependent variable, and the control factors are the monthly average temperature, pressure, relative humidity, and wind speed. As a primary check of the linearity assumption, the scatter plot matrix has been constructed for the considered variables for each governorate, and it reveals an acceptable linearity trend.

Three models were fitted to study the relations between the mentioned factors, namely, the Pooled Regression Model (PRM), the Fixed Effects Model (FEM), and the Random Effects Model (REM). 90% of the data is used to estimate the models, and the remaining 10% is used to verify the quality of the appropriate estimated model using prediction property. Table 4 presents the estimates of each model parameter associated with their standard error.

Table 4. Panel data models for the metrological data.

Coeff.	PRM	FEM	REM
Constant	-129.631* (62.981)	-	-129.631* (62.981)
TEMP	-6.280 * (0.415)	-7.336* (0.530)	-6.280* (0.415)
PRESS	0.232* (0.055)	-1.508* (0.718)	0.232* (0.055)
HUMID	0.756* (0.250)	0.858* (0.303)	0.756* (0.250)
WIND	2.664* (0.905)	4.403* (1.135)	2.664* (0.905)

* Statistically significant at 0.05 significance level.

Hausman's test is performed to compare the results of the fixed effects estimator with the results of the random effects estimator. The Hausman's test statistic is obtained to be 31.508 with p-value= 0.000, which shows that the random effects estimator is inconsistent, and therefore the fixed effects estimator is the best choice.

Table 5. Fixed effects for each governorate.

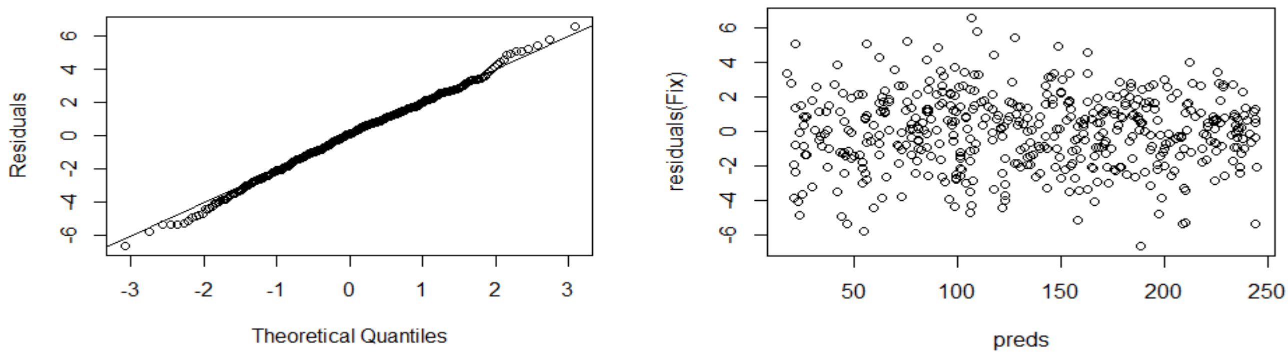
City	Hebron	Jenin	Jericho	Nablus	Ramallah
Effect	-114.876	61.416	149.738	-8.961	-87.317

Table 5 shows the estimated specific effect (fixed effect) for each governorate in this data set. This effect can be explained as a result of the combination effect of independent variables and related omitted factors. From Tables 4 and 5, the estimated model is formulated as follows:

$$RAIN = -7.336\ TEMP - 1.508\ PRESS + 0.858\ HUMID + 4.403\ WIND - 114.876\ Hebron + 61.416\ Jenin + 149.738\ Jericho - 8.961\ Nablus - 87.317 Ramallah + \varepsilon \quad (9)$$

The coefficient of determination (R^2) of model (9) equals 0.468, which means that the fixed effect model interprets 46.8% of the change in the total monthly rainfall, and the fitted model is significant where the F-statistic is 93.129 with p-value 0.000.

The residuals of the fixed model are normally distributed, where the Kolmogorov-Smirnov test value was 0.03182 and p-value = 0.716, as also graphically presented in Figure 2 (a). Furthermore, the plot of the residuals against the fitted value s in Figure 2 (b) reveals the constant variance of the residual s.



(a) (b)

Figure 2. Plots of the residuals of the fixed model, (a) QQ normal plot, and (b) plot of the residuals against the fitted values.

From the fitted model in (9), the coefficients could be interpreted as follows:

There is a significant negative effect of temperature on the total rainfall, where the increase in temperature by 1 (C) leads to a decrease in the total monthly rainfall of 7.336 millimetres.

There is a significant negative effect of pressure on the total rainfall, where the increase of pressure by 1 (millibar) leads to a decrease in the total monthly rainfall of 1.508 millimetres.

There is a significant positive effect of relative humidity on the total rainfall, where the increase in humidity by 1% leads to an increase in the total monthly rainfall of 0.858 millimetres.

There is a significant positive effect of wind speed on the total rainfall, where an increase of wind speed by 1 Km/hour leads to an increase in the total monthly rainfall of 4.403 millimetres.

Furthermore, there are different effects for each governorate on the monthly total rainfall, where Nablus, Ramallah, and Hebron have a positive effect, while Jenin and Jericho have a negative effect. The elevations of the first three governorates are more than 570 m, while the last two governorates are less than 178 m.

V. CONCLUSION

This article has reviewed the main panel data models with a focus on the panel unit root tests. These statistical methods have been applied to a meteorological data set of five governorates in Palestine in the time period from Jan. 2007 to Dec. 2014. The fixed effect model has been fitted to explain the effect of temperature, pressure, relative humidity, and wind speed on the rainfall. It explained more than 46% of the variability in the total monthly rainfall~~,~~ and illustrated effects on the elevation of each governorate.

Further studies could be conducted by considering any or some of these metalogical factors and asses their effects on crops yields, pollutions and other economic factors.

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