Water Resources Management through the use of GIS

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Abstract

Water resources information in Albania is very scarce. The country does not have a consolidated monitoring network to collect hydrological and other related data and the quantity and quality of the carried out measurements carried out is limited. The water institutions are very fragmented and the monitored and collected data are being stored in different databases, and non-standardized formats, making it hard for the data to be easily retrieved and exchanged. This paper provides a case of the multiple uses of climate data in a water resources geodatabase through compiling of a mean annual precipitation map for Albania. It also demonstrates the importance of geodatabases to support decision making in the management of water resources, and also to the research activities in this area.

Keywords: GIS, water resources, precipitation

INTRODUCTION

Today water resources all over the world are facing significant challenges. Increasing population and urbanization put a pressure on limited freshwater resources. Climate change together with its impact on the hydrological cycle, causing floods and droughts, poses another global concern. Man-made threats such as pollution, waste, and mismanagement, account for the depletion in quality and quantity of water resources.

Water managers, planners, and decision makers all over the world have to respond to these challenges in their countries. They need to make sure that the water resources of their country are managed in a way that ensures that they remain pollution free, and that they will fulfill the water demands today and in the future. In addition, water managers have to be prepared to respond to water related extreme events such as flooding and drought, by using both forecasting techniques and applying emergency response plans.

In order to fulfill each of the tasks of managing, planning and forecasting, and at the same time ensure a comprehensive decision-making process, the managers need to stay updated and well informed on the condition of the water resources as well as other related information. This information is provided by the data collected from hydrological measurements and observations of water quality, water quantity such as level of reservoirs and river flows, meteorological observations such as precipitation and temperature, soil moisture, groundwater, etc. (Maidment, 2012)

Collecting hydrological data is not enough. The data need to be "polished" by checking for errors, converted into a standardized format, and stored in a central geodatabase along with a description on the data (metadata). Additionally, the geodatabase should allow for easy access and retrieval of the data by the users and should be able to connect to models in order to produce further information on the water quantity or quality, depending on the model used.

As for Albania, although a country abundant in water resources, today Albania has limited information on the quality, quantity, and even location of its water resources. The National Hydrological Network of Albania (NHNA) is limited in the quantity and quality of the hydrometeorological measurements that it provides. In addition, due to the fragmentation of the water institutions, the monitored and collected data are being stored in different databases, and in non-standardized formats, making it hard for data to be easily retrieved and exchanged.

The objective of this paper is to demonstrate one of the multiple uses of climate data in a water resources geodatabase. For that purpose, a mean annual precipitation map is being developed for Albania. The methodology being used to create the precipitation map is based on the PRISM method (PRISM Climate Group, 2013) which is the used method for developing precipitation maps in the U.S. In addition, another precipitation map with precipitation values received from the stations is being created and shared in ArcGIS Online.

The data being used are precipitation records collected by the Hydrometeorological Institute of Albania from 147 gages all over the country. For each station, data have been assembled over a 30 year period of time (1951-1980) and then they have been averaged to give long-term monthly and annual precipitation values. The long-term annual precipitation values were the ones used to develop the precipitation map.

Additional data being used include the 7.5 arc-second Digital Elevation Model (DEM) raster developed by the Shuttle Radar Topography Mission (SRTM) and downloaded from the website of U.S. Geological Survey (USGS). Also, the shapefile of the administrative boundaries of Albania obtained from DIVA-GIS (DIVA-GIS, 2013) and a shapefile of the coastline obtained from ISCIENCES, L.L.C (ISCIENCES, L.L.C, 2013) were used in this analysis.

METHODOLOGY

The methodology used for developing the precipitation map is based on the Parameter-elevation Regressions on Independent Slopes Model (PRISM) developed by the PRISM Climate Group. PRISM is the standard method used for preparing precipitation maps in the U.S. and it is based on a simple elevation regression function, where precipitation increases with elevation. (PRISM Climate Group, 2013)

Prior to running the regression function, the following data were developed using the 7.5 arc second DEM raster. Using ArcMAP, elevation values for each precipitation station were extracted. Further, slope and aspect were calculated for each DEM cell together with the coastal proximity values.

The PRISM method takes into account the influences of the above mentioned topographic factors such as elevation, slope, aspect, coastal proximity, in order to predict the precipitation at a certain point of the grid. Each of these factors together with the parameters used to characterize them is explained in the following sections.

Reconditioning of the DEM

Before starting with calculating the weights for each station, a reconditioning of the DEM was done. This was a necessary step in order to fulfill the requirement about the minimum number of stations (see Table no 1) falling in the same facet (area over which the slope direction is constant) as the target grid cell.

Table 1: Description and Values for the Parameters used in the Precipitation Model. (Daly, Gibson, et al. 2002)

Parameter	Description	Value
Elevation weightingb		
Fh	Elevation weighting exponent	1
Δh m	Elevation weighting importance scalar	0.2
	Minimum station-target grid cell elevation difference	100 m
Δh x	Maximum station-target grid cell elevation difference	2500 m
Facet Weighting		
c	Facet weighting exponent	0.01
Coastal Proximity Weighting		
px	Maximum coastal proximity difference	100 km
v	Coastal proximity weighting exponent	0.01
Regression Function		
r	Radius of influence	30 km
sf	Minimum number of on-facet stations desired in regression	3
st	Minimum number of total stations desired in regression	7
amin*	Minimum regression slope	0.00006 1/m
amax*	Maximum regression slope	0.00065 1/m
ad	Default regression slope	0.3 mm/m
a0	Intercept	0.9

*) normalized by the mean precipitation in the regression function; i.e. (100 mm/km slope)/ (1000 mm mean precipitation) = 0.1 km-1 normalized slope)

In this case, the DEM was reconditioned in order to broaden the spatial extent of the facets and hence allow for a minimum of 3 and a maximum of 7 stations falling in the same facet as the target grid cell. The DEM was processed through a five-point filter where the elevation at cell hij is calculated as:

hij = 0.5 hij + 0.125(hi+1j + hi-1j + hij+1 + hij-1) (Daly, et al., 2002)

Then, six different facet grids were computed: 1) Facet grid derived from the unfiltered DEM; 2) DEM is being filtered 8 times; 3) DEM is being filtered 16 times; 4) DEM is being filtered 24 times; 5) DEM is being filtered 32 times; 6) DEM is being filtered 40 times. During this process the elevation of the cell is recalculated, starting with 8 times up to 40 times, using the elevation from the surrounding grid cells. This process modifies the aspect of the grid cells through creating a smoother DEM.

Station Weighting

Before entering the regression function, each station was assigned weights based on its influence on the target grid cell in terms of elevation, slope, aspect, and coastal proximity. The total weight accounting for each of the aforementioned factors was calculated as:

W = [Fh W2h]1/2 Wcp Wf (Equation 2)

Wh: elevation weight,
Wcp: coastal proximity weight,
Wf: facet weight,
Fh: elevation weighting importance scalar, default value 0.2 (Daly, et al., 2008)

Elevation weighting

Using the elevation weighting, a station's weight increases as the elevation distance from the target grid cell decreases. The elevation weight was calculated as follows:

$$Wh = \begin{cases} \frac{1}{\Delta h_m^b}; \ \Delta h \leq \Delta h_m \\ \frac{1}{\Delta h^b}; \ \Delta h_m < \Delta h < \Delta h_x \\ 0; \ \Delta h \geq \Delta h_x \end{cases}$$ (Daly, et al., 2002) (Equation 3)

Δh: the absolute elevation difference between the station and the target grid cell,
b: the elevation weighting exponent,
Δhm: the minimum elevation difference,
Δhx: the maximum elevation difference.

Facet weighting

A station that lies on a similarly oriented facet as the target grid cell is assigned a higher weight. The facet weight for a station was calculated as:

$$Wf = \begin{cases} 1; \ \Delta f \leq 1 \ and \ B = 0 \\ \frac{1}{(\Delta f + B)^c}; \ \Delta f > 1 \ or \ B > 0 \end{cases}$$ (Daly, et al., 2002) (Equation 4)

Δf: the absolute orientation difference between the station and the target grid cell,
B: the number of barrier cells with an orientation different than that of the target grid cell,
c: the facet weighting exponent.

Coastal Proximity weighting

Using the information from the coastal proximity raster developed in ArcMap, this weight selects the stations based on their coastal proximity similarities to the target grid cell. The coastal proximity weight for a station was calculated as:

$$Wcp = \begin{cases} 1; \ \Delta p = 0 \\ 0; \ \Delta p > p_x \\ \frac{1}{\Delta p^v}; 0 < \Delta p \leq p_x \end{cases} \quad \text{(Daly, et al., 2002)} \quad \text{(Equation 5)}$$

Δp*:* the absolute difference of coastal proximity index between the station and target grid cell,

v: the coastal proximity weighting exponent,

px: the maximum proximity difference.

Elevation Regression Function

As a final step, the elevation regression function was computed using the elevation, precipitation pairs from the measuring stations surrounding the target grid cell within a specified radius r. The simple linear regression has the form:

$P = a X + a_0; a_{min} \leq a \leq a_{max}$ (Daly, et al., 2002) (Equation 6)

P: the predicted precipitation,

a: regression slope

a0: intercept,

X: DEM elevation at the target grid cell

amin: minimum valid regression slope

amax: maximum valid regression slope

Another parameter used in the regression function is the default slope, ad. This parameter is being used by the model in cases when the regression slope does not fall within the amin and amax range values. In this case the model will try to identify the stations causing the anomaly by rerunning and picking stations one by one starting with the ones with the lowest weights up to those with the highest. In case the slope will still not fall within the range, and the total number of stations has reached st, then the default slope, ad, is being picked by the regression function.

Model Calibration

After developing the regression function, the model was run several times using different combinations of values for the four regression parameters:

a_{min}: minimum valid regression slope,

a_{max}: maximum valid regression slope,

a_d: default regression slope,

a_0: intercept.

The precipitation values received for each scenario were compared to the observed precipitation values from the stations. Then the Mean Square Error (MSE) was computed for each case using the following formula, and the model with the least MSE was accepted as the best solution.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (P_i - O_i)^2 \quad \text{(Equation 7)}$$

Table 2 shows a summary of the four scenarios with the lowest MSE value:

Table 2: MSE Values for Different Model Calibration Scenarios.

Case	a_{min}	a_{max}	a_d	a_0	MSE
1	0.00018	0.0005	0.25	0.65	375,642
2	0.00018	0.0005	0.375	0.75	294,347
3	0.00018	0.0005	0.4	0.9	268,632
4	0.00006	0.00065	0.3	0.9	254,323

The regression function with the lowest MSE value (254,323) was the one picked to develop the precipitation map.

RESULTS AND DISCUSSION

Precipitation Map

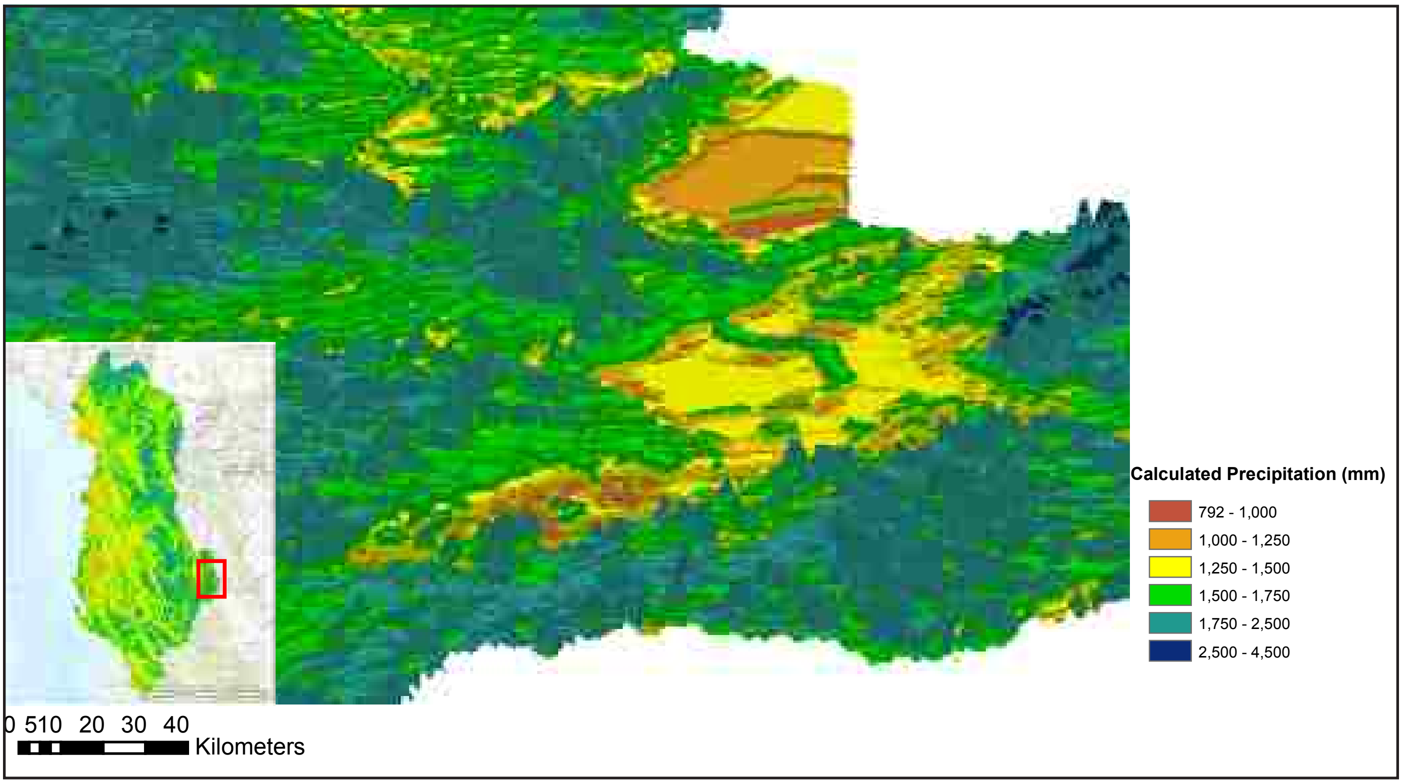
Figure 1: Precipitation map of Albania

The map shows the spatial variation of precipitation and the elevation-precipitation relationship with the precipitation increasing with elevation. These patterns appear to be consistent when compared to the variations in elevation shown in the DEM map in Figure 2.

Figure 2: DEM Map of Albania.

The precipitation model demonstrates also the orographic effects with the highest precipitation values occurring on top of the mountains and the lower precipitation values near the coast and on flat areas. An example of this is the rain shadow in the east, near the Korca region (Figure 3).

Figure 3: Rain Shadow in the Korca Region.

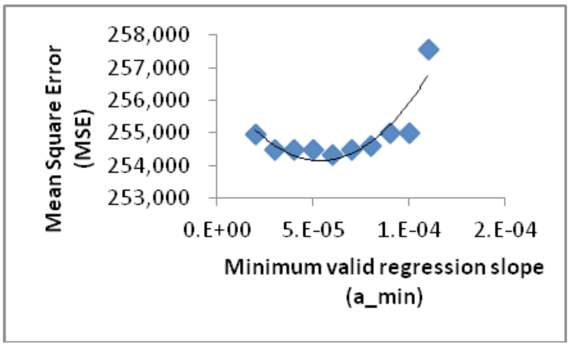


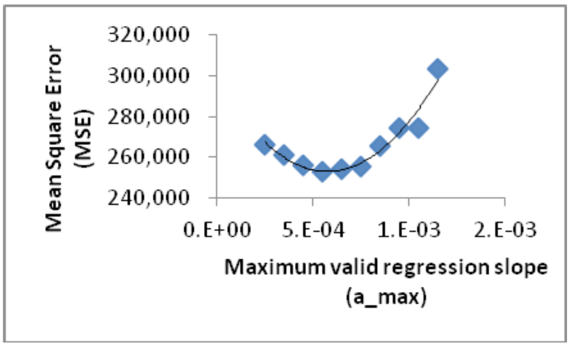
The rainfall regime in Albania is defined by the interaction of several climate factors such as the trajectory of the cyclones and air masses, the horizontal wind speed and the wind direction relative to the barrier, the topographic characteristics, etc. From the map in Figure 5.1 it can be noticed that the highest precipitation occurs in the Alps in the north. These high values of precipitation occur because of the movement of air masses in a perpendicular direction with the mountains. (Pano, 2008)

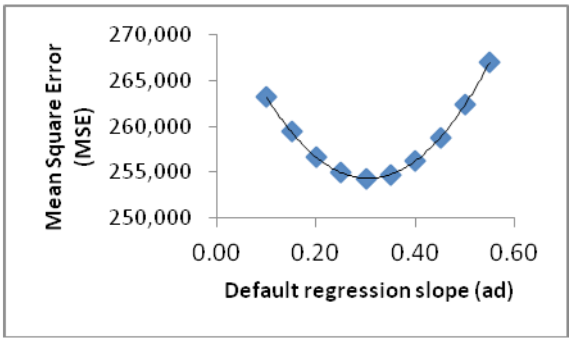
Sensitivity Analysis

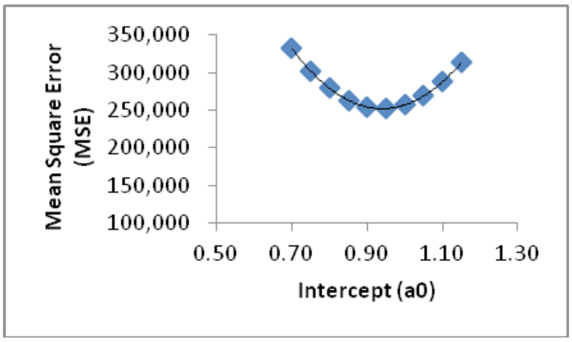
In order to test the response of the precipitation model against the different values of regression parameters, a sensitivity analysis was done for each of the four parameters: amin: minimum valid regression slope, amax: maximum valid regression slope, ad: default regression slope, a0: intercept. The following graphs show the results of the sensitivity analysis.

Figure 4: Sensitivity Analysis for the Regression Parameters.









From each of the above graphs, the minimum MSE value of 254,323 was received for the following values of regression parameters:

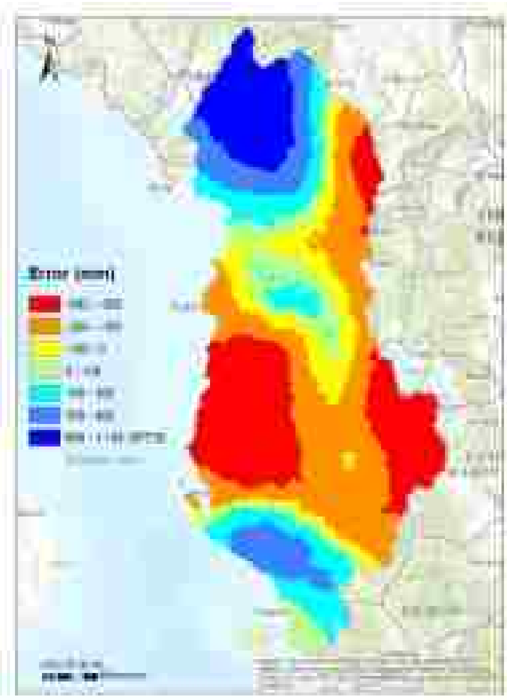
amin	amax	ad	a0
0.00006	0.00065	0.3	0.9

Precipitation Error Map

The precipitation error map is shown on Figure 5. The results were obtained by interpolating the difference in precipitation between the model and measured precipitation at the stations grid cells. The blue areas show over estimation of precipitation on the high mountains on the north and south. The red areas show underestimation of precipitation by the model, with the error being the highest in the coastal area on the west as well as south east.

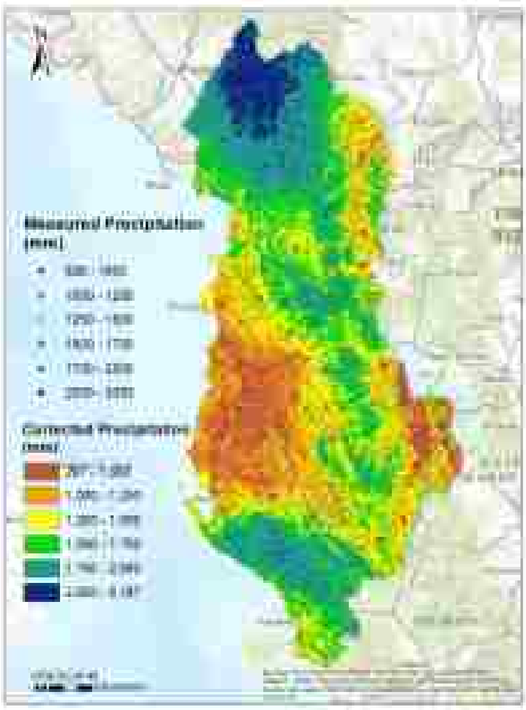
Though this map gives a general distribution of the error, the accuracy of the results is limited. The calculation of the error is based at the stations points only, and for the rest of the country, the error is calculated from the interpolation of the errors at the station points.

Figure 5: Error Map.



In order to correct for the error, an attempt was made by adding the error map to the precipitation map developed by the model. Results are shown in Figure 6.

Figure 6: Corrected Precipitation Map.

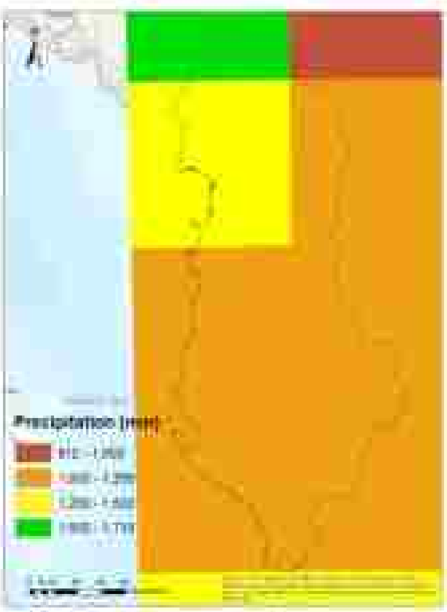


The corrected map shows a better match between the station values and the calculated precipitation. However, the extreme values of precipitation obtained by the corrected map, 297 – 5,187 mm, still exceed the range of precipitation in the literature, 700 – 3500 mm. (Pano, 2008)

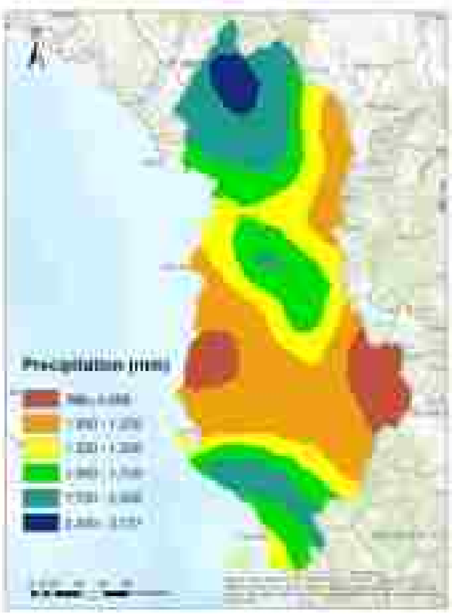
Comparing the PRISM Precipitation Map Results to Kriging Method and GPCC Precipitation Maps

Using Ordinary Kriging Interpolation method, a precipitation map was compiled. The Semivariogram model picked is spherical and the search radius falls within 12 points. In the same time, long range (1951–980) mean monthly precipitation data were downloaded as ASCII format from the Global Precipitation Climatology Centre (GPCC) (GPCC 2013). The data were converted to raster format, were georeferenced and projected using ArcGIS. After that the data from each year were compiled together to create a single mean annual precipitation raster.

Figure 7 shows the results obtained from Kriging as well as the GPCC precipitation map against the precipitation map developed by the model.

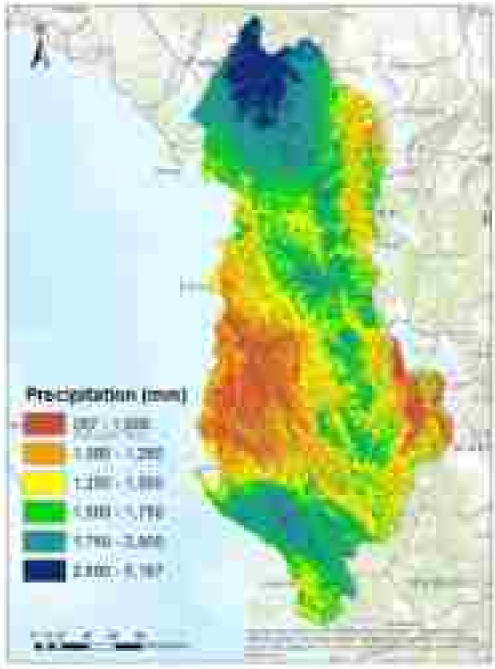


Map1: GPCC



Map2: Ordinary Kriging Interpolation

Map 3: PRISM Model



Map 4: Corrected map

The precipitation map obtained from GPCC shows no regional variability in the country ignoring completely the impact of topography and other climate factors in the precipitation distribution. According to the map, in almost 70% of the country, the precipitation ranges between 100-1250 mm.

The precipitation map developed from Ordinary Kriging Interpolation shows some regional distribution. However, looking at the highest precipitation values developed by Kriging it appears that these values are far from the maximal value of 3500 mm found in the literature.

The PRISM map and the Corrected map (compiled from adding the error map to the PRISM map), show a better regional distribution of the precipitation and a clear orographic effect with the highest precipitation values occurring on top of the mountains. However they both tend to overestimate precipitation in some areas, and in the case of the corrected map, underestimation occurs as well.

The statistics are calculated for each of the maps shown in Figure 7, by comparing in each case the precipitation values at the station points with the precipitation measured at the stations.

Table 3: Statistics at the gage points.

Case	Mean at gages (mm)	Mean error (mm)	StdDev (mm)	RMSE (mm)
PRISM	1472	2	524	522
Corrected	1480	10	214	214
GPCC	1095	- 375	440	576
Kriging	1474	4	183	182
Stations	1470			

PRSM model has the lowest mean error, however it has the highest standard deviation. Comparing the corrected map to PRISM, the mean error is higher (10 mm), however the standard deviation is much lower in this case. GPCC map shows a very high mean error, as well as a high standard deviation. Kriging shows also a low mean error (4 mm) and the lowest standard deviation. This is explained by the fact that Kriging Interpolation relies highly on the precipitation values from the stations.
Statistics are calculated as well for each of the cases, through the entire map, and the results are presented on Table 4.

Table 4: Statistics over the entire country.

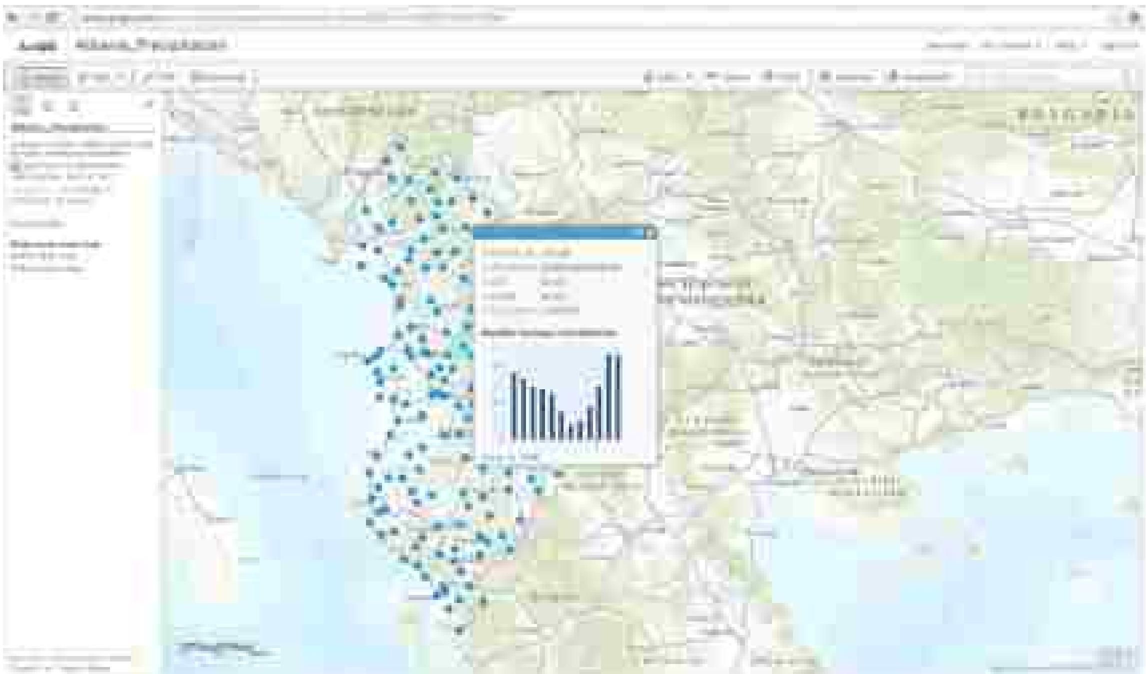
Case	Min (mm)	Max (mm)	Mean (mm)
PRISM	792	3723	1472
Corrected	269	5432	1480
GPCC	1032	1248	1095
Kriging	798	1937	1474
Literature (Pano, 2008)	700	3500	1485

When comparing the statistics over the whole map, the mean precipitation from the Corrected map (1480 mm) is closer to the mean provided by the literature (1485 mm) as opposed to the PRISM mean (1472 mm).
The GPCC statistics compared to the literature show that the minimum, maximum, and man precipitation values are far from those shown in the literature. The minimum and mean precipitation values provided from Kriging are close to those shown by the literature. The maximum precipitation value from Kriging is much lower than that from the literature. This shows again the limitation of Kriging in interpolating above the highest stations.

Precipitation Map on ArcGIS Online

Using the precipitation values from the stations a precipitation map was developed and shared on ArcGIS Online (Figure 8). The map has information on the long-term monthly and annual average precipitation. This information along with a graph of the monthly precipitation can be received by clicking on each of the stations.

Figure 8: ArcGIS Online Precipitation Map of Albania.



CONCLUSIONS

In conclusion, compiling gridded precipitation maps is a complex task which requires optimization of many parameters and knowledge of local terrain characteristics. PRISM represents a model that considers the effects of terrain and climate in predicting the precipitation, however the model needs further optimization of parameters in order to show more accurate results. Further research should include the use of more recent precipitation data as a way to study the temporal trend of precipitation. In addition, other types of data, such as temperature, air humidity, evaporation, river flow data, can be added to the model and allow for further analysis. Easing the process of data access, would benefit such research activities in Albania.

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