Fog-water harvesting Capability Index (FCI) mapping for a semi-humid catchment based on socio-environmental variables and using artificial intelligence algorithms

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Abstract

Fog is an important component of the water cycle in northern coastal regions of Iran. Having accurate tools for mapping the precise spatial distribution of fog is vital for water harvesting within integrated water resources management in this semi-humid region. In this study, environmental variables were considered in prediction mapping of areas with high concentrations of fog in the Vazroud watershed, Iran. Fog probability maps were derived from four artificial intelligence algorithms (Generalized Linear Model, Generalized Additive Model, Generalized Boosted Model, and Generalized Dissimilarity Model). Models accuracy were assessed using Receiver Operating characteristic Curve (ROC). Three social variables were also selected according to their relevance for fog suitability mapping. Finally, Fog-water harvesting Capability Index (FCI) maps were produced by multiplying fog probability by fog suitability maps. The results showed high accuracy in fog probability mapping for the study area, with all models proving capable of identifying areas with high fog concentrations in the south and southeast. For all models, the highest values of importance were obtained for sky view factor and the lowest for slope curvature. Analytic Hierarchy Process results showed the relative importance of social conditioning factors in fog suitability mapping, with the highest weight given to distance to residential area, followed by distance to livestock buildings and distance to road. Based on the fog suitability map, southeast and southern parts of the study area are most suitable for fog water harvesting. The fog spatial distribution maps obtained can increase fog water harvesting efficiency. They also indicate areas for future study with regions where fog is a critical component in the water cycle.

Keywords: *Fog probability and suitability maps; GIS; fog-water harvesting Capability Index (FCI).*

1. Introduction

Water is one of the most abundant natural resources on Earth, but only 3% of free water is potable (Olivier, 2004). In some parts of the world, potable water shortage is a serious problem and many people have no access to potable water, which is one of the most serious problems worldwide (Sharma et al., 2016; Harb et al., 2016). With increasing global population and climate change, lack of drinking water in both arid and humid climates will be a growing problem for modern civilization (Rajaram et al., 2016; Al-Jawad et al., 2019). To tackle these problems, there is a need for implementation of integrated water resources management (IWRM) applying robust methods on basin system scale (Maier et al., 2014; Barbosa et al., 2016; Al-Saidi, 2017). In IWRM, water supply managers are obliged to plan for the use of all available water resources, taking into account economic, social, cultural, health, and environmental issues (Barbosa et al., 2017; Mapani et al., 2017; Sadegh et al., 2018). Optimal use of available water resources and identifying ways to access new water resources are possible solutions to the global water challenges. One potential option is to use humidity in the air as a source of water supply (Klemm et al., 2012). Fog is a source of potable water and collection of fog water using innovative methods could be a sustainable strategy to obtain drinking water for human and animal consumption in foggy areas (Fessehaye et al., 2014; Dodson and Bargach, 2015; Gürsoy et al., 2017). An important feature, especially in coastal or mountainous areas (that are difficult to access and utilize by local people), is that even in the absence of vegetation mountain fog can be captured as a source of water (Khosravi et al., 2015; Olivier, 2004; Sharma et al., 2016; Harb et al., 2016). Countries such as Chile, Peru, Ecuador, Canada, Namibia, and Nepal have already implemented fog water harvesting, with large amounts of fog water harvested in some cases. For example, in one village in Chile with a fog water extraction system, on average 11,000 liters of water are extracted daily from this source (Cereceda et al., 1992; Imteaz et al., 2011; Fessehaye et al., 2014; Sharma et al., 2016; Rajaram et al., 2016). Various techniques for fog water harvesting are applied around the world, depending on the region's conditions. These include dew ponds, air wells, fog fences, and fog harvesting from a variety of fog moisture collection systems.

Fog water harvesting for the purpose of the freshwater consumption has been suggested in recent decades for sites where it is economically justifiable (Klemm et al., 2012; Mahmoud, 2013; Batisha, 2015). Precise knowledge about potential sources for fog water extraction is critical in cost/benefit analysis, as careful site selection can reduce the costs and achieve better results (Choudhury et al., 2007; Hiatt et al., 2012; Kutty et al., 2018). It is particularly important to prepare fog water capability maps based on socio-environmental conditioning factors. The aim of the present study is to develop fog water capability maps for IWRM, using Generalized Linear Model

(GLM), Generalized Additive Model (GAM), Generalized Boosted Model (GBM), and Generalized Dissimilarity Model (GDM), and combining these with background information on natural conditions for fog and environmental variables that affect the fog formation (Domen et al., 2014; Elhag and Bahrawi, 2014; Haghighi et al., 2016; Mustonen et al., 2016). Environmental variables refer to the climate, topographical, and hydrological conditions that govern fog formation. Here, remote sensing data were used to estimate some of these environmental variables.

The specific objective of the work is developing a new computational framework by preparing fog-water harvesting suitability maps based on the selected environmental variables. The novelty and main contribution of the work lies in developing a Fog-water harvesting Capability Index (FCI) based on the socio-environmental variables and artificial intelligence algorithms to select the best sites for implementation of fog water harvesting technology.

2. Material and methods

2.1. Study area

The site selected for the study was the Vazroud watershed (36°14′26″-36°25′54″N, 52°01′46″-52°52′30″ East), which extends across 1400 km^2 in northern Iran (Fig. 1). Based on aridity index of 0.67 (Sahin, 2012: Darabi et al., 2019), mean annual rainfall of 672 mm, and potential evapotranspiration of 1005 mm (in the period 2001-2018), climate type in the Vazroud watershed is semi-humid. The watershed is characterized by mountainous terrain and rugged topography (elevation from 278 to 3577 meter above sea level) (Fig. 1). This is accompanied by frequent intense foggy and cloudy weather, especially in headwater areas. At the same time, there is a severe shortage of fresh water for households and livestock elsewhere in the watershed. Based on these characteristics, fog water harvesting in the Vazroud watershed should be explored.

Fig. 1. SOMEWHERE HERE

2.2. Methods

2.2.1. Artificial intelligence models

A number of artificial intelligence models have been developed in recent years, including those tested here (GLM, GAM, GBM, and GDM) (Guisan et al., 2002).

Generalized Linear Model (GLM)

Generalized linear models are extensions of linear models that are widely used in regression analysis and represent an important class of statistical models that allow for non-linearity and non-constant variance structures in the data (Nelder and Wedderburn, 1972; Guisan et al., 2002; Yeo, 2007). They are based on the relationship between the response variable and linear combination of the independent variables. Thus, GLMs are flexible and well suited for analyzing environmental interactions, which can be weakly described by classical Gaussian distributions (Austin, 1987).

Generalized Additive Model (GAM)

Generalized additive models were first developed by Hastie and Tibshiran (1987). The methods available in GAM are techniques developed to combine characteristics of GLMs with additive properties, in which the predictor depends linearly on unexplored functions of predictor variables and focuses on reasoning about these functions. GAMs also provide an effective framework for mapping point-based data (Hastie and Tibshirani, 1987; Webster et al., 2006).

Generalized Boosted Model (GBM)

Generalized Boosted Models are a combination of two techniques, decision tree and boosting algorithms, and are robust to missing values and outliers. GBMs fit many decision trees repeatedly to achieve results with high accuracy. In each model, the input data for a new tree are weighted data that were weakly modelled by older trees. The model attempts to improve its accuracy by taking into account the fit of previous trees. This continuous method is only used for the boosting approach (Elith et al., 2008; Franklin, 2010; Sánchez-Mercado et al., 2010).

Generalized Dissimilarity Models (GDM)

Generalized dissimilarity models were developed by Ferrier et al. (2007) for modeling the spatial distribution of environmental variables. GDMs are an extension of matrix regression, which can be applied in environmental studies (Ferrier et al., 2007). GDMs require point data from a range of locations over the study area (as dependent variables) to fit a model which predicts the merger dissimilarity between pairs of points as a nonlinear multivariate function of the environmental factors (independent variables) of these locations (Koubbi et al., 2011).

2.2.2. Fog sampling (field measurements)

Data on foggy zones in the study area were collected based on field surveys and Global Positioning System (GPS; Garmin 76cx). The input data included an inventory showing areas under fog during foggy weather in 2018. Consequently, a fog inventory with a point base map as dependent variable was considered in the analysis, where each point referring to an actual foggy area in the Vazroud watershed. In preparation of the fog potential map, 100 fog-prone points (assigned a value of 1) which were divided into two groups: model training data (70% of the inventory data, n=70) and model validation data (30% of the inventory data, n=30) and 90 non-fog-prone points (assigned a value of 0) were chosen randomly (Darabi et al., 2019). To better evaluate site selection for fog water harvesting, field observations were used in verification of the model outputs.

2.2.3. Environmental predictor variables for the fog probability map

Fourteen environmental predictor variables were selected based on their relevance for fog formation and categorized into three groups: hydro-climatic predictor variables (precipitation, temperature, leeward effect, windward effect, topographic wetness index, and diurnal anisotropy heating); topographical predictor variables (elevation, slope aspect, slope variability, slope curvature, sky view factor, and terrain ruggedness index); and remote sensing predictor variables (land use/land cover and land surface temperature) (Casu et al., 2017). All these variables are explained below.

2.2.3.1. Hydro-climatic predictor variables: In many environments, hydro-climatic variables show high spatial changes, often occurring within short distances of less than a kilometer. Understanding the spatial variability in hydro-climatic conditions is essential for effective IWRM (Dietrich and Böhner, 2008; Yang et al., 2015; Zhu et al., 2018). The six hydro-climatic variables used here as predictor variables in fog potential mapping are described below.

Precipitation: Daily precipitation data for 2001-2018 were obtained from the Iranian Meteorological Organization (IRIMO) and used to produce a precipitation map for the study area by applying the inverse-distance weighting (IDW) interpolation method in ArcGIS GIS 10.4. The recorded annual precipitation amount ranges from 832 mm in the east of the study area to 349 mm in the west (Fig. 2a). Mean annual precipitation in the Vazroud watershed is 672 mm.

Temperature: Daily temperature data for 2001-2018 obtained from IRIMO were used to produce a temperature distribution map by applying IDW in ArcGIS GIS 10.4. The recorded temperature ranges from 11.59°C mm in the southwest of the study area to 15.41°C mm in the north (Fig. 2a). Mean annual temperature in the Vazroud watershed is 13.13°C.

Leeward effect (LE): The leeward side is the downwind (downslope) side of a mountain facing away from the wind at the point of reference (Fig. 1). It is protected from the moist prevailing wind and is typically drier with lower barometric pressure (Scholl et al., 2007; Vikram and Chandradhara, 2016).

Windward effect (WE): The windward side is the upwind (upslope) side of a mountain facing the wind at the point of reference (Fig. 1). It generally has higher barometric pressure and is wetter than the leeward side (Scholl et al., 2007; Vikram and Chandradhara, 2016).

Topographic wetness index (TWI): Among the many hydrological variables available, TWI was used here as it can quantify the local topographic conditions in hydrological processes and express the surface saturation and spatial variability of soil moisture. The relevance of TWI can be described by the following equation (Pei et al., 2010; Zhu et al., 2018):

$$\mathrm{TWI} = \ln\left(\frac{\alpha}{\tan\beta}\right) \qquad (1)$$

where α is the specific catchment area (SCA) and $\tan\beta$ is the local slope (Pei et al., 2010). The TWI for the study area was calculated using SAGA GIS algorithms based on a digital elevation map (DEM, 12.5 m spatial resolution).

Diurnal anisotropy heating (DAH): DAH was calculated as (Böhner and Antonić, 2009):

$$H_\alpha = \cos(\alpha_{max} - \alpha) \times arctan(\beta) \qquad (2)$$

where α_{max} describes the aspect with the maximum total heat surplus, α is the aspect of the slope and β is the slope gradient. Fig. 2 shows the DAH for the study area, which was calculated using the SAGA GIS program.

2.2.3.2. Topographic predictor variables: The spatial distribution of most environmental variables is controlled by topographic characteristics, such as elevation, slope variability, slope aspect, and slope curvature, and topographic parameters such as sky view factor (SVF) and terrain ruggedness index (TRI).

Elevation*:* A medium-resolution Advanced Land Observation Satellite-Phased Array type L-band Synthetic Aperture Radar (ALOS PALSAR) derived DEM with 12.5-m spatial resolution (Fig. 2c) was obtained from the Alaska satellite facility (https://vertex.daac.asf.alaska.edu/). The elevation of the Vazroud watershed ranges from 278 to 3577 masl.

Slope aspect: A slope angle map was derived from the 12.5-m DEM and expressed as a percentage using the "slope tool, Spatial Analyst" in ArcGIS GIS 10.4. The slope in the Vazroud watershed area varies from 0 to more than 78.76% (Fig. 2d).

Slope variability (SV): SV, a measure of the relief of slope, refers to the difference between the minimum and maximum slope angle within a certain area (i.e., SV = $slope_{max} - slope_{min}$). SV was calculated based on the slope roughness variation method (Ruszkiczay-Rudiger et al., 2009) in ArcGIS GIS 10.4 from the 12.5-m DEM.

Slope curvature: Slope curvature is another conditioning factor in foggy areas. In this study, slope curvature was derived from the DEM and allocated to one of three classes: concave (<-0.05), flat (-0.05 to 0.05), and convex (> 0.05) (Fig. 3c). A positive value represents an upwardly convex surface, whereas a negative value indicates an upwardly concave surface, at a given pixel location (Mandal and Mandal, 2018: Tehrany et al., 2019; Das, 2019).

Sky view factor (SVF): SVF is defined the ratio at a point in space between the visible sky and a hemisphere centered visible from the ground over the analyzed location (Zakšek et al., 2011: Bernard et al., 2018). It varies significantly in regions with different topography and is an adjustment factor used to account for obstruction of the overlying sky hemisphere by surrounding land surface, with areas with higher visibility less related to fog abandonment (Olcinal, 2013). It is calculated as:

$$\mathrm{SVF} = \frac{1}{N} \times \sum_{i=1}^{N} [\cos\beta \times cos^2\beta\varphi_i + sin\,\beta \times \cos(\emptyset_i - \alpha) \times (90 - \varphi_i - sin\varphi_i \times cos\varphi_i)] \quad (3)$$

where N is the number of directions used to represent the full unit circle, φ_i and $\emptyset$ are horizon angle and azimuth directions the *i*th direction, respectively, around each point in a DEM, and α and β are the slope aspect and angle, respectively. In this study, the SVF was calculated using SAGA GIS software and it varies from 1 for completely horizontal surface or peaks and ridges to 0 for completely obstructed land surface (Böhner and Antonić, 2009). Fig. 2 shows the spatial distribution of SVF for the Vazroud watershed.

Terrain ruggedness index (TRI): TRI is a metric developed by Riley et al. (1999) to express the elevation difference between a cell and the mean of an eight-cell matrix of surrounding cells. It can also quantify surface roughness through consideration of absolute elevations in the surroundings of a given raster cell for DEM (Riley et al., 1999; Zhu et al., 2018). TRI was calculated using SAGA GIS software and it varies from 771.22 m (highly rugged) to 0 m (completely level surface) in the Vazroud watershed (Fig. 2).

2.2.3.3. Remote sensing predictor variables: Remote sensing data can be used within environmental science for hydrological impact assessment and water resources management, and it is generating a huge interest within the geoscience community (Casu et al., 2017; Xu et al., 2019).

Land use/land cover (LULC): A LULC map was prepared using Landsat 8 Operational Land Imager images or OLI (Path/Row: 164/035) acquired on 11 June 2016 (from the USGS dataset). In image pre-processing, atmospheric correction of Landsat 8 images was carried out using QUick Atmospheric Correction (QUAC) in ENVI 5.3, followed by image classification using the supervised classification and maximum likelihood method in ENVI 5.3 (Liang et al., 2001; Darabi et al., 2014; Pullanikkatil et al., 2016, Haghighi et al., 2019). There are five land use types in the Vazroud watershed: dense forest, low-dense forest, rangeland, farmland, and residential zone, occupying an area of 80.21 km^2 (57.19%), 14.22 km^2 (10.10%), 38.34 km^2 (27.24%), 4.87 km^2 (3.46%), and 2.84 km^2 (2.01%), respectively. The overall accuracy and Kappa coefficient of classification have been determined to be 95 and 0.93, respectively (Pullanikkatil et al., 2016). Based on the Landsat images, land use maps were generated for 2016 as illustrated in Fig. 2.

Land surface temperature (LST): LST plays an important role in surface energy processes and water balance at local and global scales (Sobrino et al., 2004; Liang et al., 2013). Landsat satellite data were used in emissivity estimation for atmospheric impacts using the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercube (FLAASH) algorithm in the ENVI 5.3 software (Vlassova et al., 2014). The LST was prepared from the thermal bands; the digital numbers were converted into radiance and then to at-sensor brightness temperature, which was converted to LST. The LST map for the study areas was produced based on 20 Landsat-TIRS images from 2013-2017 (21.10.3013; 07.02.2014; 12.04.2014; 28.04.2014; 06.11.2014; 25.01.2015; 14.03.2015; 15.04.2015; 01.05.2015; 11.12.2015; 12.01.2016; 13.02.2016; 03.03.2016; 10.10.2016; 27.11.2016; 30.01.2017; 15.02.2017; 20.0402017; 06.05.2017, and 22.05.2017). The mean all these LSTs was used as the final LST map (Huang et al., 2016).

Fig. 2. SOMEWHERE HERE

Fig. 3. SOMEWHERE HERE

Fig. 4. SOMEWHERE HERE

2.2.4. Social variables for the fog potential map

In this study, three social variables (as maps) were selected according to their relevance to the fog suitability map for the Vazroud watershed. These were: distance to residential area, distance to livestock buildings, and distance to road.

Distance to residential area: Distance from villages and residential areas is an important criterion in a suitability map for fog water harvesting, because the greater the distance between human settlements and areas where conditions are suitable for fog harvesting, the more difficult and costly it is to transport the water harvested. Hence, in the present study, regions closer to residential areas were given higher priority. According to a field survey and local authorities, most villages in the study area, but not all, are affected by a lack of potable water. The distance to the villages was derived using the distance module in GIS 10.4 (Fig. 5a).

Distance to livestock buildings: Distance to livestock also plays in important role in a suitability map for fog water harvesting. As with distance to residential areas, shorter distance between fog harvesting areas and buildings used for domestic animal rearing was prioritized in this study. The distance to livestock buildings was derived using the distance module in GIS 10.4 for each raster cell (Fig. 5b).

Distance to road: Distance to road is an important factor in a suitability map for fog water harvesting. The distance to road in the study area was derived using the distance module in GIS 10.4 for each raster cell (Fig. 5c).

Fig. 5. SOMEWHERE HERE

2.2.5. Fog-water harvesting Capability Index (FCI) map

Fog-water harvesting Capability Index (FCI) maps were produced by multiplying fog probability by the fog suitability map (Hiatt et al., 2012; Darabi et al., 2019):

$$FCI = Fog\ probability\ \times fog\ suitability \quad (4)$$

where the probability map was determined from the 14 conditioning factors (precipitation??, temperature??, leeward effect, windward effect, diurnal anisotropy heating, topographic wetness index, elevation, slope variability, slope aspect, slope curvature, sky view factor, and terrain ruggedness index, land use, and land surface temperature), using the GAM, GBM, GDM and GLM models; and the suitability map was based on the social factors (distance to residential areas, livestock buildings, and road).

3. Result

3.1 Performance of artificial intelligence algorithms

The accuracy of the GAM, GBM, GDM, and GLM models was assessed using Area Under the Receiver Operating characteristic Curve ROC-AUC (Table 1). The highest AUC values during training were obtained for GAM (0.958) and GDM (0.925), followed by GBM (0.885) and GLM (0.876) (Table 1). The highest AUC values during testing performance were obtained for GDM (0.892), followed by GBM (0.775), GLM (0.764), and GAM (0.759) (Table 1; Fig. 6).

Table 1. SOMEWHERE HERE

Fig. 6. SOMEWHERE HERE

3.2. Fog probability maps

The fog probability maps derived using the GAM, GBM, GDM, and GLM models, indicating regions with high and low concentrations of fog, are shown in Figures 7a-7d. All models showed areas with a high concentration of fog in the south and southeast of the study area, with light fog mostly located in the north. Zones with the highest (0.99) and lowest (0.00) concentration of fog were successfully recognized by the GBM and GDM model, respectively.

Fig. 7. SOMEWHERE HERE

Importance variables were determined based on model functions and the impact of the variables from the field survey data. For all models, maximum values of importance were obtained for SVF and minimum values for slope curvature. The highest and lowest values obtained were, respectively, 0.78 and 0.32 for GAM, 0.74 and 0.38 for GBM, 0.79 and 0.40 for GDM, and 0.77 and 0.35 for GLM (Table 2).

Table 2. SOMEWHERE HERE

3.2. Fog suitability map

Weight and rank values of the conditioning factors and their classes were assigned according to their importance in the case study. Based on expert knowledge and using AHP results to evaluate the relative importance of fog suitability variables, the social factor with the greatest weight was distance to residential area (0.45), followed by distance to livestock buildings (0.32) and distance to road (0.23) (Table 3).

Table 3. SOMEWHERE HERE

By using the weighted factors, total scores were applied and then each pixel of the output fog suitability map was assigned a value reflecting its factor (Fig. 8). Based on the results, southeastern and southern areas of the Vazroud watershed have the highest suitability for fog water harvesting.

Fig. 8. SOMEWHERE HERE

3.3. Fog-water harvesting Capability Index (FCI)

The FCI values obtained for different parts of the study area by multiplying probability by fog suitability maps areas is shown in Fig. 9a-9d, where areas with high and low FCI have high and low capability for fog water harvesting, respectively. The results confirmed that southeastern and southern areas of the Vazroud watershed have the highest capability for fog water harvesting.

Fig 9. SOMEWHERE HERE

4. Discussion

Prevailing hydro-climate conditions result in fog formation in the north of Iran. With increasing population and growing demand for potable water, harvesting fog water as a drinking water supply for rural communities can play an important role in IWRM in this region. The suitability of a watershed in the region for fog water harvesting was examined in this study through a field survey and calculations considering socio-environmental variables performed with artificial intelligence algorithms. Proper prediction of the spatial distribution of fog is vital to reduce socioeconomic losses in IWRM. The present study attempted to identify areas with high concentrations of fogs in areas most suitable for fog water harvesting in the study watershed by considering 14 environmental variables (precipitation, temperature, leeward effect, windward effect, diurnal anisotropy heating, topographic wetness index, elevation, slope variability, slope aspect, slope curvature, sky view factor, terrain ruggedness index, land use/land cover, and land surface temperature). Fog probability maps were derived using four artificial intelligent algorithms (GAM, GBM, GDM and GLM) and model accuracy was assessed using ROC-AUC. Three social variables (distance to residential area, distance to livestock buildings, and distance to road) were also selected according to their relevance to fog suitability maps. Fog-water harvesting Capability Index (FCI) maps were then produced by multiplying fog probability by the fog suitability maps.

Fog water harvesting has been studied previously by many researchers using hydrological variables to simulate the physical processes of fog water conditions, but this approach requires sophisticated datasets and abundant computations. Thus in this study, artificial intelligence algorithms were used in socio-environmental modeling to identify foggy areas in the Vazroud watershed, in which mapping-based models are important. Models have been used for mapping to support water sustainability strategies by other researchers, but not in fog probability mapping. Artificial intelligence algorithms have now become more popular in the field of spatial distribution analysis modeling, especially in IWRM. A key advantage of these models is that limited knowledge is required. Moreover, the approach is parsimonious, since in areas where climate and hydrological data are lacking, some predictive variables, namely hydrological, topographical, or land use properties, can be used in artificial intelligence algorithms.

5. Conclusions

Fog water harvesting can be an important component of IWRM in water-scarce regions with intensive and prolonged fog events. Preparing a distributed map that reflects both the extent and suitability of different areas for fog water harvesting is essential for success. This study examined a mapping approach based on 14 relevant environmental conditioning factors for identifying areas with a high concentration of fog in the Vazroud watershed, Iran. To overcome input data limitations, four artificial intelligence algorithms (GLM, GAM, GBM, and GDM) were used in mapping. All four achieved good accuracy of mapping, with order of accuracy GAM > GDM > GBM > GLM for the training data and GDM > GBM > GLM > GAM for the testing data. The novel value of the work was in developing a Fog-water harvesting Capability Index (FCI) based on socio-environmental variables in the four artificial intelligence algorithms. The FCI can be used to improve the quality of decision making and the efficiency of harvesting fog water resources. Overall, our approach gave high accuracy in FCI mapping for the study area, but the accuracy could be improved with better data on inter-annual or even intra-annual distribution of fog occurrences. This information was not available to us, but is likely to be in future with advances in IWRM in the Vazroud watershed.

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