



## A Method for Correction of Tropical Rainfall Measuring Mission Satellite Temperature Network in Mazandaran Province

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### PAPER INFO

#### Paper history:

Received 15 June 2023

Accepted in revised form 02 August 2023

#### Keywords:

3D linear regression

Interpolation

Isothermal map

Remote sensing

Satellite product

### ABSTRACT

Accurate spatial estimation of temperature is very important in meteorological research. This study investigated the efficiency of temperature products of the Tropical Rainfall Measuring Mission (TRMM) satellite in estimating temperature in Mazandaran Province, and its accuracy were compared with inverse distance weighting and Co-Kriging interpolation methods. Finally, a new method was proposed to improve the accuracy of temperature estimation by combining the TRMM temperature products and terrains. Data recorded at 25 meteorological stations and 26 monthly and annual TRMM satellite images in 2012 and 2013 were used. The results showed a significant correlation between temperature data and satellite products, latitude, and altitude in significance level of 95%. Analyzing error indices showed that TRMM products have underestimation error that this bias error contributed to about 60% of error in these satellite images. Despite the larger error of TRMM products than interpolation methods, the regression analysis results demonstrated the superiority of satellite temperature products over interpolation methods. Furthermore, higher correlation of observed and estimated data showing that satellite products give a better understanding of cold and hot points of the study area despite its underestimation error. Combining satellite temperature products with influential covariates of altitude and latitude in the regression equation reduced the temperature estimation error of the TRMM products by 80%. The estimation precision increased over 70% compared to other temperature interpolation methods. Analyzing isotherm maps indicate the higher temperature of eastern coasts than western coasts. Moreover, evaluating different temperature estimation methods showed the higher precision of the methods that involved covariates than other methods.

doi: 10.5829/ijee.2024.15.01.10

### INTRODUCTION

Many scientific centers worldwide give high priority to various weather issues. Climatic prediction of weather conditions through evaluating annual variations of the low-layer atmosphere is among the basic activities in these centers [1]. Temperature is among the most substantial climatic elements with a basic role in dispersing other climatic elements [2]. Air temperature is also a basic weather component and an important parameter in hydrological, meteorological, and

agricultural studies. This parameter plays a key role in biological, physical, and biogeochemical processes between hydrosphere, biosphere, and atmosphere. As a result, it is necessary to know this parameter in many aspects, including soil-plant-atmosphere system simulation models and running plant growth and yield simulation models [3]. The mean daily temperature is the most climatic parameter which can be exactly and approximately calculated at meteorological stations. The mean maximum and minimum daily temperatures are considered the mean daily temperature in the approximate

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method. In contrast, thermograph data are used in the exact method, and the mean daily temperature is calculated by integrating daily variations of temperature. According to the literature, the precision of the first method is low on a daily scale and even differs 3°C from the actual value. Instead, the second method is accurate, showing a slight difference in the integration precision order with the actual value [4]. Air temperature measured at meteorological stations gives limited information on the spatial distribution of air temperature patterns [5]. Therefore, it seems necessary to have the technology to eliminate deficiencies of meteorological stations in calculating temperature in sampling intervals and in impassable places where meteorological stations cannot be constructed [6]. Exact spatial estimation of air temperature at ungauged points and impassable highlands is a key prerequisite for agricultural planning and water resource management by different methods such as empirical, semi-empirical, and intelligent models [7]. Remote sensing has high potential in large-scale air temperature estimation using surface temperature images [8]. New sciences such as remote sensing have recently provided new techniques for monitoring the environment and acquiring and analyzing environmental data, presenting a wide range of environmental parameters. This technology is raised a vital growing information source to study climate changes directly influencing ground surface temperature [9]. In addition to remote sensing, interpolation is also used to measure climatic parameters in places lacking meteorological stations. Spatial data interpolation techniques are used to estimate a variable in a specific point from measured actual data at adjacent points [10]. By weighting surrounding data of the estimated point, Inverse distance weighted (IDW) interpolates to obtain the unknown quantity. It is also assumed that closer points are more similar than far points, leading to the larger weight of closer points [11]. Kriging is an advanced interpolation technique suitable for data with defined local trends. Kriging interpolates with the least estimation variance, and its error depends on variogram specifications [12]. The Co-Kriging (CK) method is used in the case of insufficient sampling of the main variable when the statistical estimation of intended precision cannot be performed. Estimation can be corrected, and its precision can be improved in such cases by considering a spatial correlation between the main variable and a sufficiently sampled auxiliary variable. This method is used when the correlation coefficient between the main variable and covariates is significant, larger than 0.50 [13]. Linear regression methods are based on the linear relationship between the main variable and covariates, assuming a linear trend in length, width, and height of the region. In the 3D linear regression method, the main variable can be estimated at unknown points of known longitude, latitude, and altitude by fitting a multiple linear regression between the main variable and covariates [14]. Numerous studies

have been conducted in this area; some are reviewed below.

Vali et al. [15] investigated the effects of land use, geological formation, and climatic and topographical factors on the surface temperature of Kharestan, Iran, using Landsat satellite images in June-July from 2000 to 2017. According to their results, the mean surface temperature was 43°C, the normalized difference vegetation index (NDVI) was 0.144, and the normalized difference moisture index (NDMI) was -0.068. Considering image classification with overall precision of 99.96% and  $\kappa=0.96$ , rangelands and gardens had the highest and lowest surface areas, respectively. Arvin [3] examined Landsat 8 satellite images to calculate and estimate Esfahan air temperature and its surrounding region. Sobrino's split-window algorithm (SWA) was used to estimate the ground surface temperature. The use of this method on the satellite images of Esfahan covered by urban, green space, and industrial regions shows its ability and the proportions of images for this purpose. Zadmeihri and Farrokhian Firouzi [16] estimated the soil temperature in Khuzestan Province in a 25-year interval (1994-2018) using meteorological parameters and multi-layer perceptron neural network (MLPNN), extreme learning machine (ELM), and multi-linear regression (MLR). Their results showed the relatively similar performance of MLPNN and ELM, outperforming the MLR technique. However, the computational speed of ELM was much higher than other techniques. [17] studied a relatively small region and found a higher precision of piecewise multi-variable linear regression in estimating air temperature in a few cases than simple regression. Meteorological stations are the major sources of climatic data, and these stations provide climatic statistics at specific points. However, temperature varies at different distances of meteorological stations, increasing or decreasing relative to the intended station. Amini et al. [18] evaluated 11 geostatistical methods for zoning and temperature estimation using observed mean maximum and minimum monthly temperatures recorded at 18 meteorological stations in the Zayandehrud basin. According to the results of implementing these models, linear kriging and natural neighborhood with a mean absolute error of 1.82 and 1.18 showed the best result for the maximum temperature. Molavi Arabshahi and Shavli Koh Shori [14] evaluated different interpolation methods for temperature and precipitation in Ramsar, Babolsar, and Bandar Anzali synoptic stations from 1951 to 2017. According to their results, the Neville and Spline methods give more precise approximates for all studied stations. Chunling et al. [6] in a study aims to produce both daily and instantaneous Ta datasets at 1 km resolution for the Jingjinji area, China during 2018–2019, using machine learning methods based on remote sensing data, dense meteorological observation station data, and auxiliary data (such as elevation and normalized difference vegetation index). The random forest (RF) algorithm

outperformed the others (such as decision tree, feedforward neural network, generalized linear model) and RF obtained the highest accuracy in model validation with a daily root mean square error (RMSE) of 1.29 °C. Analysis showed that land surface temperature (LST) was the most important factor contributing to model accuracy, followed by solar declination and DSR, which implied that DSR should be prioritized when estimating  $T_a$ . Chen et al. [5] retrieved monthly average temperature (RMSE between 1.29 and 1.45 °C) and eight-day average temperature (RMSE between 0.8 and 1.29 °C) for China in 2010 using a model based on remote sensing data and a geographically weighted regression (GWR) algorithm; the elevation was the only secondary auxiliary variable; the results show that the GWR method performs better than the multiple linear regression method and the regression Kriging method.

According to the literature, covariates improve the efficiency of spatial temperature estimation methods. Given the good correlation between altitude and temperature and its accessibility, altitude can often be used as an auxiliary variable to improve spatial temperature estimation [19]. Given the development of various satellite temperature products such as ground air temperature maps and regular compact networks of climatic data in recent years and the estimation error of these networks in temperature estimation, integrating interpolation techniques and satellite temperature products can increase the precision of isothermal mapping. The literature shows the complex topography of Mazandaran Province, particularly in Alborz Highlands. Most meteorological stations are scattered in the plains of Mazandaran, and dense meteorological stations cannot be built due to impassable highlands. On the other hand, achieving exact temperatures at altitudes lacking meteorological data is of great importance due to some high peaks in Mazandaran highlands and their vital role in water resource management, agricultural planning, Hyrcanian forest management and tourism management. Accordingly, this study presents a new method to increase the precision of isothermal maps by combining TRMM satellite network temperature products and interpolation methods in Mazandaran Province and comparing them with conventional interpolation methods. The method proposed in this study can be used to correct temperature networks.

## MATERIAL AND METHODS

### Study area

Covering 23756.4 km<sup>2</sup>, Mazandaran Province is located between longitudes 50° 34' and 54° 10' and latitudes 35° 47' and 36° 35' on the south of Caspian Sea and north of Alborz Mountains, playing a key role in the regional weather conditions. The elevation in Mazandaran

Province varies from -61 to 5610 m. Factors affecting the regional weather conditions include Alborz mountains and their direction, elevation, proximity to the sea, vegetation, local winds, the mean latitude, and northern and western air masses [20].

### Required data

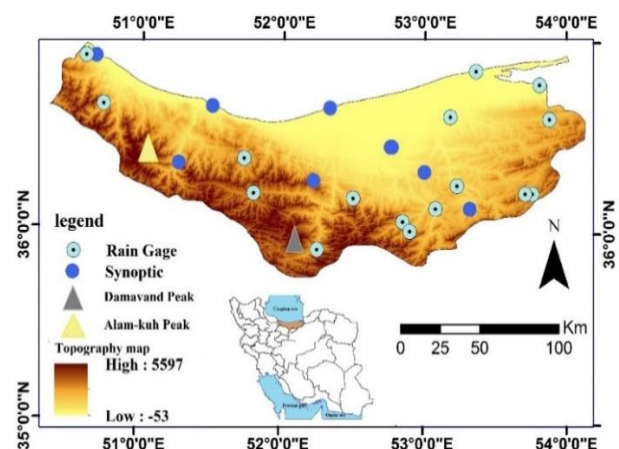
Data recorded at 24 meteorological stations and 26 TRMM satellite temperature images were used to estimate the temperature in Mazandaran Province. Figure 1 and Table 1 displays the geographical location of these stations. Due to complete station data in the statistical period 1991-2018, the years 2012 and 2013 were selected to evaluate the precision of the TRMM temperature network and compare it with interpolation methods.

### TRMM satellite

This satellite is a joint product of Japan and the United States, located at an altitude of 350 km above the ground. The products of this satellite are presented from the latitude 50°E to 50°N. The minimum and maximum spatial resolutions of recording precipitations are 0.25°×0.25° (25×25 Km). TRMM passes through different parts of the earth several times a day to survey the required information. It rotates the earth within 91.538 min, passing 16 orbits with an inclination angle of 35°. TRMM satellite data are presented in different formats, including KMZ, TXT, TIF, NETCDF, ASCII, and HDF formats [21].

### Methodology

Interpolation is an applied science used by climatologists for zoning climatic variables [18]. Various interpolation techniques are classified into statistical and geostatistical categories. Geo-statistics is a branch of applied statistics science capable of presenting a broad set of statistical



**Figure 1.** Location of meteorological stations used in Mazandaran province

**Table 1.** Weather station information

Climate of the station	Z	Y	X	Station
Very humid moderate	21	36.9	50.66	Ramsar
Very humid moderate	-18	36.65	51.5	Nowshahr
Semi-humid temperate	10	36.55	53	Sari
Cold semi-wet	1688	36.21	53.55	Kiasar
Cold semi-wet	1991	36.25	51.3	Siabishe
Semi-humid temperate	105	36.46	52.38	Amol
Moderately humid	-21	36.71	52.65	Babolsar
Semi-humid temperate	37	36.48	52.88	Ghaemshahr
Cold semi-wet	1023	36.6	53.88	Sefud chah
Cold semi-wet	1028	36.21	53.67	Berma
Semi-humid temperate	530	36.25	53.23	Soleyman tange
Cold Mediterranean	1256	36.18	52.5	Gat kolla
Moderate Mediterranean	221	36.9	50.6	Zarodak
semi dry cold	1476	36.01	52.9	Paland
Cold Mediterranean	2005	36.85	50.46	Javaher deh
semi dry cold	2316	36.37	52.12	Gazensara
Cold Mediterranean	2199	36.09	52.08	Nemarestagh
Semi-humid temperate	632	36.2	52.65	Firozjiah
Semi-humid temperate	1434	36.91	52.25	Sangede
Semi-humid temperate	16	36.61	53.18	Dasht naz
Moderate Mediterranean	1128	36.13	53.08	Pol sefid

estimators to estimate the intended feature at unsampled points using information obtained at sampled points [22]. A known value of surrounding points is used in geostatistical methods to estimate a variable so that a weight is assigned to each measured sample, as shown in Equation (1) [23].

$$Z = \sum_{i=1}^N \lambda_i Z_{V_i} \tag{1}$$

where z represents the estimated variable,  $\lambda_i$  the weight or significance of the quantity related to ith sample, and  $Z_{V_i}$  is the known parameter of the ith sample [7]. Various geostatistical methods differ in determining coefficients of known points. For instance, the IDW method is based on the assumption that the effect of adjacent points decreases with increasing the distance. In this method,

distance is used as the known variable weight for predicting unmeasured points. On the other hand, the effect of spatial dependence intensity can be applied by the IDW method [18]. One or several secondary variables related to the intended variable are used for interpolation in the CK method. This method is suitable for areas lacking meteorological stations, assuming that the correlation between variables can increase the estimation precision [9]. It is assumed in the regression method that there is a kind of trend in a different direction in the study area, and this trend is assumed a polynomial of order n. The order (n) is assumed unity in all directions in the linear regression method. In other words, the spatial variable linearly varies in all directions. The dimensions of a linear regression method are equal to the number of covariates. The covariates include longitude, latitude and elevation variables. A multiple linear regression should be established between climatic factor and covariates to achieve an n-dimensional linear regression equation [19].

**Combining satellite images and regression method**

TRMM satellite images were combined with interpolation methods. After receiving satellite images from the TRMM network, the intended file was entered into GIS software to extract temperature information. Geographical information of stations was entered into the software to obtain their temperatures from the TRMM network images. Information of each point was then obtained by extracting images and station points.

Satellite images, topographical maps, latitude, and longitude are used as predictors in the regression equation. The trend of data is calculated using the multiple linear regression between the main variable and covariates, and the role of the satellite as the auxiliary variable in estimating precipitation is tested. According to the above discussion and considering that the altitude of meteorological stations in Mazandaran Province varies from -21 to 2300 m, temperature data is not available for highlands above rain-gage stations. Latitude, longitude, and altitude were used as covariates beside TRMM temperature, forming the following regression equation to increase the precision of TRMM satellite temperature data.

$$Y_i = a_1 * X_{(1,i)} + a_2 * X_{(2,i)} + \dots + a_{n-1} * X_{(n-1,i)} + a_n * X_{(n,1)} \tag{2}$$

where  $Y_i$  is the spatial variable estimated at point i,  $X_{(1,i)}$ ,  $X_{(2,i)}$ ,  $X_{(n-1,i)}$ ,  $X_{(n,1)}$  are independent variables at point i including geographical location variables and topography,  $a_1$ ,  $a_2$ ,  $a_n$ , and  $a_{n-1}$  are equation parameters, and n is the number of independent variables.

**Evaluation criteria**

The root mean square error (RMSE) and mean bias error (MBE) were used to evaluate TRMM satellite data with actual data. RMSE and MBE are calculated as follows [16].

$$RMSE = \sqrt{\frac{\sum_{i=1}^N [Z(x_i) - Z(x_i)]^2}{N}} / 100 \tag{3}$$

$$MBE = 1/N \sum_{i=1}^N [\hat{Z}(X_i) - Z(X_i)] \tag{4}$$

where  $\hat{Z}(X_i)$  is the estimated value,  $Z(X_i)$  the observed value,  $N$  is the number of data. Minitab 16, GS+2018, Arc GIS 10.3, NDVI 5.3, and Excel 2016 were used in this study.

**RESULTS AND DISCUSSION**

**Linear regression of temperature and covariates**

Table 2 reports the correlation results of actual temperature data with covariates of latitude, longitude, altitude, and satellite temperature products. As shown, although the annual data is somewhat correlated with latitude so that temperature decreases from north to south, the temperature is not significantly correlated with latitude in the studied month. However, increasing altitude in most months has a significant negative correlation with temperature in Mazandaran Province. Moreover, temperature data in Mazandaran Province are insignificantly correlated with longitude. According to the table, satellite temperature product (TRMM column) has a significant positive correlation with annual data in most months.

**Relationship between temperature and TRMM satellite images**

TRMM satellite images were used as covariates along with latitude and altitude in the regression equation to estimate temperature and plot isothermal maps. As shown in Table 3, the coefficient of determination of regression equations is above 0.80 except for a few cases. The coefficient of determination of annual data is also greater than 0.9.

**Selecting the best temperature estimation method**

Tables 4 and 5 show the RMSE and MBE of estimated precipitation in 2012 and 2013, respectively. The highest temperature estimation error was observed in January, February, May, and August 2012 and in January, November, and December 2013. The lowest error was observed in March, April, and December 2012 and 2013. According to Tables 4 and 5, the highest and lowest temperature estimation errors were observed in winter and autumn.

Comparing interpolation methods shows that CK and IDW methods have the highest temperature estimation errors. Despite good correlation with actual data, the TRMM satellite cannot properly estimate temperature alone. Given the negative MBE in all months, the temperature products of this satellite have a lower estimation error. Temperature estimation by the regression method in 2013 reduced error by 55% relative

to CK and IDW methods and by 68% relative to the TRMM satellite. Error reduction in 2012 by the above methods was 65 and 70%, respectively.

Comparing interpolation methods in different months showed that among the IDW, CK, regression, and TRMM satellite network, the regression method, as a combination of interpolation and TRMM satellite network data, has the lowest temperature estimation error in all months, and the TRMM satellite network alone shows a relatively large error. Analyzing the MBE of temperature estimation methods shows the highest error for the TRMM satellite, ranging from 2 to 5. The regression method showed the lowest MBE of zero among the studied methods. According to the error analysis results of methods used in

**Table 2.** correlation results of monthly and annual Temperature with covariate variables

TRMM	Z	Y	X	Year	Month
r*	r**	r*	r		
0.58	-0.92	0.52	0.12	2012	Jan.
0.61	-0.91	0.44	0.24	2013	
0.2	-0.43	0.23	0.24	2012	Feb.
0.6	-0.92	0.52	0.12	2013	
0.42	-0.64	0.33	0.42	2012	March
0.51	-0.82	0.32	0.24	2013	
0.58	-0.92	0.32	0.33	2012	April
0.57	-0.93	0.52	0.23	2013	
0.59	-0.81	0.44	0.24	2012	May
0.58	-0.94	0.53	0.34	2013	
0.63	-0.92	0.42	0.24	2012	June
0.61	-0.93	0.52	0.38	2013	
0.63	-0.92	0.53	0.23	2012	July
0.62	-0.94	0.54	0.24	2013	
0.59	-0.82	0.43	0.21	2012	August
0.63	-0.93	0.52	0.33	2013	
0.66	-0.94	0.51	0.32	2012	Sep.
0.62	-0.93	0.52	0.23	2013	
0.63	-0.92	0.51	0.23	2012	Oct.
0.6	-0.91	0.53	0.34	2013	
0.61	-0.91	0.54	0.23	2012	Nov.
0.59	-0.92	0.44	0.32	2013	
0.57	-0.93	0.53	0.13	2012	Dec.
0.56	-0.92	0.42	0.32	2013	
0.65	-0.93	0.51	0.22	2012	Annual
0.63	-0.94	0.53	0.32	2013	

\*: significant at 95%

\*\* : significant at 99%

**Table 3.** Temperature regression equation of Mazandaran province

Year	Month	Regression Equation of Regres	R <sup>2</sup>
2012	Jan.	$t = - 63.3 + 1.54 Y - 0.00294 Z - 0.033 \text{ trmm}$	0.79
2013		$t = 3.8 - 0.73 Y - 0.00359 Z + 0.117 \text{ trmm}$	0.82
2012	Feb.	$t = - 192 + 3.95 Y - 0.00129 Z - 0.187 \text{ trmm}$	0.40
2013		$t = - 27.3 + 0.55 Y - 0.00317 Z + 0.048 \text{ trmm}$	0.82
2012	March	$t = - 156 + 2.67 Y - 0.00159 Z - 0.113 \text{ trmm}$	0.49
2013		$t = - 2.4 - 0.52 Y - 0.00293 Z + 0.050 \text{ trmm}$	0.70
2012	April	$t = 16.8 - 1.02 Y - 0.00333 Z + 0.121 \text{ trmm}$	0.81
2013		$t = - 89.5 + 1.87 Y - 0.00245 Z - 0.082 \text{ trmm}$	0.84
2012	May	$t = 26 - 1.02 Y - 0.00441 Z + 0.186 \text{ trmm}$	0.84
2013		$t = - 137 + 2.80 Y - 0.00302 Z - 0.119 \text{ trmm}$	0.86
2012	June	$t = - 53.3 + 0.85 Y - 0.00421 Z + 0.097 \text{ trmm}$	0.83
2013		$t = - 134 + 2.80 Y - 0.00321 Z - 0.087 \text{ trmm}$	0.89
2012	July	$t = - 51.3 + 0.96 Y - 0.00421 Z + 0.127 \text{ trmm}$	0.84
2013		$t = - 91.9 + 2.05 Y - 0.00329 Z + 0.023 \text{ trmm}$	0.87
2012	August	$t = 18 - 0.64 Y - 0.00457 Z + 0.190 \text{ trmm}$	0.72
2013		$t = - 123 + 2.64 Y - 0.00311 Z - 0.069 \text{ trmm}$	0.91
2012	Sept.	$t = - 126 + 2.49 Y - 0.00332 Z - 0.002 \text{ trmm}$	0.92
2013		$t = - 71.7 + 1.45 Y - 0.00339 Z + 0.012 \text{ trmm}$	0.86
2012	Oct.	$t = - 84.1 + 1.60 Y - 0.00370 Z + 0.028 \text{ trmm}$	0.92
2013		$t = - 107 + 1.98 Y - 0.00352 Z - 0.066 \text{ trmm}$	0.95
2012	Nov.	$t = - 96.2 + 1.86 Y - 0.00365 Z - 0.019 \text{ trmm}$	0.93
2013		$t = - 76.9 + 1.08 Y - 0.00389 Z - 0.001 \text{ trmm}$	0.9
2012	Dec.	$t = - 45.1 + 0.92 Y - 0.00324 Z - 0.023 \text{ trmm}$	0.9
2013		$t = - 114 + 1.87 Y - 0.00313 Z - 0.037 \text{ trmm}$	0.82
2012	Annual	$t = - 69.8 + 1.24 Y - 0.00338 Z + 0.015 \text{ trmm}$	0.93
2013		$t = - 88.9 + 1.67 Y - 0.00326 Z - 0.030 \text{ trmm}$	0.95

this study (Tables 4 and 5), the 3D multiple linear regression is the best temperature estimation method in Mazandaran Province. It can be concluded that using the auxiliary variable of the TRMM satellite increases the precision of temperature estimation methods while decreasing errors.

#### Regression analysis of temperature estimation methods

Diagrams were plotted for 2012 and 2013 for the regression analysis of the methods used in this study. Similar results were obtained. To this end, the diagram for 2013 in Figure 2 was used. In this diagram, the actual and estimated temperatures were plotted, and the line equation was fitted on data for different interpolation methods. According to the equations and resulting diagram, the regression method gives the best line of  $y=x$

as the closest line equation than other methods. The analysis results revealed the regression method as the top method.

#### Analysis of isothermal maps

Annual isothermal maps of 2012 and 2013 were plotted in ArcGIS to better compare and understand the performance of the regression method in correcting the TRMM satellite for estimating the annual temperature of Mazandaran Province. Equations in Table 3 were used to plot the regression map in Figure 3.

Analyzing the map plotted by the IDW method shows that this method only gives a correct estimation in the vicinity of meteorological stations. Due to not using the auxiliary variable, a suitable isothermal map was not obtained compared to other methods, not showing a correct spatial distribution of temperature, particularly in

**Table 4.** RMSE and MBE values of interpolation method for monthly and annual average temperature data for 2012

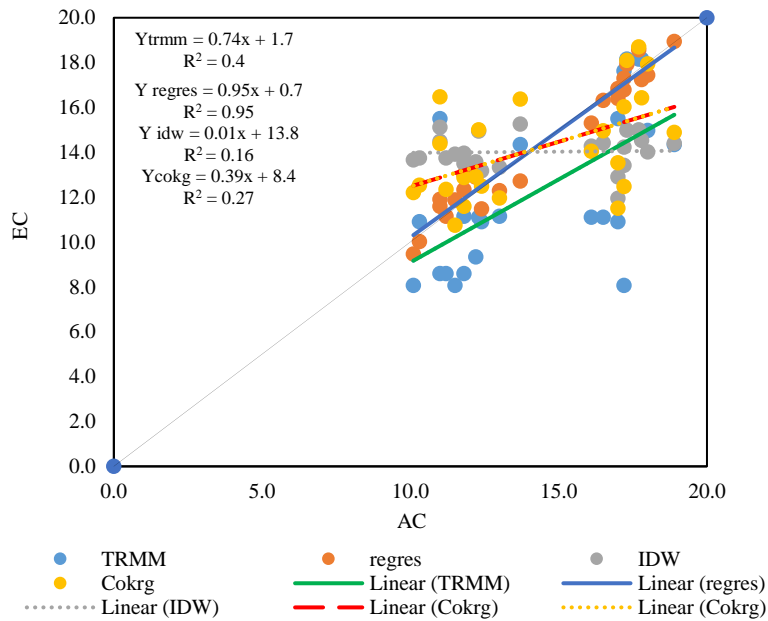
TRMM		Cokrg		IDW		Regres		Month
RMSE	MBE	RMSE	MBE	RMSE	MBE	RMSE	MBE	
4.7	-3.1	2.5	-0.09	2.8	-0.03	1.3	0	Jan.
7.4	-5.5	3.8	-0.47	3.2	0.01	2.7	0	Feb.
5.3	-3.9	2.7	-0.18	2.4	0.04	1.8	0	March
3.5	-1.2	3.1	-0.03	3.3	0.09	1.4	0	April
3.8	-0.2	4.4	-0.06	4.7	0.05	2.3	0	May
3.7	-1.5	3.9	0.08	4.3	0	1.7	0	June
3.4	-1.2	3.8	0.04	4.3	-0.40	1.7	0	July
3.9	-0.4	4.7	0.08	5.0	0	2.5	0	August
3.4	-2.1	3.0	0.05	3.4	-0.03	0.9	0	Sep.
3.7	-1.8	3.4	0.06	3.7	-0.01	1.0	0	Oct.
4.2	-2.6	3.1	0.01	3.5	0.01	0.9	0	Nov.
4.6	-2.8	2.6	-0.03	2.9	-0.64	0.9	0	Dec.
3.6	-2.2	2.8	0.02	3.1	0.01	0.8	0	Annual

**Table 5.** RMSE and MBE values of interpolation method for monthly and annual average temperature data for 2013

TRMM		Cokrg		IDW		Regres		Month
RMSE	MBE	RMSE	MBE	RMSE	MBE	RMSE	MBE	
4.4	-1.5	3.4	0.02	3.6	0.06	1.5	0	Jan.
3.4	-1.4	3.2	-0.4	3.4	-1	1.3	0	Feb.
3.6	-1.1	3.3	-0.3	3.2	-0.6	1.6	0	March
3.3	-2.0	2.2	-0.09	2.4	-0.2	0.9	0	April
4.2	-3.0	2.4	-0.1	2.8	-0.2	1.1	0	May
3.7	-2.7	2.6	-0.06	3.1	-0.2	1.1	0	June
2.9	-1.4	2.8	-0.05	3.3	-0.2	1.2	0	July
3.5	-2.6	2.7	-0.07	3	-0.2	0.9	0	August
2.9	-1.1	2.9	-0.05	3.3	-0.2	1.2	0	Sep.
3.7	-2.1	2.7	-0.1	3.1	-0.2	0.7	0	Oct.
4.1	-2.2	3.3	-0.1	3.7	-0.4	1.1	0	Nov.
4.8	-3.2	3.1	0.04	3.2	0.04	1.3	0	Dec.
3.4	-2.0	2.6	-0.1	3.01	-0.27	0.7	0	Annual

Mazandaran highlands. Despite better temperature distribution in coasts and highlands from the isothermal map obtained from the CK method compared to the IDW method, it gives no correct understanding of temperature distribution of coastal regions, not properly showing the temperature distribution of the western regions of Mazandaran province because of its complex topography. The isothermal map plotted by the regression method

properly displays the temperature range of Alborz highlands. This isothermal map also properly shows the temperature algorithm of Caspian coasts so that temperature increases from eastern coasts to Nowshahr. Maps generated by this method consider a very good spatial distribution, especially in the west of Mazandaran Province, showing a good temperature distribution. These two maps show that spatial temperature variations are

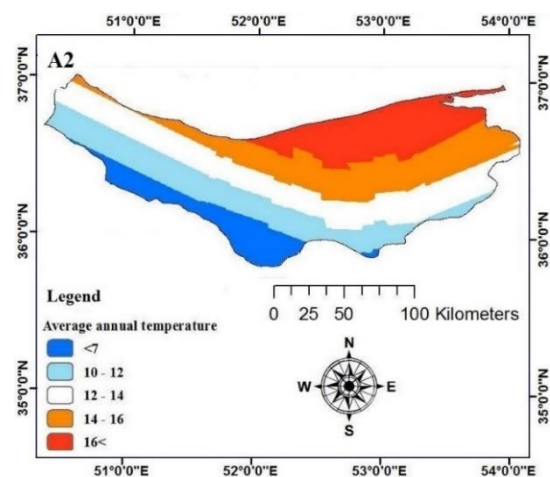
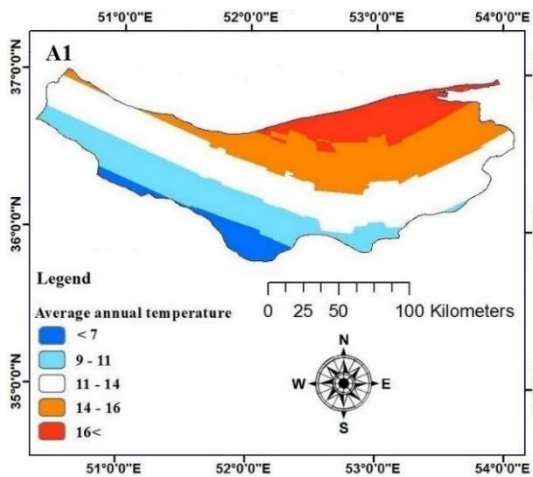


**Figure 2.** Regression analysis of different methods of locating average temperature data for 2013

displaying the temperature distribution of Mazandaran Province more properly. Accordingly, the regression method is the best method for spatial temperature estimation and map plotting, indicating increased precision of the methods using the auxiliary variable of the satellite image than other methods.

The proposed method gives a more exact understanding of temperature distribution in the region, properly showing temperature variation in the eastern and western areas and coastal regions. According to the results, methods in which an auxiliary variable (such as CK and regression methods) is used are more precise than other methods [21]. In similar researches where the temperature was estimated by analyzing satellite images

of different bands, higher error of temperature estimation was obtained. For instance, extracting the ground surface temperature from thermal band of Landsat 5 [23] was associated with an error of 7°C. Also, the land surface temperature (LST) of Modis satellite showed an error of 4.7°C [8]. The results of this study can be used for eliminating deficiencies of meteorological stations, expanding the temperature network of Mazandaran Province, and estimating the temperature of highlands which lacking meteorological stations. almost the same, and temperature increases in the eastern part of Mazandaran Province. In total, maps obtained from different methods showed the higher precision and accuracy of the regression method than other methods,





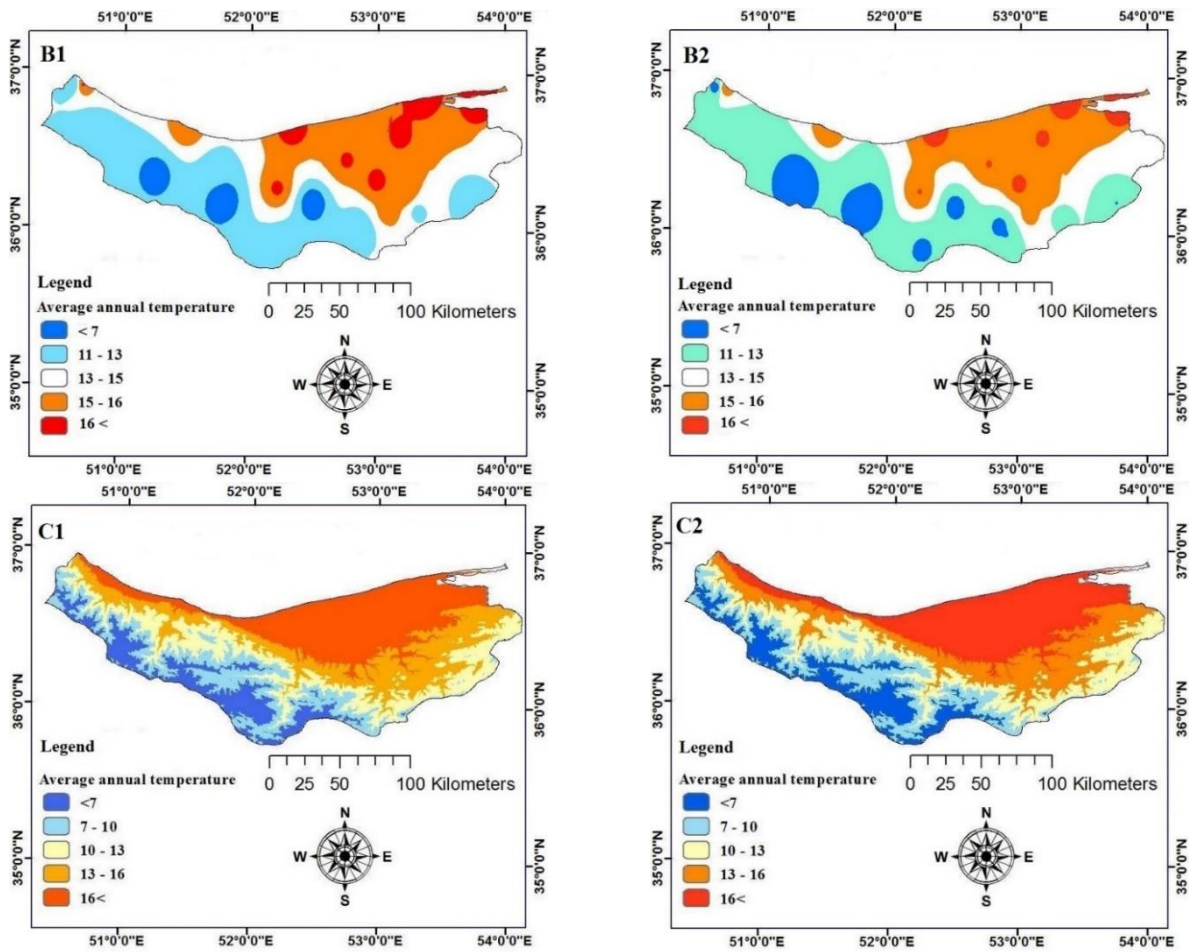


Figure 3. Temperature map of Mazandaran province with methods studied (A, B, C are Cokrg, Idw, Regres and 1, 2 are 2012, 2013)

## CONCLUSION

This study investigated the use of TRMM satellite temperature products and presented a method to employ the temperature products of this satellite. According to the results, despite the good correlation of TRMM satellite temperature product with actual data recorded at meteorological stations and the ability to detect cold and hot points in Mazandaran Province, it underestimated temperature almost across the province and correcting this network significantly improved the precision of this satellite in temperature estimation. A regression model was presented given the significant correlation of temperature with altitude, latitude, and satellite temperature products to use TRMM temperature products as an effective auxiliary variable in temperature estimation. While eliminating temperature underestimation by the TRMM temperature products, the results showed an increase in the precision and accuracy of temperature estimation by this method. The MBE reached zero, and RMSE significantly decreased. For example, the mean error of annual temperature estimation

in other methods was above 3°C, reduced to 1°C by the combined method proposed in this study. The significance of the proposed method is understood in climate change studies at ungauged points as large temperature estimation error (3°C) is the same as temperature rise caused by climate change, challenging climate change studies at points lacking temperature data. In addition to lower error, the method used in this study takes less time and can be calculated and estimated by the simplest method without correction, data extraction from satellite images, and downloading large images. It can be used in a short time with low-volume suitable information.

## ACKNOWLEDGEMENT

The author(s) would like to thank the Sari Agricultural sciences and Natural Resources University (SANRU) for financial support of this Research under contract number: 02-1400-07.

## CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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#### Persian Abstract

#### چکیده

تخمین دقیق دما اهمیت ویژه‌ای در مطالعات اقلیم‌شناسی دارد. در این پژوهش کارایی محصولات دمای ماهواره TRMM در تخمین دمای استان مازندران بررسی و با دو روش درون‌یابی وزنی عکس فاصله و کوکریجینگ مقایسه شد و در نهایت یک روش جدید برای تخمین دقیق دما با ترکیب محصولات دما ماهواره‌ای TRMM و عوارض زمینی، ارائه شد. به همین منظور از ۲۵ ایستگاه هواشناسی و ۲۶ تصویر ماهانه و سالانه دمای ماهواره TRMM استفاده شد. همچنین از آمار استان مازندران در دو سال ۲۰۱۲ و ۲۰۱۳ استفاده شد. نتایج نشان داد همبستگی داده‌های واقعی دما با محصولات دمای ماهواره‌ای، طول جغرافیایی و ارتفاع در همه ماه‌ها در سطح ۹۵ درصد معنادار است. تحلیل شاخص‌های خطا نشان داد دمای ماهواره TRMM مقدار دما را کمتر از داده‌های واقعی برآورد می‌کند به طوری که میانگین خطای اریبی تصاویر TRMM در همه موارد منفی بوده و در حدود ۶۰ درصد از خطای این تصاویر مربوط به خطای اریبی است. نتایج نشان داد گرچه برآورد دما توسط تصاویر TRMM خطای بیشتری نسبت به روش‌های درون‌یابی دما دارد اما نتایج تحلیل رگرسیونی حاکی از برتری تصاویر ماهواره‌ای دما نسبت به روش‌های درون‌یابی است. به علاوه همبستگی بیشتر داده‌های مشاهده‌ای و برآوردی توسط دمای ماهواره‌ای نشان‌دهنده این واقعیت است که گرچه دمای ماهواره‌ای دچار خطای کم برآوردی اما درک بسیار بهتری از نقاط سرد و گرم منطقه دارد. بنابراین ترکیب محصولات دمای ماهواره‌ای با متغیرهای کمکی موثر ارتفاع و عرض جغرافیایی در فرم معادله رگرسیونی، خطای برآورد دما ماهواره TRMM را تا ۸۰ درصد کاهش داده و نسبت به سایر روش‌های درون‌یابی دما نیز دقت تخمین بیش از ۷۰ درصد افزایش یافت. تحلیل نقشه‌های هم دما با روش منتخب گواه آن است که سواحل شرقی استان دارای دمای بالاتری نسبت به سواحل غربی استان است. به علاوه بررسی روش‌های مختلف تخمین دما نشان داد، روش‌هایی که از متغیر کمکی استفاده می‌کنند دقت بالاتری نسبت به سایر روش‌ها دارند.