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Reservoir water temperature modeling by geostatistical analysis of ASTER images (Case Study: Dez Dam, Iran)

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Abstract: Satellite data have been used for temperature modeling both in urban areas and water. This paper studies viability of ASTER satellite images that provide high spatial and spectral resolution to model water surface temperature, as a fundamental water quality parameter. This study is focused on Dez dam reservoir residing in Khuzestan province, south west of Iran. After the image corrections required for the ASTER image, the NDWI was determined. Water pixels extraction was done using the NDWI equal to 0.88. Using multiple linear regression analysis (MLR), water temperature model was retrieved by a recursive approach. The suggested model estimates the water surface temperature measured at ground control stations data. A high R-square of 0.87 was observed between the control station data and modeled temperature. After validation test of the temperature model at ground control station, the validity of the interpolated data in long distance was assessed. The spatial auto-correlation (Moran-I) and clustering analysis (Hot Spot) of the result also show that while long distance interpolation in the inner area of the dam reservoir seems acceptable, different interpolations are required at shores of the dam reservoir and at river outlets to model water surface temperature of the dam reservoir.

Keywords: *ASTER Satellite Imagery; Dez Dam; GIS; Remote Sensing; Water Temperature*

INTRODUCTION

Many environmental parameters like clarity, turbidity, suspended matter, phytoplankton, total nitrogen and phosphorus, total dissolved solids (TDS), chlorophyll, electrical conductivity (EC), and temperature are required to assess water quality (Hellweger *et al.*, 2004). These parameters are assessed through sampling and interpolating in order to create water quality map. Fixed networks including a limited number of ground stations are usually designed and implemented to generate the required sample data. This method is costly and has low spatio-temporal density that causes inaccurate assessment of water quality maps while it assumes that very long distance interpolations between the sample data are valid without providing concrete proofs of spatial correlation and auto-correlation in data. This paper investigates validity of this assumption for water surface temperature deriving a model for measuring water surface temperature densely using remotely sensed images. It studies viability of ASTER images for modeling water surface temperature of Dez dam reservoir that is one of the most important dams resides in Khuzestan, south west of Iran (Fig. 1).

Water temperature is one of the critical water quality parameters as it affects other chemical and physical parameters of water such as dissolved oxygen level and biological processes including metabolism,

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growth and reproduction (Chapman, 1992). Every 10°C increase in water temperature doubles metabolism and the need for oxygen in aquatics (Perlman 2013). The increase of water temperature also causes the decrease of density and viscosity of water resulting in faster settling of suspended solids (Tarantino 2012). This sedimentation reduces the operational lifetime of dams.

Sensing water temperature remotely is based on the fact that the light reflection from water surface increases by wavelength while its electromagnetic energy decreases pseudo-exponentially. The maximum light reflection from water surface happens within the green and blue portion of the light spectrum which limits the methods used to detect and measure reflected light from water surface (Ritchie *et al.,* 2003). Besides, the precision of the remotely sensed water surface temperature depends upon the sensor sensitivity to the mentioned spectral reflectance. It entails accurate satellite images radiometric corrections especially atmospheric corrections that require precise measurement of meteorological parameters at the time of image acquisition (Matejicek *et al.,* 2006). Hence, it is expected that multi-spectral and hyper-spectral sensors be more suitable for modeling of water pollution.

Considering advantages of remote sensing technology that provides cheap, rapid and dense sampling of the earth surface, researches has been conducted in recent years in order to study the feasibility of remote sensing for water resources quality assessment. Ritchie *et al.* (2003) studied different applications of remote sensing data for modeling water quality. Mathematical models were investigated to establish a relationship between recorded spectral reflections of water zones by satellite sensors data and the water quality parameters such as suspended solids in water, chlorophyll, and temperature. Matejicek *et al.* (2006) proposed a model for integration of satellite imagery and spatial analysis in water quality assessment application in urban areas. Their results admitted viability of remote sensing for detection of water pollutants. Identification of different kinds of materials in water was shown to be possible based on the way they affect water characteristics. For example, it is shown that nitrate accumulation is inversely proportional to water surface temperature (Calzada *et al*., 2008; Sarangi 2011).

In some researches for modeling water surface temperature, sensors like LANDSAT/ETM and NOAA/AVHRR have been used (Wooster *et al*., 2001). Hellweger *et al.* (2004) studied water quality in New York Harbor by remote sensing methods using LANDSAT TM and MODIS images and validated the results against ground control points. They showed that using a time-averaged spatial analysis, turbidity as determined from ground observations, had correlation with LANDSAT TM reflectance values with R-square equals 0.85. Brivio *et al.* (2001) used different series of LANDSAT TM images and ship-based radiometric and atmospheric measurements for assessing water quality parameters of two lakes in Italy. They reported a root mean square difference between spatial and terrestrial measurements close to 0.010 in reflectance for each TM band (Brivio *et al*. 2001).

Due to the major role of water vapor in absorbing thermal radiation, the temperature recorded in thermal bands is usually undervalued and distorted. As the above-mentioned satellites have low spectral resolution, sensing the temperature and the effect of water vapor cannot be modeled effectively (Lillesand *et al.,* 2007). However, multispectral satellite sensors like ASTER and MODIS contain special sensors to measure temperature. Specifically, ASTER senses 14 bands using its three sensors including SWIR, VNIR, and TIR.

ASTER TIR sensor may improve water surface predictions combining its bands since the absorption ratios of its bands are different (Kishino *et al*., 2005). ASTER TIR has 5 bands (bands 10 to 14) that cover 8 to 12 microns wavelengths of the Electromagnetic spectrum (Fig. 2). Besides, ASTER TIR sensor also has higher spatial resolution (90 m) which promises more viable and precise methods to model water surface temperature (Chavula *et al*., 2009; Oesch *et al*. 2008).

Matsuoka *et al.* (2011) used ASTER images in a research conducted in Japan for modeling water temperature and showed that its results shown to be acceptable (Matsuoka *et al* 2011). ASTER sensor is selected due to its superiority in terms of spectral and spatial resolution compared to other available satellite imagery, especially MODIS, also used for water resources assessments. The validation, using independent modeling, showed that R-square of the developed ASTER sea surface temperature (SST) against the MODIS SST was 0.455°C. The results of Purkis and Klemas (2011) also showed that imageries of multispectral sensors, especially ASTER, provide the required precision to study the environmental conditions such as assessment of land cover changes and water abnormalities in regional and local scales (Purkis and Klemas 2011).

In section 2, the research methodology of the paper is presented that is based on a recursive approach of finding the optimum combination of ASTER image bands and analyzing the spatial characteristics of the results. The proposed method is implemented for modeling water surface temperature in Dez dam and the results are discussed in section 3. Finally, the conclusions are presented in section 4.

MATERIAL AND METHODS

The method proposed in this paper is based on a recursive approach of finding the optimum combination of ASTER image bands for water surface temperature mapping and analyzing the spatial auto-correlation and clustering of the results. Fig. 3 presents the proposed methodology.

At step 1, the image corrections are carried out (Fig. 4). ASTER image raw data (L1A) requires some radiometric and geometric corrections and transformations including: a) compensation for atmospheric errors, b) image enhancement and elimination of the major errors caused by variations in attitude and position of ASTER platform (Terra Satellite), and c) geo-referencing the image. This level of correction in ASTER imagery is called L1B which includes registered radiance at the sensor.

Water has strong absorption in the near infrared (NIR) range of the spectrum and has a unique spectral response in the visible range compared to the surrounding non-water objects. Based on this criterion, normalized difference water index (NDWI) can define water bodies. In the present research, NDWI is used to derive water-only map from the ASTER image (Equation 1).

$$NDWI = \frac{Green - NIR}{Green + NIR} \quad (1)$$

where *Green* and *NIR* correspond to DN values in green and near infrared portion of a multi-band image, respectively (Ganaie *et al*. 2013). The NDWI of an ASTER image is defined according to equation 2.

$$NDWI_{ASTER} = \frac{B_2 - B_4}{B_2 + B_4} \quad (2)$$

where B_2 and B_4 correspond to DN values in green and NIR bands of ASTER image, respectively.

The recursion in the proposed methodology (Fig. 2) is used to select the optimum combination of ASTER TIR bands that represent water surface temperature parameter. The selection is carried out among a series of standard and experimental combinations defined based on a retrieval procedure. The retrieval procedure was first proposed by Matsuoka *et al*. (2011). Although that study was done over Sendai Bay Japan, hear we applied the same procedure with different data and different results for our case study in Dez dam. The methodology is to use different band combination of ASTER TIR and each time compare the result of the modeled temperature with in-situ measurement. The optimum combination will have the least R-square comparing to the ground control data. It will be used to create the desired water surface temperature map.

The final step of the proposed methodology is analyzing the created temperature map to define the level of spatial auto-correlation and clustering exists globally and locally. They define whether temperature of water surface presents a clustered, dispersed, or random pattern in global and local scales. They provide the required basis for interpolation of ground control stations data into a temperature map especially for evaluating the validity of the typical long distance interpolation carried out to make water surface temperature maps from a few distant ground control stations.

The spatial auto-correlation and clustering at global scale are defined calculating Moran Index (Moran-I) showed in equation 3 and ranges from -1 to + 1.

$$I = \frac{n}{S_0}\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} {z_i}^2} \quad (3)$$

Where z_i is the difference between element i and its mean value, $w_{i,j}$ is the spatial weight between element i and j, n is the number of all spatial objects and S_0 is the sum of all spatial weights. Moran-I of a dispersed, random, or clustered pattern nears 1, 0, or -1 respectively.

On the other hand at local scale Getis-Ord is measured as shown in equation 4 that defines whether a location is surrounded by other correlated and rather similar value locations or different higher/lower value locations.

$$G_i = \frac{\sum_{j=1}^{n} w_{i,j} x_j - X \sum_{j=1}^{n} w_{i,j}}{S\sqrt{k}} \quad (4)$$

Where X_j is the value of each element, w shows

Fig. 1. Dez reservoir dam in Khuzestan province, south west of Iran

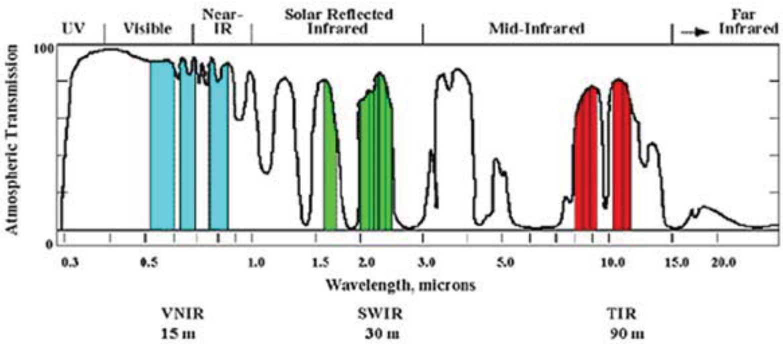

Fig. 2: Spectral bands of ASTER sensors

the spatial weight of every two elements and n is the number of all elements. This positive value of Getis-Ord index shows the high value clustering while the negative shows clustering of lower values.

RESULTS AND DISCUSSION

The proposed methodology is implemented for Dez dam that is one of the most important water reservoirs in Iran located in Khuzestan province, south-west of Iran. The height of Dez dam is 203 meters and its reservoir is 65 km long, covering 17000 km^2. It takes about 3.3 millions m^3 of water from its 125,000 m^2 watershed mainly related to Dez River.

Within the temperate region of Dez dam, there is a strong vertical stratification in deep lake resulting in nutrient depletion in upper trophic region as they

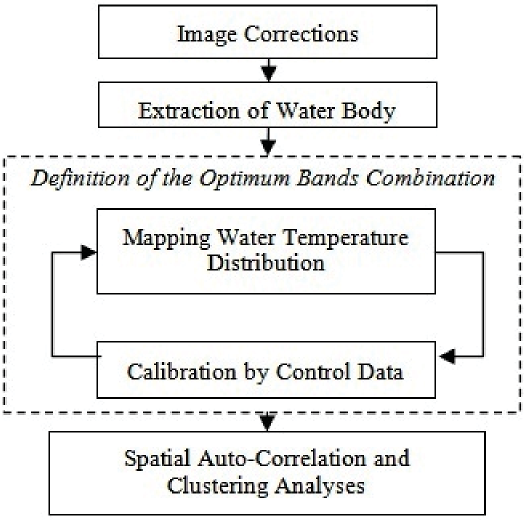

Fig. 3: Research methodology

are trapped in lower trophic regions. Besides, when the temperature of epilimnion and metalimnion approach each other, the mixing takes place that increases the growth rate of phytoplankton and other living organisms in subsequent trophic levels. As this phenomenon is also temperature dependent, the precise thermal structure of a lake can bring about precious information regarding the productivity of the whole ecosystem. It is expected that the temperature

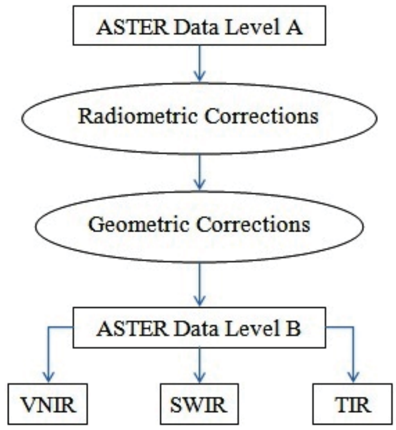

Fig. 4: ASTER data preparation procedure

maps derived from remote sensing data can provide information related to thermal structure and seasonal stratification of Dez dam reservoir.

Six sampling stations are established in Dez dam reservoir for measuring the water quality parameters. As shown in Fig. 6, four of these stations (A2, A3, T, and F) reside where the river pours into the dam reservoir and the remaining three stations (D1, D2, and E) are in the Dam reservoir area. The temperature at desired locations of the dam reservoir is typically calculated by interpolating data from the mentioned

Fig. 4: ASTER data preparation procedure

stations. Considering the stations distance (Fig. 6), long distance interpolation is required that needs to assume that spatial auto-correlation and homogeneity in the water temperature exists at long distances.

The in-situ temperature measurements were carried out in 2003. At the time the ASTER images were captured, temperature measurements of six stations were carried out. Therefore the synchronous in-situ

Table 1: In-situ and modeled temperature values of Dez dam reservoir

Station	Band_10	Band_11	Band_12	Band_13	Band_14	In Situ Temperature (°C)	Modeled Temperature (°C)
D1	10,79466	11,44778	11,72771	11,75483	11,18764	14.535	15.087
D2	10,81379	11,48516	11,77276	11,78725	11,23318	15.065	15.143
E	10,77687	11,46617	11,74526	11,76442	11,21418	14.653	15.112
A2	10,81993	11,49003	11,78075	11,81297	11,25299	15.281	15.165
A3	10,79901	11,51738	11,77943	11,78533	11,21896	15.200	15.192
T	10,78358	11,42989	11,74361	11,77808	11,19033	15.062	15.042

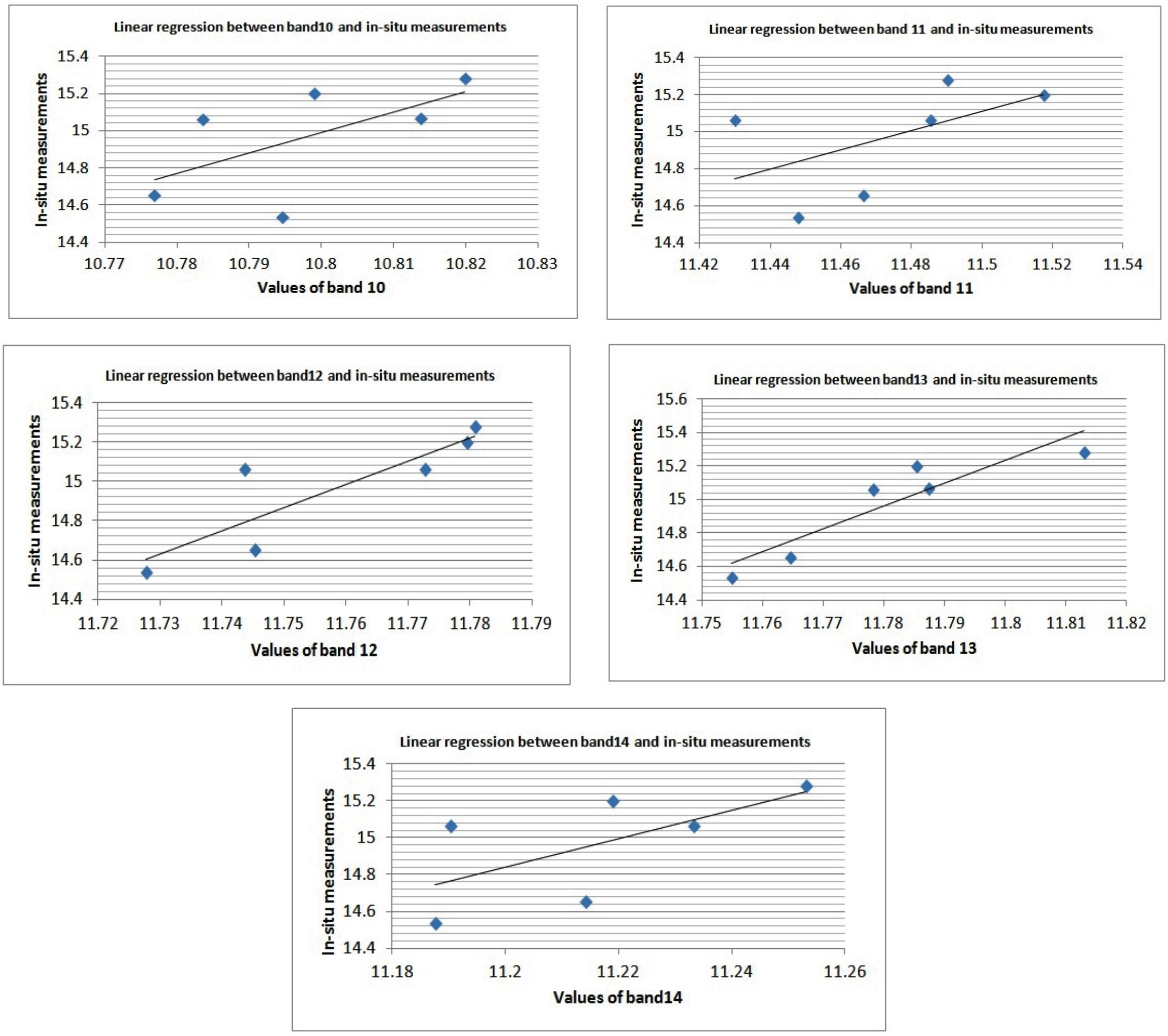

Fig. 6: Regression of real and spectral values for water surface temperature in five TIR bands of ASTER

measurements belong to six ground control stations showed in Fig. 5.

The ASTER image used in this research was captured in 2003. The ASTER imagery for this study was provided by GSI. This product is an orthophoto of the original scene which is atmospherically and geometrically corrected. For the purpose of the study only the conversion of the DN to radiance was done. The ASTER user guide provides users with methodology required for this conversion (Abrams *et al* 2003).

In order to extract water, accurate NDWI for the case study needs to be determined. After each time applying equation 2 on ASTER image, the result image was also visually assessed. As a result the NDWI equal to 0.88 was used for Dez dam case.

To establish a mathematical relationship between the temperature samples from the ground stations and ASTER TIR bands data, multiple linear regression analysis (MLR) was used provided that adequate field measurements are available for calibration. Table 1 shows the in-situ water temperature values at the sampling stations and their corresponding converted DN values obtained from five bands of ASTER TIR sensor. Each value is the average of surrounding pixels.

The results of the linear regressions between ground data and image data from 5 bands of ASTER TIR are illustrated in Fig. 6. The results show that band 12 and

Table 2: linear regression between ground data and five TIR bands

Band number	R^2 value
Band 10	0.37
Band 11	0.29
Band 12	0.76
Band 13	0.83
Band 14	0.41

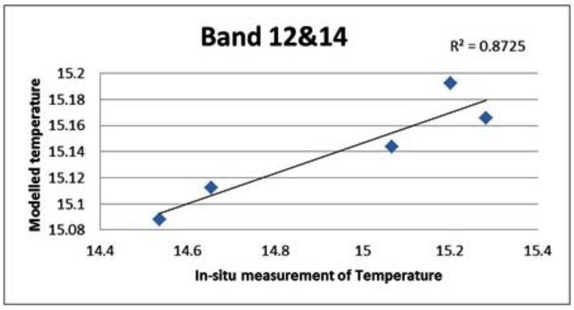

Fig. 7: Optimum regression of real and modeled values for water surface temperature

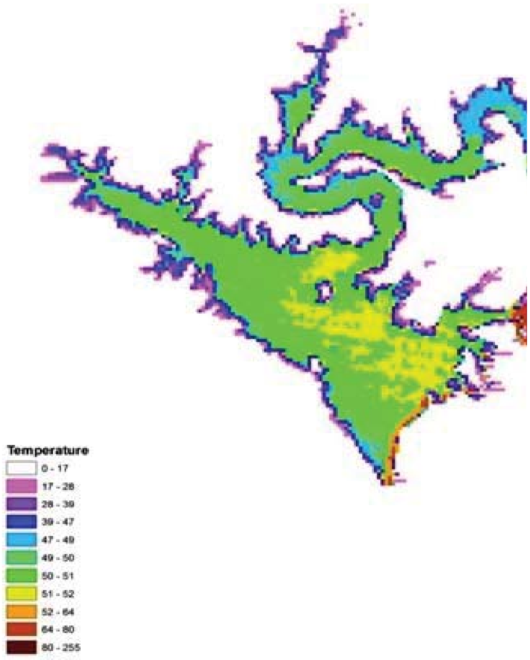

Fig. 8: Dez dam water surface temperature map derived from processing of ASTER image

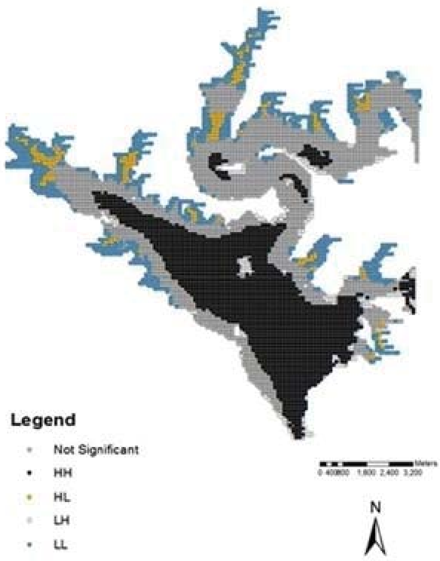

Fig. 9: Dez dam water surface temperature cluster map derived from ASTER image

band 14 have lower R-square and are more suitable to make optimum combination for fitting the water surface temperature samples to DN values (Table 2).

Then it is expected that their combination has the maximum desired information since it uses bands with the least redundancy in the ASTER data and the best fitting with ground truth.

Equation 5 presents the optimum linear combination of bands 12 and 14 to represent water surface temperature with R-square equals 0.87 (Fig. 7).

$$Temp = 45.1619 - 0.00413 \times B_{12} - 0.01055 \times B_{14} \quad (5)$$

where B_{12} and B_{14} represent corrected DN values of band 12 and band 14 of ASTER image, respectively.

Equation 5 is used to predict values of water surface temperature for all pixels in Dez reservoir dam using ASTER image (Fig. 8). The generated temperature map shows lower level of temperature at shores and at the river outlet. The maximum temperature is shown behind the dam structure where the water currents are calmer.

The spatial auto-correlation and clustering analyses carried out using ArcGIS ArcMap 9.3 toolbox. The Moran-I of the mapped water surface temperature map (Fig. 7) equals 0.5061 that shows moderate level of spatial auto-correlation and clustering in the mapped temperature at global scale. While this result supports interpolation between the ground control stations, it does not validate the long distance interpolation. Further investigation over long distance interpolation is carried out in using Getis-Ord statistics (Fig. 9). It is done using ArcMap Hot Spot analysis. This analysis defines clusters and classifies them into five categories:

1. HH [High-High]: Cell with high temperature surrounded by other high temperature cells.
2. HL [High-Low]: Cell with high temperature surrounded by other low temperature cells.
3. LH [High-Low]: Cell with low temperature surrounded by other high temperature cells.
4. LL [High-Low]: Cell with low temperature surrounded by other low temperature cells.
5. Not Significant: Cells that do not form a specific cluster.

As shown in Fig. 9, the dam reservoir inner area is covered by a high level temperature cluster (HH [High-High]). This result shows that the mentioned long distance interpolation would be valid in the dam reservoir inner area. However, some cases weaken the mentioned assumption for long distance interpolation like:

1. The shores of the dam reservoir are not included in the inner area cluster and cannot be mapped using long distance interpolations between ground control stations. These areas do not even form a coherent significant cluster and considered as outliers.

Some discrepancies (HL [High-Low] and LH [Low-High]) like the cluster shown at north part of the dam reservoir may occur.

2. The above mentioned effects usually happen when the water currents are not calm or impurities discharge into the dam reservoir from drainages at shores or at rivers outlets or other kinds of pollutions. These effects can only be observed using remote sensing data which provide dense data. Besides they explain the moderate level of global spatial auto-correlation and clustering measured by Moran-I.

CONCLUSION

The regression accuracy of 0.87 obtained by the model presented in this paper (Equation 5) showed the efficiency and appropriateness of satellite imagery of ASTER sensor for detection, identification and estimation of water surface temperature as one of the important parameters in water quality analysis. The map derived from this model is cheaper and denser than the typical maps created by interpolating data observed at a few ground control stations. Besides the Moran-I of 0.5061 for the created temperature map shows that the data is neither dispersed nor random. Considering this moderate level of auto-correlation and the results of clustering analysis carried out, interpolation of ground stations data to model temperature is viable. However the typical long distance interpolation between ground control stations is only valid within the inner area of the dam reservoir and different interpolations are required at the river outlet and at shores. Besides, some discrepancies that may occur due to ad hoc changes in weather and chemical condition of the water just can be observed using remotely sensed images and models like what proposed in this paper. This study was part of a study concerning the integration of satellite imagery and geospatial information system (GIS) in order to improve detection and computation of water quality parameters of Iran. Extension of the proposed methodology to other water quality parameters in water reservoirs at different epochs for extraction of water pollution trend is considered by authors for further investigation and future research. It will result in an operational periodic monitoring mechanism of water bodies and a comprehensive water quality model of Iran.

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Author Contributions

Abbass Malian and Zinat Farhang conducted design, experiments in remote sensing parts of the work and writing the paper; Hani Rezayan performed the GIS analyses and Mohammad Sakkizadeh contributed in environmental interpretation.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ASTER: Advanced Space- Borne Thermal Emission and Reflection Radiometer
GIS: Geospatial Information System
EC: Electrical Conductivity
TDS: Total Dissolved Solids
SST: Sea Surface Temperature
SWIR: Short Wave Infra-Red
VNIR: Visible Near Infra-Red
TIR: Thermal Infra-Red
MLR: Multiple Linear Regression
NDWI: Normalized Difference Water Index
DN: Digital Number
GSI: Geologic Survey of Iran

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