Journal of the Earth and Space Physics, Vol. 45, No. 4, Winter 2020, P. 165-179

DOI: 10.22059/jesphys.2019.252382.1006976

Investigation of Sea Surface Temperature (SST) and its spatial changes in Gulf of Oman for the period of 2003 to 2015

Khosravi, Y.[1*], Bahri, A.[2] and Tavakoli, A.[1]

1. Ph.D. Student, Department of Environmental Sciences, Faculty of Sciences, University of Zanjan, Zanjan, Iran
2. M.Sc. Student, Department of Environmental Sciences, Faculty of Sciences, University of Zanjan, Zanjan, Iran

(Received: 17 Feb 2018, Accepted: 1 Jan 2019)

Abstract

Considering the great application of Sea Surface Temperature (SST) in climatic and oceanic investigations, this research deals with the investigation of spatial autocorrelation pattern of SST data obtained from AVHRR sensor for Gulf of Oman from 2003 to 2015 (13 years). To achieve this aim, two important spatial statistics, i.e. global Moran and Anselin local Moran's I were employed within monthly and annually timescales. The results obtained from global Moran in the monthly scale suggested the existence of a strong autocorrelation and cluster pattern for SST data across all months, where warm months had a stronger autocorrelation in comparison with cold months. Furthermore, global Moran index within annual scale indicated an ascending trend for autocorrelation and clustering of SST data within the 13 studied years. To represent the manner of clustering, local Moran index was employed. Based on the results of this index within monthly scale, it was found that in winter, especially during January and February, low-low clusters, which represent low SST values, have been formed in western parts, while high-high clusters, which represent high SST values, have been formed in the southeastern parts of Gulf of Oman. After this season, the mentioned pattern changed, and from May to October, low-low clusters have been developed in the southeastern parts, while high-high clusters have been developed in the western parts of Gulf of Oman. The map of clusters for the annual scale suggested the growth of high-high clusters and reduction of low-low clusters of SST overtime. Based on these findings, it could be concluded that warming of SST in Gulf of Oman within this time period has been statistically significant and positive.

Keywords: Sea Surface Temperature (SST), Spatial Statistic, Global Moran's I, Anselin Local Moran's I, Gulf of Oman.

1. Introduction

Sea Surface Temperature (SST) is considered an important physical characteristic in the oceans of the world. The surface temperature of oceans is generally dependent on geographical latitudes, so that the warmest waters are found in the tropics and the coldest in the poles. When oceans absorb more heat, the water surface temperature increases, and the pattern of ocean cycles that transports warm and cold waters around the world changes (EPA, 2016). Changes in SST can bring about various effects on marine environments. One of the most important effects in long term is reduction of the ocean cycles pattern, which brings nutrients from the depths to the sea surface, while carrying dissolved oxygen from the surface into the deep ocean (Pratchett et al., 2004). Furthermore, due to the interaction between the atmosphere and oceans, SST can bring about dramatic effects on climate change. For example, increasing of SST can increase the amount of water vapor that is present over the oceans. The water vapor feeds climate systems, causing heavy rain and snowfall around the world. In addition, SST can also alter storm paths and potentially cause increased drought in some regions (IPCC, 2013).

According to the previous studies, SST and its changes are among the most important factors of alteration of wind speed and direction, where variations of this climatic element can alter the status of atmosphere and climate in a region (Stewart, 2008). In the past three decades, SST has increased more than ever. SST changes differ from region to region, so most parts of oceans experience increasing surface temperature, and only a few parts such as parts of the North Atlantic Ocean have experienced decreasing temperature (EPA, 2016). Therefore, monitoring and measuring SST changes at global scale and in the long term

*Corresponding author: khosravi@znu.ac.ir

are very important owing to its role in the study of changes in heat balance, which results from human interference in nature and in the effects of this parameter on the composition of gases that present in the atmosphere (Nieves et al., 2007). Various studies have been conducted about investigation of SST within long-term periods, but in this context, most studies have focused on times series analysis. For example, Khosravi et al. (2011) investigated the effects of Oman Sea Surface Temperature (SST) on the autumn and winter precipitation of its northern coast. The results showed that the spring warm (cold) SST conditions in Oman Sea can decrease (increase) precipitation in the selected stations of regions. Besides, the winter and autumn precipitations on northern coasts is remarkable, being synchronous to positive anomalies of summer SST. Takahashi et al. (2013) investigated long-term trend of SST in Omura Gulf using daily thermal equilibrium data, extracted from National Pearl Research Laboratory (NPRL) within a 40-year period (1955-1995). They found that during the warm period (from March to August), the surface temperature tended to decrease. On the other hand, throughout most of the cold period (September to February), temperature increased. Furthermore, the minimum and maximum thermal changes have been related to August and January, respectively. Tavakoli et al. (2016) investigated statistical prediction of the monthly mean sea surface temperature over the northwestern of the Indian Ocean. Their results showed that, in all of the study regions, the correlation coefficient between the observed and the predicted SST for the independent dataset is higher than 0.9. Similarly, Muhammad et al. (2016) investigated seasonal and spatial pattern of SST in northern regions of Arabian Sea from 2001 to 2012 using MODIS sensor data. They found that SST has experienced different phases of spatiotemporal changes within a certain year. However, within a long-term annual period, these changes have had a repetitive pattern. Furthermore, these researchers found that four different trends can be seen in SST increasing in the region, such that from January to March, first the southeastern parts experienced temperature increase. Then, during April and May, this growth has been observed in southern parts. Thereafter, rising temperature has been extended to northeastern parts until August, and eventually continues until December, when temperature rise is observed again in the southeastern parts. In another research, Casal and Lavender (2017) studied spatiotemporal changes of SST within a 34-year period between 1982 and 2015 in Ireland waters using AVHRR sensor data. Their climatic analyses indicated that the gradient of SST changes is dependent on latitude, as warmer waters have been observed in the south, while colder waters have been seen in the north of the region. It was also observed that the lowest and highest SST values have been recorded in March and August, respectively. They also concluded that spatiotemporal changes of SST in Ireland waters are dependent on Atlantic Multidecadal Oscillation (AMO) and the warming caused by emission of CO_2 by human beings. Furthermore, the warming trend in the region has been positive and significant. Modabberi et al. (2017) investigated the spatiotemporal variations of sea surface temperature in the Oman Sea during the last three decades. They found that the SST of Oman Sea, had a gentle increasing slope as it had an 1°C increase during last 34 years and the maximum and minimum values of SST occurs in shallow areas where Oman Sea connects to the Persian Gulf. To gain more information about the investigation of SST within long-term periods (see Kumar et al., 2016; Mustapha et al., 2016; Park et al., 2015; Stramska and Białogrodzka, 2015), by reviewing the studies, it was found that most researchers have used remote sensing and classic statistical methods for SST investigation. However, so far spatial statistical methods, given their various characteristics and applications, have not been used in monitoring and analyzing this parameter. Nevertheless, these instruments have been used in investigation of parameters including atmosphere temperature and precipitation (Bajat et al., 2015; Balyani et al., 2017; Javari, 2017; Luković et al., 2015), Land Surface Temperature (LST) (Guo et al., 2015; Ren et al., 2016), and water vapor (Khosravi et al., 2017), which have similar characteristics to this parameter.

Spatial statistics can be considered a set of techniques for describing and modeling spatial data, which are able to evaluate patterns, trends, distributions, processes, and spatial relations (Scott and Getis., 2008). Most classic statistical methods are based on independence of observations of the sample extracted from the population. However, in practice, there are many cases where observations are not independent and they are interdependent given their location in the studied space (Mohammadzadeh, 2006). Unlike classic statistics, spatial statistical techniques employ space and environment, distance, proximity, orientation, and spatial relations directly in their calculations (Scott and Getis, 2008). This research has been conducted with the aim of investigating the status of spatial autocorrelation of SST in Gulf of Oman using spatial statistical techniques within a 13-year period. As was observed in the background of the research, this study can be considered as the first research on SST monitoring with the help of spatial statistics in this area.

2. Materials and methods

2-1. introduction of the studied region

Gulf of Oman is a water zone located in the northwest of Arabian Sea and Indian Ocean and East of Strait of Hormuz and Persian Gulf and connects Persian Gulf to the Indian Ocean; therefore, this gulf is one of the most crowded seas in the world. This gulf is relatively deep, and its depth reaches 3550 m, while around the west, its depth decreases, reaching 72 m in the proximity of Strait of Hormuz. Due to the passage of Tropic of Cancer from this water zone, this gulf is one of the warmest seas of the southwestern Asia. Iran and Pakistan are located in the north of this gulf, while Oman and a small part of UAE are situated in the south of it. Gulf of Oman is located in the coordinates of 22-27° of northern latitude and 56-61° of Eastern longitude. Fig. 1 presents the location of this water zone on the map.

The Gulf of Oman is at the northern edge of the tropical weather systems in the Arabian Sea and Indian Ocean. In this region, Monsoon circulation produces southerly winds in the summer and strong northerlies in the winter (Reynolds, 1993). Water exchange in the Gulf of Oman is mediated by the seasonality of monsoonal winds resulting in a simply described three-layered system of water exchange consisting of: (First) a relatively fresh Indian Ocean Surface Water entering the Gulf of Oman on its northern side. (Second) the Persian Gulf Water Mass deep outflow propagating along the southern side through the Strait of Hormuz, and (Third) the surface outflow from the Persian Gulf of intermediate salinity water on the southern side as well (Johns et al., 1999; Yao and Johns, 2010; Piontkovski and Chiffings, 2014). The direction of water surface currents during winter is parallel to Gulf of Oman coast from northwest to the southeast. However, the general extension of currents during winter is from Gulf of Oman towards Persian Gulf, and vice versa during summer (Reynolds, 1993).

Figure 1. The location of the studied region on the map.

2-2. The Required Data

The satellite data required by the research were extracted from National Oceanic and Atmospheric Administration (NOAA) of the US (from this data set; http://oceanwatch.pifsc.noaa.gov/thredds/catalog.html). The satellite data of SST were extracted in Netcdf format with 0.1° spatial resolution (8 km approximately) for 2003 to 2015 within 13 years from AVHRR Pathfinder V.4.1 sensor. For averaging, the downloaded Netcdf files were converted to rasterized layers by ArcMap 10.2 software, and then averaged. Next, using this software, the rasterized data were converted to point data and for performing the spatial statistical analyses, they were introduced into ArcMap 10.2 and Geoda software. To investigate and compare spatial autocorrelation of SST data in Gulf of Oman, monthly and annually time separations were used, and spatial statistical analyses have been calculated for these scales. The reason of selection of these scales is the provision of a more accurate comparison of SST data across different time levels. In this research, for spatial statistical analysis, global spatial autocorrelation index (global Moran's I) and local spatial autocorrelation (Anselin local Moran's I) were used. For the verification of used data, the AVHRR Pathfinder V.4.1 data was compared with ERA-Interim dataset of European Centre for Medium-Range Weather Forecasts data (ECMWF). The results of this comparison can be observed in Fig 2. According to this Figure, the AVHRR data is compatible with ERA-Interim dataset, so that the high value of the R^2 (0.86) is evidence of this statement. The ERA-Interim reanalysis is produced with a sequential data assimilation scheme, advancing forward in time using 12-hourly analysis cycles. In each cycle, available observations are combined with prior information from a forecast model to estimate the evolving state of the global atmosphere and its underlying surface. This involves computing a variational analysis of the basic upper-air atmospheric fields (temperature, wind, humidity, ozone, surface pressure), followed by separate analyses of near-surface parameters (2 m temperature and 2 m humidity), soil moisture and soil temperature, snow, and ocean waves (Dee et al., 2011; Poli et al., 2010; Raziei and Sotoudeh, 2017).

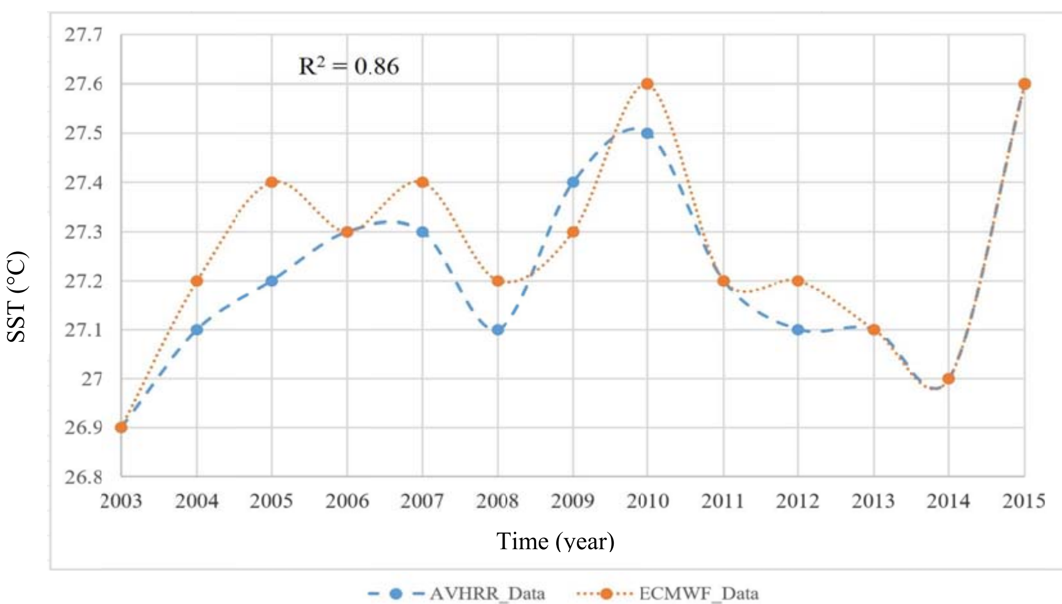

Figure 2. The results of comparison between the AVHRR Pathfinder V.4.1 data with ERA-Interim dataset of European Centre for Medium-Range Weather Forecasts data (ECMWF).

2-3. Global spatial autocorrelation (Global Moran)

According to Anselin (1992), space has two types of effect, spatial dependence and spatial heterogeneity. The first one is spatial correlation or spatial continuity, which directly follows the first Law of Geography, Tobler law. This means that close values have a greater similarity with each other, causing spatial accumulation. The second one is the spatial effect belonging to regional or spatial differences, which follows the intrinsic uniqueness of each space. Determination of the degree of distribution or clustering of features in space is possible through global spatial autocorrelation statistic. Indeed, this statistic is used with the aim of describing spatial characteristics of a variable throughout the entire region, through which it is possible to identify the mean spatial difference between all spatial cells and their adjacent cells (Sadeginia et al., 2013). In global Moran index, in addition to attention to the arrangement of features, the properties of features are also taken into account and the status of spatial autocorrelation is examined given the spatial location and internal values of the features. The spatial autocorrelation index of global Moran is calculated by the following relation (Anselin, 1992):

$$I = \frac{n}{s_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i.j} z_i z_j}{\sum_{i=1}^{n} z_i^2} \quad (1)$$

where, n is the number of observations, Z_i represents the difference between the value of property of feature i and its mean value ($X_i - \overline{X}$), $W_{i,j}$ shows the spatial weight between features i and j, representing the range of the dependence effect on spatial structure and is determined based on the neighborhood relationship, and S_o is the total spatial weights, which is calculated by the following relation (Anselin, 1992):

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i.j} \quad (2)$$

Global Moran index generates a number through which one can measure degree of distribution or clustering of spatial features or data in the space (Getis and Ord, 1992; Illian et al., 2008; Levine, 1996; Mitchel, 2005). If the value of this index is close to +1, then the data have spatial autocorrelation and a cluster pattern. On the other hand, if the value of this index is close to -1, then the data are disperse and sporadic. Regarding this index, the null hypothesis is that there is no spatial clustering between the characteristic values associated with the geographical features of interest. Now, when P-Value is very small and the calculated Z value (its absolute value) is very large, then the null hypothesis can be rejected (Asgari, 2011).

2-4. Local spatial autocorrelation (Anselin local Moran's I)

There are various spatial techniques for representation of spatial distribution of phenomena in the space. One of the most valid techniques is Anselin Local Moran's I. By having weighted spatial features and using this index, one can represent points with low or high values, which have been distributed in cluster or values with a high value difference (outlier). Anselin Local Moran's I deals with interpretation of the spatial relationship pattern of a spatial parameter in neighborhood range. This index was devised by Anselin with the aim of identifying local spaces and suggesting individual effective spaces in spatial links (Yamada and Thill, 2007). For region i, this index defines the spatial link between one value in i and close to it through the following method (Cliff and Ord, 1981):

$$\mathrm{I_i} = \frac{\mathrm{x_i} - \bar{\mathrm{x}}}{\mathrm{S_i^2}} \sum_{\mathrm{j=1.j \neq 1}}^{\mathrm{n}} \mathrm{W}_{i.j}(\mathrm{x_i} - \overline{\mathrm{X}}) \quad (3)$$

In this relation, Xi is the characteristic of the future i, $\bar{X}$ is the mean value of the related characteristic, and $W_{i,j}$ denotes the spatial weight between the features i and j, where the sum of weights is 1. In this relation, S^2_i is:

$$\mathrm{S_i^2} = \frac{\sum_{\mathrm{j=1.j \neq 1}}^{\mathrm{n}} \mathrm{W_{i.j}}}{n-1} - \overline{\mathrm{X}}^2 \quad (4)$$

where n represents the total number of features. In this index, standard score of Z is calculated and tested within a certain confidence level. The standard score of ZI_i is calculated as follows (Cliff and Ord, 1981; Goodchild, 1986):

$$ZI_i = \frac{I_i - E[I_i]}{\sqrt{V[I_i]}} \quad (5)$$

Here we have:

$$E[I_i] = -\frac{\sum_{j=1.j\neq 1}^{n} w_{i.j}}{n-1} \quad (6)$$

$$V[I_i] = E[I_i^2] - E[I_i]2 \quad (7)$$

In this analysis, if the value of I_i is positive and significant, it shows that the available cells have been surrounded by cells similar to them. Positive I_i values show that the intended feature with certain values have been surrounded by cells with values similar to those cells (high-high or low-low). This type of features is called cluster. On the other hand, negative and significant I_i values suggest that the intended feature has been surrounded by features that have absolutely no similarity with each other in terms of value (high-low or low-high). This type of features is called outlier. Existence of such features suggests negative spatial correlation.

3. Discussion

3-1. Analysis of autocorrelation of Global Moran's I

As mentioned previously, Moran's I deals with the investigation into the status of spatial autocorrelation of data and in addition to determining the type of autocorrelation, it makes decision on the type of spatial distribution pattern governing the data. Therefore, to determine the type of spatial distribution governing the SST data, first it should be specified whether the spatial distribution of SST in Gulf of Oman has spatial autocorrelation or not, and if positive, how this distribution is. In this regard, global Moran's I was calculated for SST within monthly and annual periods. The results of this analysis for monthly period can be observed in Table 1. Based on this table, showing the values of Moran index, standard Z score and p-value for SST data within the monthly period, it can be concluded that there is a strong autocorrelation between SST data in Gulf of Oman and the data have been distributed as cluster with a high concentration in the space. Therefore, considering the probable hypotheses (H0 and H1), the null hypothesis (showing lack of a spatial relationship between SST data in Gulf of Oman) has been rejected, and H1 suggesting existence of autocorrelation between these data is confirmed. Investigating Fig. 3, representing the diagram of global Moran index values across different months, it was found that the strongest autocorrelation and cluster distribution have been formed within warm months of the year. Here, due to the high number of schemas and output diagrams of global Moran analysis, only the schema and output diagram of this index for August, which had the strongest autocorrelation, has been provided as a sample (Fig. 4.5). These two figures well demonstrate cluster distribution of SST data in the studied region. In Fig. 5, the more distribution of data in the first and fourth quarter causes a negative and inverse autocorrelation, but the data distribution in the second and third quarter causes a positive and direct autocorrelation.

Table 1. The values of spatial autocorrelation of global Moran, standard Z score and p-value of monthly SST data between 2003 and 2015 in Gulf of Oman.

Month	Moran Index	Z-Score	p-value
January	0.926	44.114	0
February	0.925	52.587	0
March	0.911	43.698	0
April	0.863	45.203	0
May	0.937	51.070	0
June	0.984	54.641	0
July	0.990	54.241	0
August	0.993	55.091	0
September	0.992	55.002	0
October	0.984	55.047	0
November	0.791	42.810	0
December	0.793	41.972	0

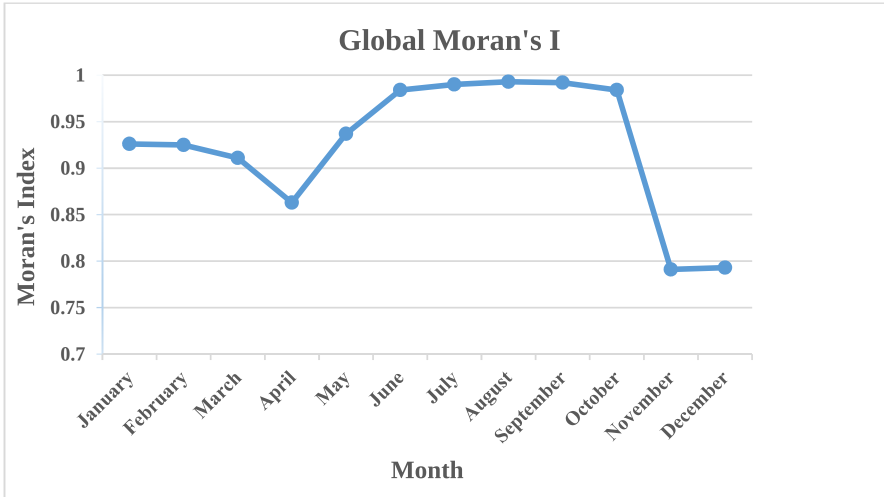

Figure 3. The temporal changes of spatial autocorrelation of global Moran for monthly SST between 2003 and 2015 in Gulf of Oman.

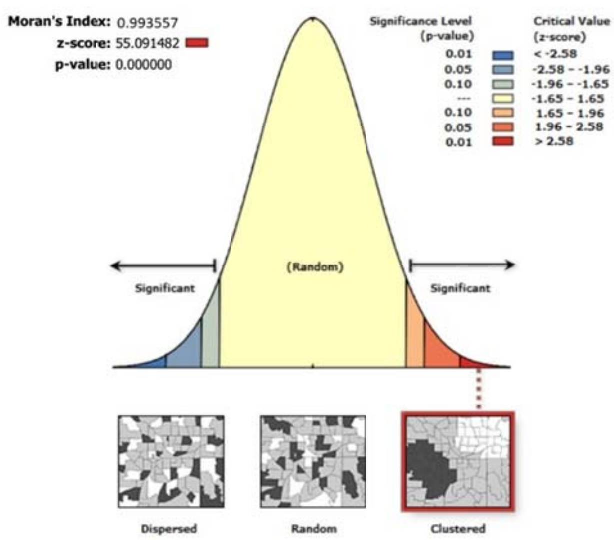

Figure 4. Graphic representation of the spatial autocorrelation results of global Moran statistic for SST in August between 2003 and 2015 in Gulf of Oman.

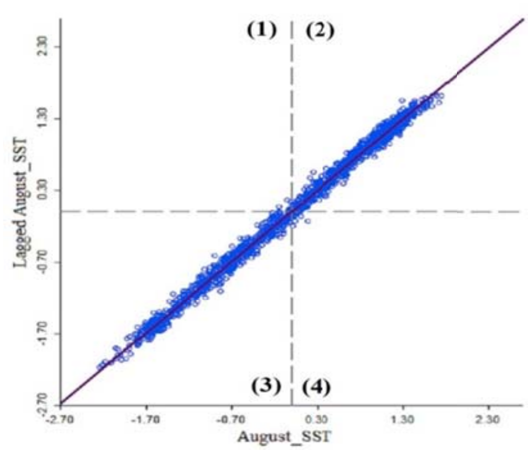

Figure 5. The scatter plot of global Moran for SST in August between 2003 and 2015 in Gulf of Oman.

Table 2 and Fig. 5 represent spatial autocorrelation status of SST values at annual scale between 2003 and 2015. Investigating Fig. 5, it is observed that changes in the autocorrelation values have had fluctuations within the studied 13 years. However, through a general investigation and according to the trend that can be observed in Fig. 6, it can be concluded that autocorrelation values of SST within the studied period have had an ascending trend, and the tendency of data to form spatial clusters has increased, so that in 2003, global Moran Index shows 0.934, while it reaches 0.962 in 2015. It should be noted that in all years the p-value has been zero.

3-2. Analysis of local spatial autocorrelation (Anselin local Moran's I)

Investigating global Moran, it was found that SST data in Gulf of Oman had a spatial structure, and they have been distributed as cluster at both time scales. This means that low or high values of surface temperature tend to concentrate or cluster in the space. Furthermore, at the annual scale, it was found that during the 13 studied years, the data found a greater tendency to clustering over time. However, global Moran index is not able to identify this type of clusters. Therefore, to specify the type of spatial clusters, discovering the site of their formation and detecting the type of elevated clusters throughout the 13 years, Anselin Local Moran's I was employed. In general, this index determines the extent of autocorrelation or spatial distinctions between the values of adjacent cells within a geographical range and tests its significance.

Table 3 indicates the number of high-high and low-low points for SST within monthly temporal scale in Gulf of Oman. Based on this table, it is observed that August and January have had the maximum and minimum high-high points, respectively. Furthermore, the minimum and maximum of low-low points have been related to October and January, respectively. Overall, it can be stated that the warm months of the year have had the maximum spatial clusters, while cold months experienced the minimum number of spatial clusters. Fig. 7 well demonstrates the number of high-high and low-low clusters for the studied months.

Table 2. The spatial autocorrelation values of global Moran and standard Z score for annual SST data between 2003 and 2015 in Gulf of Oman.

Year	Moran Index	Z-Score	Year	Moran Index	Z-Score
2003	0.934	52.177	2010	0.940	52.477
2004	0.959	53.599	2011	0.950	52.949
2005	0.953	53.169	2012	0.957	53.377
2006	0.966	53.892	2013	0.936	52.394
2007	0.927	51.678	2014	0.952	53.288
2008	0.956	53.151	2015	0.962	53.516
2009	0.936	52.364	-	-	-

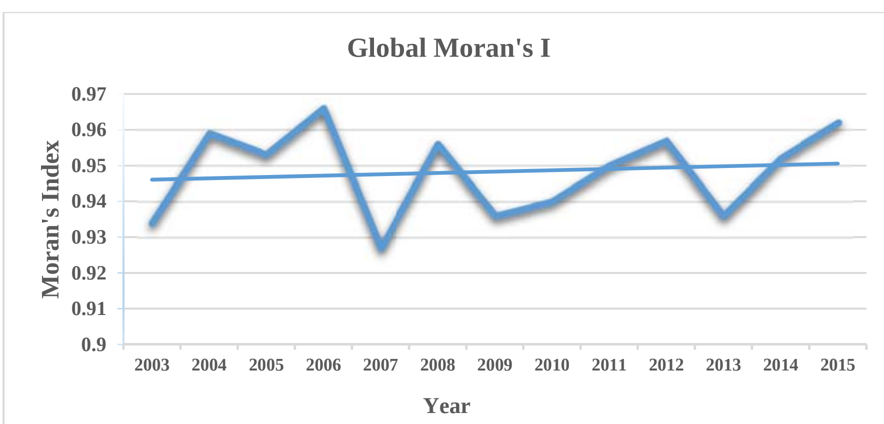

Figure 6. Temporal changes of spatial autocorrelation of global Moran's I for annual SST between 2003 and 2015 in Gulf of Oman.

Table 3. The number of high-high and low-low points for monthly SST between 2003 and 2015 in Gulf of Oman.

Month	High-High	Low-Low
January	311	212
February	366	217
March	348	227
April	323	221
May	422	417
June	429	373
July	496	384
August	500	419
September	493	428
October	446	467
November	327	245
December	338	241

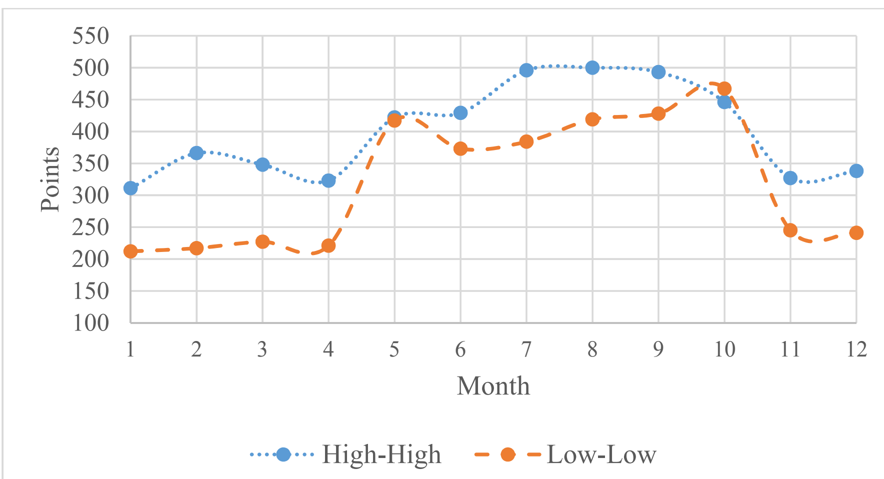

Figure 7. The temporal changes of high-high and low-low points of monthly SST between 2003 and 2015 in Gulf of Oman.

To better understand the previous points, the map of spatial SST clusters was prepared for all months, which can be observed in Fig. 8. Based on this figure, from January to March, low-low clusters have been developed in the western part of the Gulf, while high-high clusters have been extended in the southeastern parts. Next, in April, this trend has undergone changes and from May, low-low clusters give their place to high-high clusters, so until October, high-high clusters are formed in the western part, while low-low clusters are formed in the east and southeastern part of the Gulf of Oman. In November, the pattern of formation of clusters changes again and in December, the status of formation of clusters in the region become similar to the early months of the year. The significant levels of these clusters are also shown in Fig. 9. In this figure, it can be clearly seen that spatial clusters are at very high levels of significance.

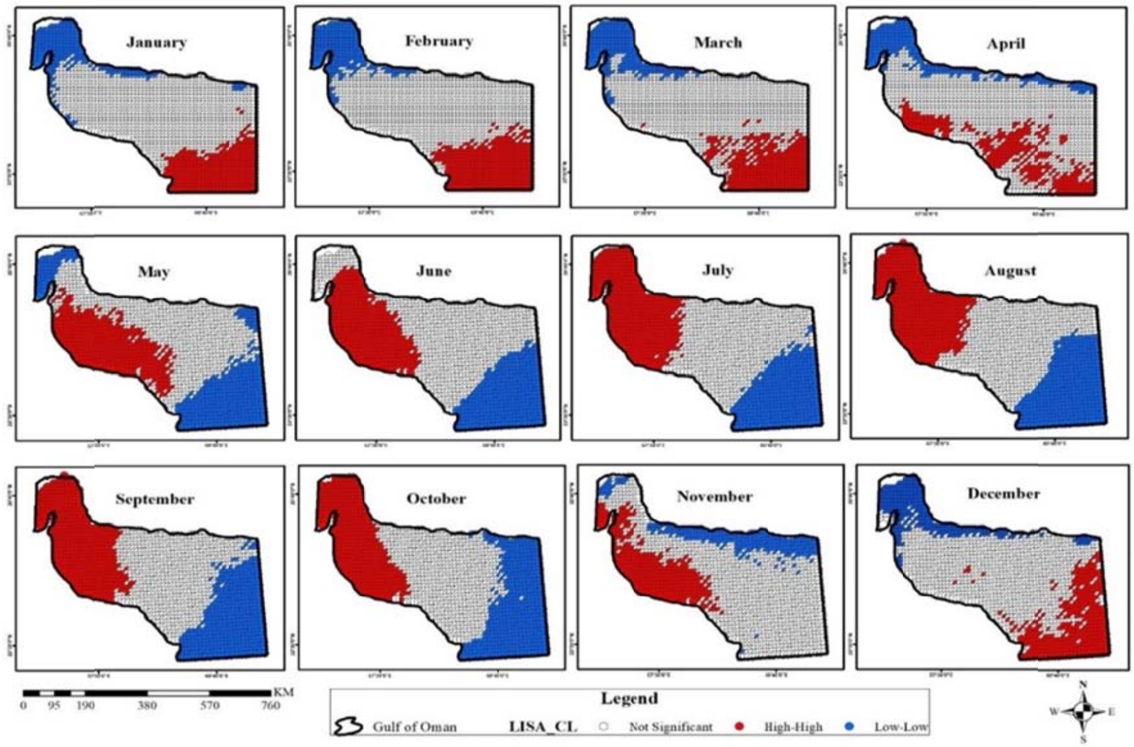

Figure 8. The status of formation of spatial clusters of SST of Gulf of Oman across different months between 2003 and 2015.

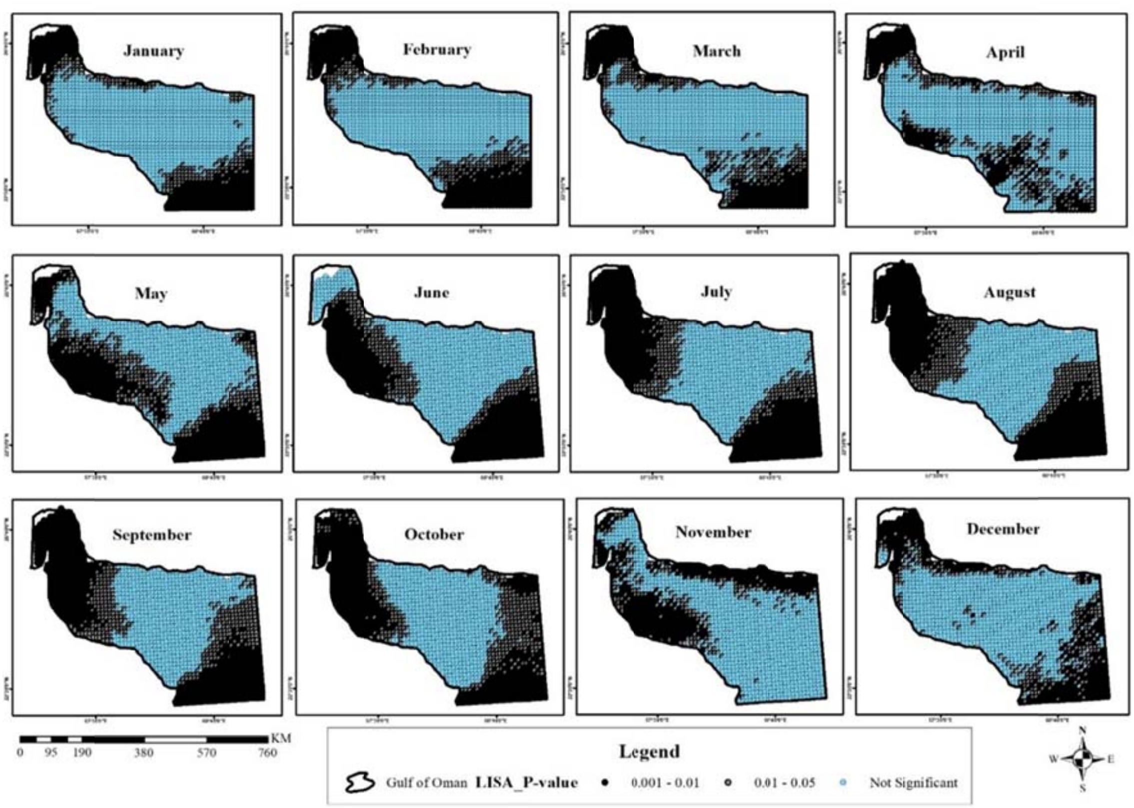

Figure 9. Significant levels of SST spatial clusters across different months between 2003 and 2015 in Gulf of Oman.

Next, annual scale of temporal changes of high-high and low-low points was analyzed, the values of each point were extracted (Table 4) and the trend of their temporal changes was surveyed (Fig. 10). Considering Fig. 10, which represents the diagram of temporal changes of low-low points throughout the 13 studied years, it was found that throughout these years, temporal changes of the number of low-low points have had some fluctuation. However, generally over time, the number of these points has decreased, so in 2003, the number was 511, while in 2015, the number has decreased to 372 points. The temporal changes of the number of high-high points can be observed in Fig. 10. This diagram well represents that in spite of the fluctuations in the number of high-high points within this period, overall formation of these points in Gulf of Oman has had an ascending trend and the number of high-high points has increased from 416 in 2003 to 486 in 2015. Therefore, based on these observations, it can be stated that the ascending trend of clustering obtained by global Moran instrument, is related to high-high clusters of SST, and they are the clusters that are increasing over time in this gulf.

To better understand the points mentioned so far, the map of spatial clusters of SST was plotted for 2003 and 2015. Through corresponding these maps, the changes of formation of high-high and low-low clusters in this gulf were observed well (Fig. 11). Based on this figure, overall high-high clusters, representing warm clusters (high SST values) have been formed in the south, southwest and western parts of the region, while low-low clusters, representing cold clusters (low SST values), have been developed in the eastern, northern, and southeastern parts of Gulf of Oman. Nevertheless, the notable point in this figure is increasing of high-high points in 2015 and their development towards east (the green area). Furthermore, many of the low-low points which have existed in 2003, have disappeared completely in 2015, and a number of these points in the eastern part of Gulf of Oman has decreased (the red area). One of the important surface boundary conditions that influence the monsoon is sea surface temperature. It is generally believed that the interannual variability in monsoon activity depends on air-sea interactions, which take place during the travel of the monsoon current across the Ocean (Singh and Oh, 2007). It was cleared that higher SST bring higher latent heat fluxes under the same atmospheric conditions due to higher water vapor pressures on the sea surface. At the same time, the evaporation over the sea surface decreases the SST. In monsoon condition, the strong monsoon also increases latent heat flux, which brings abundant rainfall (Dado and Takahashi, 2017).

Table 4. The number of high-high and low-low points for annual SST between 2003 and 2015 in Gulf of Oman

Year	High-High	Low-Low	Year	High-High	Low-Low
2003	416	511	2010	435	483
2004	480	491	2011	419	395
2005	437	457	2012	463	364
2006	432	429	2013	441	448
2007	393	366	2014	471	454
2008	448	375	2015	486	372
2009	422	343	-	-	-

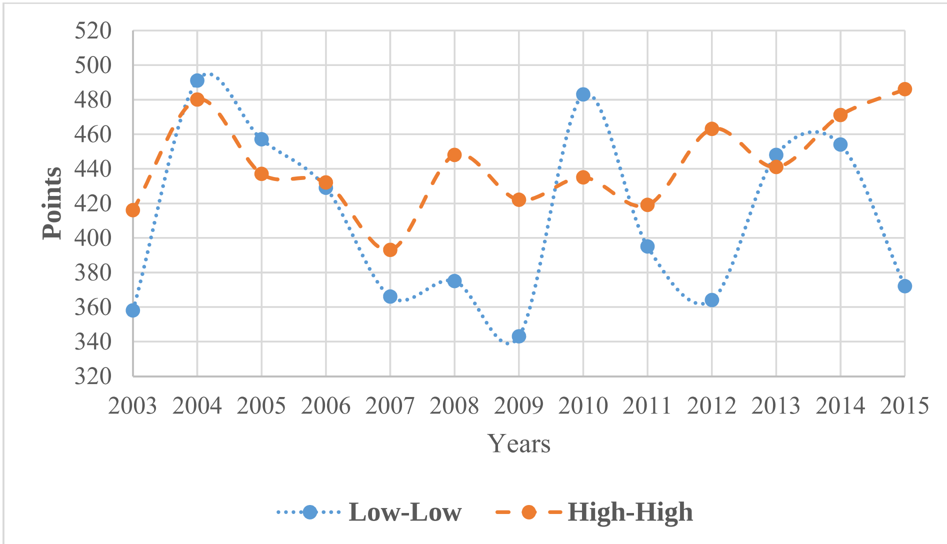

Figure 10. The temporal changes of high-high and low-low points of annual SST between 2003 and 2015 in Gulf of Oman.

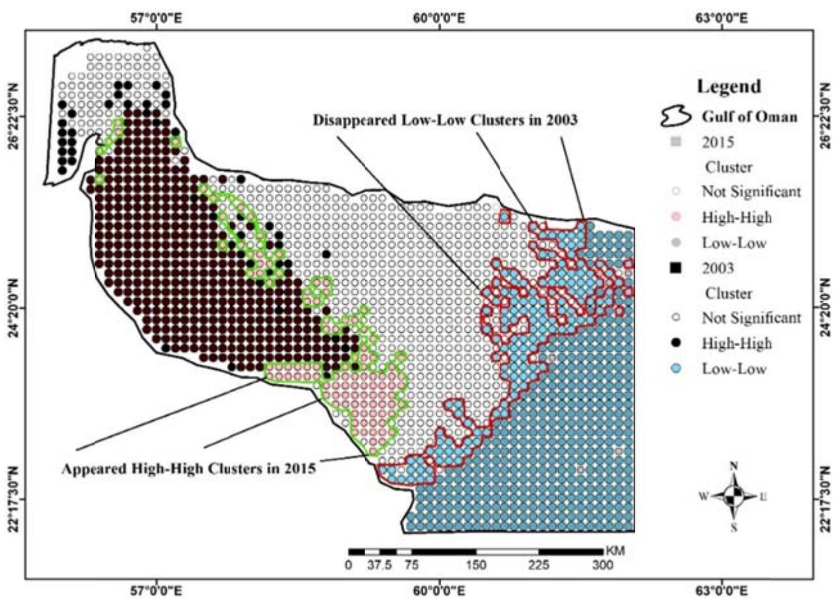

Figure 11. Spatial distribution of high-high and low-low points of SST and the trend of changes occurred between 2003 and 2015, black and dark blue points are high-high and low-low clusters that have been formed in both years.

4. Conclusion

In this research, due to the significance of SST in oceanic, atmospheric, and climatic issues, this parameter was examined using spatial statistical techniques in Gulf of Oman between 2003 and 2015. The results obtained from global Moran index for monthly SST indicated that the maximum autocorrelation has occurred in August and September, while the minimum has taken place in November and December. It was also found that they are generally the warm months claiming the maximum autocorrelation and a more clustered pattern, while in cold months, autocorrelation value is lower. However, a strong autocorrelation is observed for SST data across all months. Global Moran's I analysis was also calculated for annual timescale and the results suggested an ascending trend in autocorrelation values and clustering of the distribution pattern of SST data within the 13 years. Next, to discover the type of clustering (high-high or low-low) of the data throughout the 13 years and identify the site of formation of clusters, Anselin local Moran's I was used. The results of this index for the monthly timescale suggested a larger number of high-high and low-low clusters in the warm months in comparison with the cold months. This analysis also well indicated that the clustering trend, which has been observed in the annual timescale in global Moran index, has been related to high-high clusters, and the number of these clusters has increased gradually over time. In contrast, throughout these years, the number of low-low clusters in Gulf of Oman has diminished. The general site of formation (across all the studied years) of the high-high clusters has been southern, southwestern and western parts of the region. On the other hand, low-low clusters were formed in eastern, northeastern, and southeastern parts of the Gulf. However, investigation of the output maps of local Moran's I indicated that development of low-low clusters in the eastern parts of the region has diminished, while development of high-high clusters towards east has grown. It should also be noted that high-high clusters represent high SST values, whereas low-low clusters suggest low values of this parameter. Therefore, it can be concluded that within the 13 studied years (2003-2015), warming of surface temperature of Gulf of Oman has been statistically significant and positive. Further, considering the passage of almost one decade, significant changes have occurred in the values of this parameter in Gulf of Oman. Therefore, it can be deduced that global warming and climate change may have influenced this region. In this regards, Khan et al. (2004) reported an increasing trend for sea surface temperature in the northern parts of the Arabian Sea (including parts of Gulf of Oman). In other research, Piontkovski and Chiffings (2014) studied long-term changes of SST in the Gulf of Oman and western part of Arabian Sea, and they also found a positive trend for SST changes in this area. However, the difference between this work and those of the researchers is that this work has examined spatial changes of SST. Since SST is in direct relationship with many oceanic, atmospheric, and climatic parameters such as marine currents, chlorophyll concentration, surface wind, atmospheric temperature, water vapor, and precipitation, thus concurrent monitoring of these parameters with SST to discover their spatial relationship with each other is essential.

References

Anselin, L., 1992, Spatial data Analysis with GIS: an Introduction to Application in the Social Sciences.

Asgari, A., 2011, Spatial Statistic Analysis with ArcGIS. Information and Communication Technology Organization of Tehran Municipality Publication, Tehran, First Edition, in Persian.

Bajat, B., Blagojević, D., Kilibarda, M., Luković, J. and Tošić, I., 2015, Spatial analysis of the temperature trends in Serbia during the period 1961–2010. Theoretical and Applied Climatology, 121, 289-301.

Balyani, S., Khosravi, Y., Ghadami, F., Naghavi, M. and Bayat, A., 2017, Modeling the spatial structure of annual temperature in Iran. Modeling Earth Systems and Environment, 3, 581-593.

Casal, G. and Lavender, S., 2017, Spatio-temporal variability of sea surface temperature in Irish waters (1982–2015) using AVHRR sensor. Journal of Sea Research, 129, 89-104.

Cliff, A. D. and Ord, J. K., 1981, Spatial Processes: Models & Applications. Taylor & Francis.

Dado, J. M. B. and Takahashi, H. G., 2017, Potential impact of sea surface temperature on rainfall over the western Philippines. Progress in Earth and Planetary Science, 4, p. 23.

Dee, D. P., Uppala, S. M., Simmons, A. J., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., Balmaseda, M. A., Balsamo, G., Bauer, D. P. and Bechtold, P., 2011, The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. Quarterly Journal of the Royal Meteorological Society, 137, 553-597.

EPA., 2016, Climate Change Indicators in the United States: Sea Surface Temperature,

Getis, A. and Ord, J. K., 1992, The analysis of spatial association by use of distance statistics. Geographical Analysis, 24, 189-206.

Goodchild MF., 1986, Spatial Autocorrelation, CATMOG 47, Norwich, UK.

Guo, G., Wu, Z., Xiao, R., Chen, Y., Liu, X. and Zhang, X., 2015, Impacts of urban biophysical composition on land surface temperature in urban heat island clusters. Landscape and Urban Planning, 135, 1-10.

Illian, J., Penttinen, A., Stoyan, H. and Stoyan, D., 2008, Statistical Analysis and Modelling of Spatial Point Patterns. John Wiley & Sons.

IPCC, 2013, Climate Change 2013: The physical science basis. Working Group I contribution to the IPCC Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Javari, M., 2017, Assessment of Temperature and Elevation Controls on Spatial Variability of Rainfall in Iran. Atmosphere 8, 45.

Johns, W. E., Jacobs, G. A., Kindle, J. C., Murray, S. P. and Carron, M., 1999, Arabian Marginal Seas and Gulfs. Report of a workshop held at Stennis Space Center, Mississippi, May 11-13, 1999. RSMAS Technical Report #2000-01, University of Miami, 60pp.

Khan, T. M. A., Quadir, D. A., Murty, T. S. and Sarker, M. A., 2004, Seasonal and Interannual Sea Surface Temperature Variability in the Coastal Cities of Arabian Sea and Bay of Bengal. Natural Hazards, 31, 549–560.

Khosravi, M., Salighe, M. and Sabaghi, B., 2011, The Effects of Oman Sea Surface Temperature Anomalies in Autumn and Winter Precipitation of Southeast Coasts of Iran. Journal of Geography and Planning, 37, 59-81.

Khosravi, Y., Lashkari, H. and Asakereh, H., 2017, Spatial variability of water vapour in south and southwest of Iran. MAUSAM, 68, 9-22.

Kumar, P. K. D., Paul, Y. P., Muraleedharan, K. R., Murty, V. S. N. and Preenu, P. N., 2016, Comparison of long term variability of Sea Surface Temperature in the Arabian Sea and Bay of Bengal. Regional Studies in Marine Science, 3, 57-67.

Levine, N., 1996, Spatial statistics and GIS: Software tools to quantify spatial patterns. Journal of the American Planning Association, 62, 381-391.

Luković, J., Blagojevć, D., Kilibarda, M. and Bajat, B., 2015, Spatial pattern of north Atlantic oscillation impact on rainfall in Serbia. Spatial Statistics, 14, 39-52.

Mitchel, A., 2005, The ESRI Guide to GIS analysis, Volume 2: Spartial measurements and statistics. ESRI Guide to GIS analysis.

Modabberi, M., Ansari, E., Noori, R. and Abbasi, M. R., 2017, Investigation of the Spatiotemporal Variations of Sea Surface Temperature in the Oman Sea during the Last Three Decades. 4th Environmental Planning and Management Conference, Tehran.

Mohammadzadeh, M., 2006, Introduction to Spatial Statistics, NEDA. Student Statistical Journal. 2, 1-12 (in Persian).

Muhammad, S., Memon, A. A., Muneeb, M. and Ghauri, B., 2016, Seasonal and spatial patterns of SST in the northern Arabian Sea during 2001–2012. The Egyptian Journal of Remote Sensing and Space Science, 19, 17-22.

Mustapha, S. B., Larouche, P. and Dubois, J. M., 2016, Spatial and temporal variability of sea-surface temperature fronts in the coastal Beaufort Sea. Continental Shelf Research, 124, 134-141.

Nieves, V., Llebot, C., Turiel, A., Solé, J., García-Ladona, E., Estrada, M. and Blasco, D., 2007, Common turbulent signature in sea surface temperature and chlorophyll maps. Geophysical Research Letters 34, L23602.

Park, K. A., Lee, E. Y., Chang, E. and Hong, S., 2015, Spatial and temporal variability of sea surface temperature and warming trends in the Yellow Sea. Journal of Marine Systems, 143, 24-38.

Pionkovski, S. A. and Chiffings, T., 2014, Long-Term Changes of Temperature in the Sea of Oman and the Western Arabian Sea, International Journal of Oceans and Oceanography, 8, 53-72.

Poli, P., Healy, S. B. and Dee, D. P., 2010, Assimilation of Global Positioning System radio occultation data in the

ECMWF ERA–Interim reanalysis. Quarterly Journal of the Royal Meteorological Society, 136, 1972-1990.

Pratchett, M. S., Wilson, S. K., Berumen, M. L. and McCormick, M. I., 2004, Sublethal effects of coral bleaching on an obligate coral feeding butterflyfish. Coral Reefs, 23, 352-356.

Raziei, T. and Sotoudeh, F., 2017, Investigation of the accuracy of the European Center for Medium Range Weather Forecast (ECMWF) in forecasting observed precipitation in different climates of Iran. Journal of the Earth and Space Physics, 43, 133-147.

Ren, Y., Deng, L. Y., Zuo, S. D., Song, X. D., Liao, Y. L., Xu, C. D., Chen, Q., Hua, L. Z. and Li, Z. W., 2016, Quantifying the influences of various ecological factors on land surface temperature of urban forests. Environmental Pollution, 216, 519-529.

Reynolds, R. M., 1993, Physical oceanography of the Gulf, Strait of Hormuz, and the Gulf of Oman—Results from the Mt Mitchell expedition, Marine Poll Bull., 27, 35-59.

Sadeginia, A. R., Alijani, B., Zeaiean Firouzabadi, P. and Khaledi, S., 2013, Application of Spatial autocorrelation techniques in analyzing the heat island of Tehran. Journal of Applied research in Geographical Sciences, 30, 67-97 (in Persian).

Scott, L. and Getis, A., 2008, Spatial statistics. InKemp K (ed) Encyclopedia of geographic informations. Sage, Thousand Oaks, CA.

Singh, G. P. and Oh, J. H., 2007, Impact of Indian Ocean sea-surface temperature anomaly on Indian summer monsoon precipitation using a regional climate model. International Journal of Climatology: A Journal of the Royal Meteorological Society, 27, 1455-1465.

Stewart, R. H., 2008, Introduction to Physical Oceanography.

Stramska, M. and Białogrodzka, J., 2015, Spatial and temporal variability of sea surface temperature in the Baltic Sea based on 32-years (1982–2013) of satellite data. Oceanologia, 57, 223-235.

Takahashi, T., Nakata, H. and Kimura, S., 2013, Long-term trends in sea surface temperature in coastal water in relation to large-scale climate change: a case study in Omura Bay, Japan. Continental Shelf Research, 66, 73-82.

Tavakoli, M., Shirvani, A. and Nazemosadat, M. J., 2016, Statistical prediction of the monthly mean sea surface temperature over the northwestern of the Indian Ocean. Iranian Journal of Geophysics, 10, 66-76.

Yamada, I. and Thill, J. C., 2007, Local Indicators of Network-Constrained Clusters in Spatial Point Patterns. Geographical Analysis, 39, 268-292.

Yao, F. and Johns, W. E., 2010, A HYCOM modeling study of the Persian Gulf: 1. Model configurations and surface circulation. Journal of Geophysical Research, 115, C1 1017.