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Significant wave height prediction by using a spatial model

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Abstract

Spatial assessment of variables in a considered region saves its significance for engineering applications. Branches in ocean engineering need the results of this assessment like radius of influence of stations that records the wave measurements and various meteorological variables values. Classical approaches like Kriging do not provide radius of influence for the concerned station. On the other hand, prediction of these measurements from other surrounding stations in the region is a basic requirement. In this paper, it is aimed to predict significant wave height records in a specific region by using trigonometric point cumulative semivariogram (TPCSV) concept. The main difference of this approach from the point cumulative semivariogram (PCSV) approach is the determination of influence radius. More accurate results can be obtained by TPCSV. The spatial correlation and weightings are also obtained through the TPCSV where the distance between two sites is known. The proposed method yields the least prediction error compared with other objective methodologies. The implementation of this methodology is presented for a set of offshore locations distributed along the west United States coastline.

Keywords: Area of influence; Estimation; Interpolation; Objective analysis; Radius of influence; Semivariogram; Significant wave height

1. Introduction

Spatial features of wave climatology have not been taken into consideration as frequent as temporal variations. Özger et al. (2004a,b) have discussed the temporal

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features of the wave energy by using stochastic and statistical models. Jönsson et al. (2002) investigated the temporal and spatial variation of waves. The surface waves in the Baltic sea are hindcast with a spectral wave model during a 12-month period. The model results show a strong temporal and spatial variation in the wave field due to the physical dimensions of the different basins and the predominant wind field. Altunkaynak and Özger (2004) established an adaptive model considering the temporal changes and made an attempt to predict significant wave height from wind speed.

Matheron (1963) laid the foundations for quantifying regional variabilities within any event provided that there are sample measurements at distinct sites. It has been applied in mining industry for estimating the ore grades, recoverable reserves and in planning optimum operations. Collectively, these techniques are referred as the geostatistical methods and they are applicable throughout the earth sciences especially where information is incomplete. Among the examples of such applications are mapping and modelling groundwater (Gambolati and Volpi, 1979; Kitanidis and Vemvoris, 1983; Myers et al., 1984), rainfall monitoring (McCullagh, 1975), distribution of atmospheric pollutants (Lajaunie, 1984), in soil science (Burges and Webster, 1980).

Thatti and Islam (2000) used Kriging method in characterizing the spatial structure of the Little Washia soil moisture data measured by passive microwave remote sensing. The model uses the soil moisture values and operates on a far larger scale than is available through the remote sensors. Chouinard et al. (1997) investigated the influence of the local oceanographic features on the hurricane severity. They proposed a statistical model and an estimation procedure that accounts for the spatial variation of the probability distribution function of hurricane severity. It is suggested that regions of severe hurricanes are centered near the maxima in subsurface water temperature and have similar spatial characteristics.

The term geostatistics is now widely applicable for regional variability modelling in earth sciences as a special branch of applied statistics originally developed by Matheron (1963). Unlike random variables, the ReV has a continuous spatial change. The semivariogram (SV) is used to express the rate of this change along a specific distance orientation (Davis, 1986).

As for the wind energy, the spatial modelling procedures are not available in the literature except classical contour maps, which cannot help to make dynamic predictions. Lalas et al. (1983) have shown that the adjusted Weibull and lognormal distributions are adequate for the wind potential estimation in the Aegean sea region. Additional assessments of wind power in this region are performed by various authors as Şahin and Şen (1995), Öztopal et al. (2000) and Şahin and Şen (2001). However, these studies assess data by not considering regional dependence function.

The main purpose of this paper is to develop a methodology that first depicts the regional dependence from an irregular set of stations scattered in an area. Subsequently, radius and area of influences are obtained for each site. By considering the measurement sites within the area of influence the regional prediction is obtained by weighted average method. The application of the methodology is achieved for a set of offshore stations distributed in the Pacific Ocean along the USA cost.

2. Overview of classical methodologies

The basis of the methodology depends on the semivariogram (SV) (Matheron, 1963), CSV (Şen, 1989) and point cumulative semivariogram (PCSV) (Şen, 1991, 1997; Şen and Şahin, 1997, 1998, 2001; Şen and Habib, 1998) and concepts.

Any phenomenon that evolves in the atmosphere has spatial and temporal variabilities that are recorded time wise at a single point or spatial wise at many irregular points. Any regional aims to study to search for simple but effective means for capturing the regional dependence structure of the phenomenon concerned such as the efficient procedure proposed by Matheron (1963) in mining reserve simulation studies. His proposal is known in the literature as the semivariogram (SV) method, which provides basis for the optimum interpolation approach through the Kriging method. Ordinary SV shows the change of regional variability in terms of half-squared differences between two station records and the distance between these stations. In general, the greater the distance the more will be the independence, i.e. at small distances the two records are expected to be closer to each other, and consequently, the change of half-squared differences with the distance is expected to have a non-decreasing form. Unfortunately, this theoretical requirement has not been observed in the experimental SVs. On the other hand, Şen (1989) has explained the reasons of such discrepancies and subsequently suggested a new version of the SV called CSV where only their summations are considered in depicting the regional dependence rather than the half-squared differences.

The PCSV, as a version of ordinary CSV, suggested by Şen (1989) was applied to investigate some meteorological data by Habib (1993). This is a simple procedure for measuring and then interpreting the regional variability of the ReVs such as the wind speed and energy amounts at various irregularly scattered stations within a given study area. The PCSV procedure is proposed, herein, in identifying the spatial behavior of any variable around a site. In other words, it presents the regional effect from all other sites within the study area on this site, and hence, the number of PCSVs is equal to the number of sites. Comparisons and groupings of the PCSVs provide valuable information for the heterogeneity and isotropy involved in the ReV concerned. The treatment of the following steps leads to desired sample PCSV for the pivot site among n available sites (Şen, 1989).

(a) Calculate distance between the pivot and the remaining sites. If there are m sites, then the number of distances will be $m-1$.
(b) For each pair (pivot and any other site) find the half-squared differences between data values. In this case, the wind velocity or elevation values. By this way, each distance will have its half-squared value.
(c) Plot distances versus corresponding successive cumulative sums of half-squared differences after ranking the distances in ascending order. This procedure will give a non-decreasing function which is the sample PCSV at the pivot site.
(d) Apply previous steps by considering different pivot site and consequently, there will be m number of sample PCSVs, $\gamma(H_i)$ obtained from a given set of irregularly scattered stations

$$\gamma(H_i) = \frac{1}{2n}\sum_{i=1}^{n-1}(H_r - H_i)^2 \tag{1}$$

where H_r and H_i represents the ReV values at the pivot and ith stations, respectively. The pivot and ith stations are d distance apart. A representative PCSV is shown in Fig. 1.

For regional prediction, consider n irregularly scattered measurement sites with a point, P, where the regional estimation of the wind velocity is desired. Logically, the weights should be inversely related to distances between each pair of sites, i.e. the smaller the distance, the more will be the effect of the station measurement on the estimation value. If the measurements are indicated by w ($i=1,2,\ldots,n$) and the estimation at point P with w_P, then in an objective interpolation technique the main idea is the estimation at P by considering a weighted average of the measured values at irregular sites. In general, the point estimation is expressed as

$$w_P = \frac{\sum_{i=1}^{n} W(r_{i,P})w_i}{\sum_{i=1}^{n} W(r_{i,P})} \tag{2}$$

where $r_{i,P}$ represents the distance between the measurement station i and estimation point, P; and $W(r_{i,P})$ is the weighting factor corresponding to this distance. Although in literature there are different approaches for radius of influence determination that are all dependent on site configuration and distances without consideration of actually recorded data (Cressman, 1959; Barnes, 1964; Sasaki, 1958; Thiebaux and Pedder, 1987). In this paper, the weights are obtained from the experimental PCSV for each station by considering the trigonometric PCSV (TPCSV) methodology as suggested in Section 3.

3. Trigonometric point cumulative semivariogram (TPCSV)

New methodology proposed by Şahin (2001) and Şahin and Şen (2004) is used in this study for an application to ocean waves. The main properties and brief explanation of this

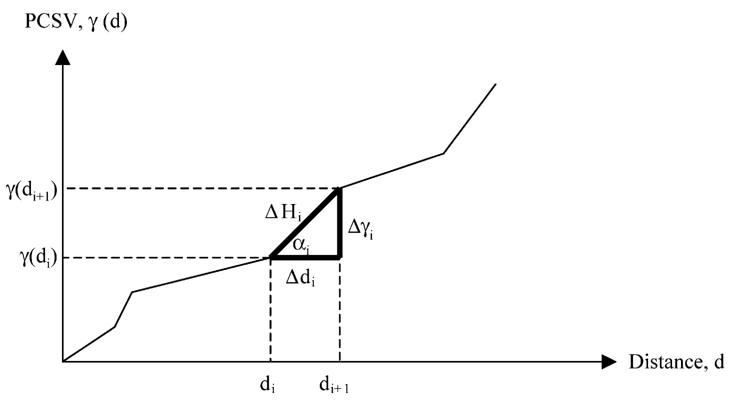

Fig. 1. Representative point cumulative semivariogram.

method is given below. As can be seen from Fig. 1. PCSV consists of cumulative broken lines. Connection between two station records is represented by broken lines and angle between two successive lines gives the measure of regional dependence. If successive distances and corresponding PCSV values are $d_1,\ldots,d_n$ and $\gamma(d_1),\ldots,\gamma(d_1)$, respectively, then the horizontal and corresponding vertical differences between two successive points are $\Delta d_i = d_{i+1} - d_i$ and $\Delta_{\gamma I} = \gamma(d_{i+1}) - \gamma(d_i)$, respectively. These two perpendicular differences constitute a right angle triangle with its hypoteneous as

$$\Delta H = \sqrt{\Delta d_i^2 + \Delta\gamma_i^2} \tag{3}$$

The cosine of the base angle α_i in this right angle triangle represents the local regional dependence trigonometrically as (Fig. 1)

$$\cos\alpha_i = \frac{\Delta\gamma_i}{\Delta H} \tag{4}$$

If $\alpha_i = 0$ or $180°$ then $\cos\alpha_i = 1$, and the two successive points in the PCSV are on the same horizontal line, which implies complete dependence. On the other hand, $\alpha_i = 90$ corresponds to $\cos\alpha_i = 0$, where the two successive points are on the same vertical implying complete independence. The measure of dependence take values from 0 to 1 that corresponds to $0 < \cos\alpha_i < 1$. Trigonometric PCSV (TPCSV), $\gamma_{\mathrm{st,Tr}}(d_i)$, is calculated by multiplying $\cos\alpha_i$ with standardized PCSV, γ_{st}, as:

$$\gamma_{\mathrm{st,Tr}}(d_i) = \gamma_{\mathrm{st}}(d_i)\cos\alpha_i \tag{5}$$

The standardized PCSV is calculated from standardized regional data, which is equal to the subtraction of areal average from each measurement and then division by the regional standard deviation. The objective analysis methods, most often use weighted averages for estimation as already shown in Eq. (2). In this study, cosine values are taken into account as weights. Hence, overall weight can be defined as

$$C = \cos\alpha_1 + \cos\alpha_2 + \cdots + \cos\alpha_n \tag{6}$$

By considering Eq. (2), it is possible to rewrite the estimation at a site P, from regional wave height values, $X(d_i)$, as

$$X_{\mathrm{P}} = \frac{1}{C}\sum_{i=1}^{n} X(d_i)\cos\alpha_i \tag{7}$$

If cosine value is practically zero, next consecutive stations do not have any contribution on the prediction point value. Further detailed discussion of the TPCSV technique is given by Şahin (2001).

Radius of influence is an important parameter not only for wave field but also for any other meteorological ReVs. It is important to know the influence distance for the ReV in any spatial estimation and prediction procedure. Any procedure based on restrictive mathematical assumptions cannot clearly represent natural events especially in meteorology. However, TPCSV method helps to avoid restrictive theoretical conditions and assumptions in calculating the radius of influence.

4. Data and application

The sample TPCSV methodology is implemented for a set of offshore locations distributed along the west coast of USA. The location map of the study area is shown in Fig. 2. The monthly average significant wave height for different stations is shown in Fig. 3. Table 1 includes the station numbers, coordinates, depths and significant wave height records for month January and annual monthly values. This information is considered as input data for the sample TPCSV calculations in this paper. The number of TPCSV's is equal to the number of measurement sites. However, due to the space limitations, only 1 month (January) and one station is considered for the estimation procedure.

Although the sample PCSVs are obtained for 22 stations, only the first six PCSVs are presented in Fig. 4. It is to be noticed that all the horizontal axis have the same scale. However, it is not possible to do the same for the vertical axis.

Individual significant wave height PCSVs at stations have rather different appearance from each other which indicates that regional significant wave height distribution is heterogeneous over the area. For instance, PCSV for 46002 and 46011 are significantly different from each other visually (see Fig. 4).

This is tantamount to saying that the wave generation in the concerned area is not a regionally smooth process. The wave generation events are under the control of some meteorological factors. This further implies that in the consideration of the spatial wave generation mechanism characteristics, uniform conditions do not prevail and a complex combination of meteorological factors such as wind direction and speed, pressure,

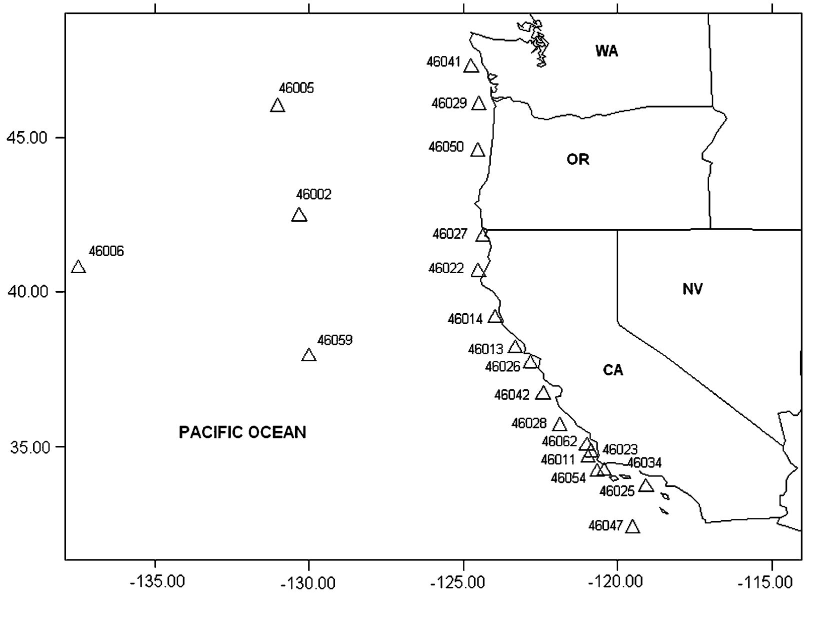

Fig. 2. Study area and its location.

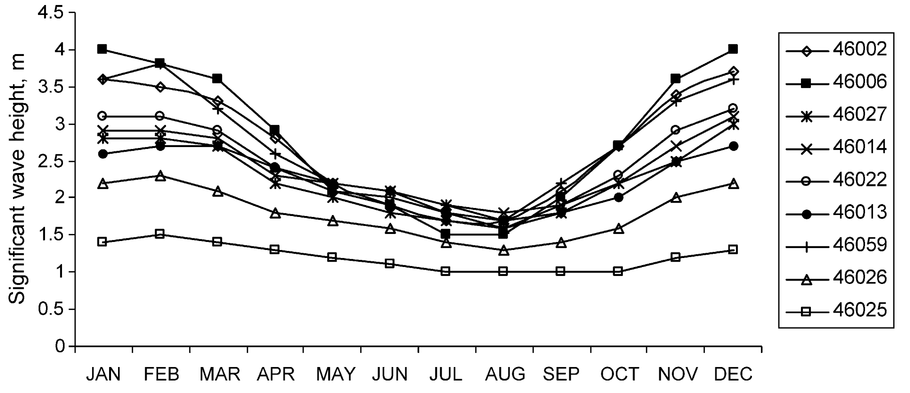

Fig. 3. The monthly average significant wave height for some stations in the study area.

temperature, sea surface temperature, influence concurrently and sequentially in addition to the depth.

The difference in wave generation areas clearly appears by abrupt changes in Fig. 5, showing the different climate regions existing in the study area. The shifts in the curves reflect a change in the wave climate regime or transition from one wave generation zone to another.

Table 1
Wave measurement station characteristics of offshore stations distributed along the west USA coastline

Station ID	Northing (m)	Westing (m)	Depth (m)	Significant wave height (m)	
				Annual	January
46002	391,619	4,708,295	3420	2.72	3.81
46005	343,728	5,101,586	2779.8	2.80	4.13
46006	290,835	4,519,482	4023.4	2.80	4.65
46011	694,767	3,861,776	188.4	2.00	3.22
46013	471,116	4,231,046	122.5	2.30	2.58
46014	416,621	4,341,265	264.9	2.40	2.99
46022	371,623	4,508,786	329.2	2.40	3.04
46023	686,202	3,843,197	384.1	2.20	2.48
46025	306,967	3,735,833	859.5	1.20	1.49
46026	514,680	4,179,076	52.1	1.80	2.49
46027	385,307	4,634,229	47.9	2.30	2.56
46028	600,376	3,955,186	1111.9	2.30	2.70
46029	383,323	5,108,118	128	2.30	3.36
46041	367,803	5,244,433	132	2.10	3.21
46042	551,549	4,067,634	1920	2.20	2.57
46047	261,838	3,591,293	1393.5	2.30	2.45
46050	378,752	4,941,998	130.1	2.40	3.19
46054	734,924	3,794,917	447.1	2.10	2.40
46059	412,450	4,204,434	4599.4	2.70	3.30
46062	681,380	3,886,036	378.9	2.30	2.50
46063	715,043	3,792,435	598	2.40	2.56
46066	364,942	5,840,433	4419.6	2.80	3.91

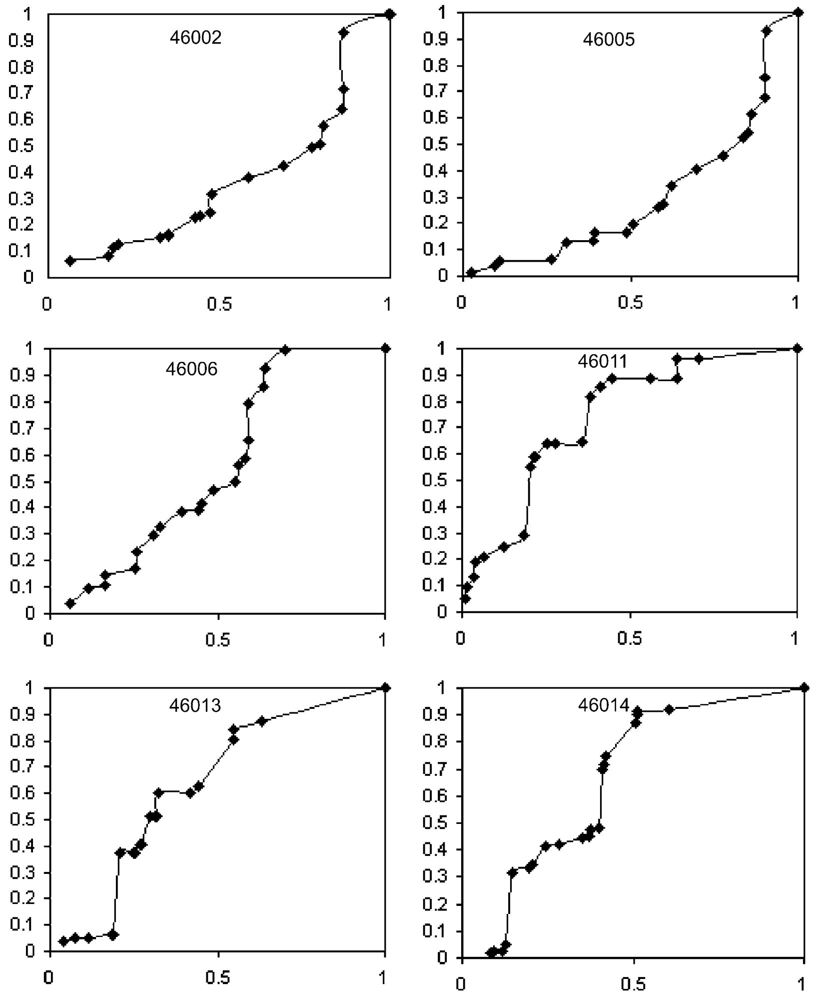

Fig. 4. Standard PCSVs variations with standard distances.

In order to estimate wave height at station H, the TPCSV concept is employed to find the cosine weighting factors. The following calculations can be done to estimate the pivot station's value from the adjacent sites. The PCSV and then the angles between successive points are obtained as explained above. For example 46014 station is selected as a pivot site. The distances from the pivot station are calculated separately and then sorted in the ascending order and the maximum distance is found as $R_{\mathrm{m}}=1\ 331$ km for this study which is used to standardize the distance values. It is expected that the highest cosine weighting factor occur at lower angles by which same characteristics with pivot station is exhibited by the concerned station. The fourth column in Table 2 includes the cosine weightings that can be calculated from Fig. 5. It is clearly seen that at small angles, the weighting factors are high and low weightings are valid for wider angles. The last column in Table 2

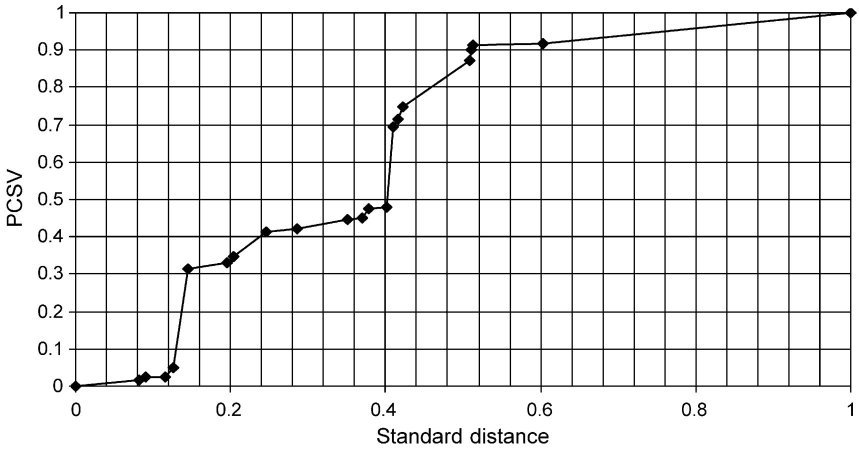

Fig. 5. PCSV graph for station 46014.

indicates the contributions from other stations that can be calculated by multiplying wave height values by the cosine weighting factors. In Fig. 6 the variation of cosine weighting factor with distance is shown where the variation is random. There are two ways to make estimation for the pivot station. The first one is by using a certain number of adjacent

Table 2
Station 46014 detailed estimation calculations

Station ID	Distance (m)	Distance ratio	cos(α)	Contributions (m)
46014	0	0.00	0.00	0.00
46013	81,493	0.08	0.75	2.53
46059	126,187	0.09	0.73	2.39
46022	173,459	0.12	0.73	3.04
46026	200,509	0.13	0.67	1.01
46006	295,023	0.15	0.65	0.34
46027	307,078	0.20	0.65	2.41
46042	359,408	0.20	0.62	0.96
46002	433,271	0.25	0.62	2.08
46028	476,433	0.29	0.59	2.64
46062	593,456	0.35	0.48	2.36
46011	599,000	0.37	0.47	3.11
46023	599,446	0.38	0.46	0.73
46050	695,534	0.40	0.43	3.15
46025	723,218	0.41	0.43	0.06
46063	735,657	0.42	0.43	0.84
46054	736,185	0.42	0.39	0.36
46005	775,653	0.51	0.17	2.37
46047	794,416	0.51	0.14	0.11
46029	800,997	0.51	0.11	0.31
46041	924,038	0.60	0.07	3.20
46066	1,331,664	1.00	0.00	3.83
		Significant wave height estimation (m)	All sites	3.05
			Restricted sites	2.94

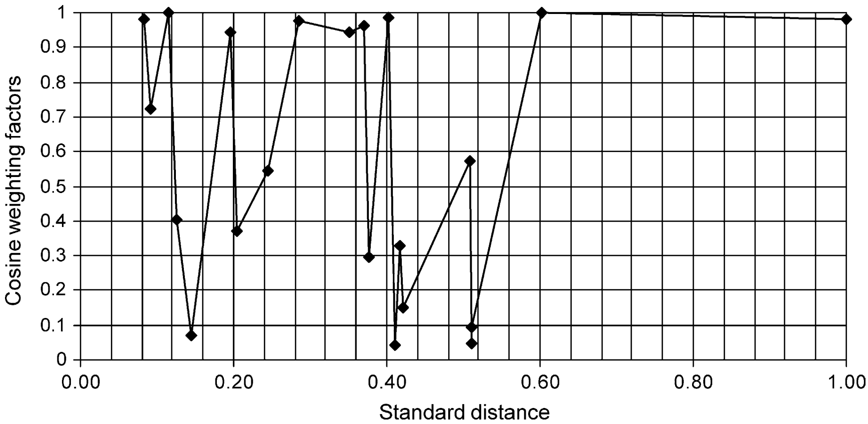

Fig. 6. Variation of cosine weightings with distance.

stations and the other one uses all of the stations. Here, the number of stations that contribute the pivot station is restricted for the weighting procedure. Substitution of these variables in Eq. (7) for three stations lead to estimation of significant wave height at station 46014 as 7.95/2.70 = 2.94. If all the sites are considered together the estimation becomes 37.82/12.42 = 3.04. The optimal number of adjacent sites is found by trial and error. For this purpose, the number of adjacent stations are increased from one to the total number of the stations. Consequently, it is observed that each station has its special number of adjacent stations for the best interpolation depending on the regional variable of the significant wave height. The differences between estimation with all and restricted station cause smoothing in wave height prediction. The plots of the cross-validation estimation and actual measurement values are presented in Fig. 7. Estimations with all sites slightly

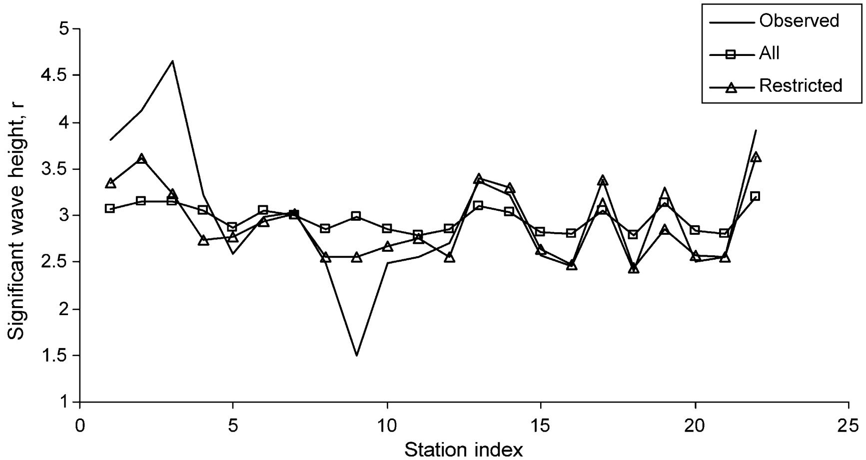

Fig. 7. Spatial estimation with all and restricted sites.

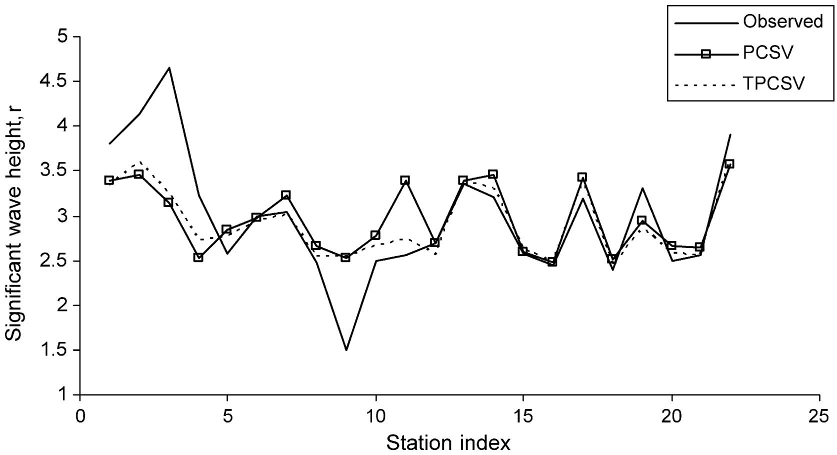

Fig. 8. Comparison of PCSV and TPCSV estimations.

outperformed those obtained by restricted sites. Similar calculations can be performed for other stations and the comparisons of PCSV and TPCSV approaches are shown (Fig. 8). Table 3 includes the summary of results for the other stations.

When one of the extreme stations are used as a pivot site, the result shows weak correlation with high relative error between observed and estimated wave heights. The relative error in estimation is nearly 40% under these extreme conditions.

5. Conclusions

Spatial behavior of the significant wave height, one of the most important element for wave climate assessment is investigated through the TPCSV approach. It is found that climate differences play a significant role on the wave characteristics. Most of the stations exhibit heterogeneities depending on various meteorological factors such as temperature, wind speed and direction, pressure, etc. Through the PCSV curves, one can easily recognize the climatic regions and the transitions from one climatic zone to another. On the other hand, estimation of the unmeasured stations is achieved by using cosine weighting factors calculated from PCSV curves. For each PCSV, broken straight line slope cosine values show the regional dependence measure, which is the basis of the proposed trigonometric PCSV (TPCSV) methodology. This methodology is easy to formulate and can be applied to any inhomogeneous regional variables with large data sets without requiring substantial computation facilities. The estimation procedure with cosine weight factors takes into account the recorded data values at all the sites. The proposed methodology has a general spatial and temporal basis because weighting factors can be calculated monthly. Two different spatial estimation procedures are presented. The first one takes into consideration all of the available measurement sites, but the results are not acceptable practically. The second alternative considers a restricted number of adjacent stations that the spatial estimation error becomes a minimum. Hence, each site has

Table 3
TPCSV estimates in the for a set of offshore stations distributed along the west USA coastline

Station ID	Significant wave height (m)	No. of adjacent sites	January significant wave height estimations (m)		Relative error (%)	
			Adjacent sites	All sites	Adjacent sites	All sites
46002	3.81	7	3.34	3.07	12.37	19.35
46005	4.13	8	3.61	3.14	12.76	23.96
46006	4.65	5	3.24	3.15	30.38	32.13
46011	3.22	12	2.73	3.05	15.29	5.38
46013	2.58	9	2.77	2.87	6.76	10.26
46014	2.99	3	2.94	3.05	1.75	1.70
46022	3.04	3	3.01	3.00	0.96	1.38
46023	2.48	4	2.55	2.84	2.96	13.00
46025	1.49	4	2.55	2.99	41.36	50.01
46026	2.49	13	2.67	2.86	6.55	12.74
46027	2.56	19	2.75	2.78	6.86	8.08
46028	2.7	9	2.56	2.85	5.07	5.36
46029	3.36	3	3.39	3.09	0.86	8.00
46041	3.21	3	3.30	3.03	2.89	5.43
46042	2.57	4	2.63	2.82	2.32	9.03
46047	2.45	9	2.48	2.81	1.03	12.68
46050	3.19	7	3.37	3.04	5.41	4.68
46054	2.4	7	2.44	2.79	1.61	14.01
46059	3.3	10	2.86	3.13	13.30	5.02
46062	2.5	6	2.57	2.83	2.63	11.56
46063	2.56	6	2.56	2.81	0.12	8.86
46066	3.91	7	3.62	3.20	7.33	18.27
Averages	2.98	–	2.91	2.96	8.21	12.77

a different number of the nearest adjacent sites for consideration in the spatial of significant wave height estimation procedure. In order to show the applicability of the methodology, 22 measurement sites located in the Pacific Ocean off California, USA is considered. The average relative error is found nearly 10% which is acceptable for engineering studies.

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