Renewable Energy 172 (2021) 667–679

Contents lists available at ScienceDirect

Renewable Energy

journal homepage: www.elsevier.com/locate/renene

A primary offshore wind farm site assessment using reanalysis data: a case study for Samothraki island

M. Majidi Nezhad [a], M. Neshat [b, *], D. Groppi [a], P. Marzialetti [c], A. Heydari [a], G. Sylaios [d], D. Astiaso Garcia [e]

[a] Department of Astronautics, Electrical and Energy Engineering (DIAEE), Sapienza University of Rome, Italy
[b] Optimisation and Logistics Group, School of Computer Science, University of Adelaide, Adelaide, Australia
[c] School of Aerospace Engineering, Sapienza University of Rome, Italy
[d] Department of Environmental Engineering School of Engineering Democritus University of Thrace, Greece
[e] Department of Planning, Design, and Technology of Architecture, Sapienza University of Rome, Italy

ARTICLE INFO

Article history:
Received 29 October 2020
Received in revised form
5 March 2021
Accepted 11 March 2021
Available online 13 March 2021

Keywords:
Offshore wind farm site assessment
Wind speed time series
Marine renewable source
ERA-Interim reanalyses datasets

ABSTRACT

The correct strategy for monitoring and assessing marine Renewable Energy Sources (RESs) is of great importance for local/national sustainable development. To achieve this goal, it is necessary to measure in the most precise possible manner the local/regional RESs potential. This is especially true for Offshore Wind (OW) energy potential, since the most precise techniques are long and expensive, and are not able to assess the RESs potential of large areas. Today, Remote Sensing (RS) satellites can be considered the most important land and marine observation tools. The RS tools can be used to identify the interested areas for future OW energy converters installations in large and small-scale areas. In this study, the OW energy potential has been analysed by means of a 40 years wind speed data from the European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis dataset of the Samothraki island surrounding area in the Mediterranean Sea. The OW speed potential has been analysed by means of monthly data from ECMWF Interim reanalysis (ERA-Interim) datasets using the Network Common Data Form (NetCDF) format. Automatically, analyses have been carried out using the Region Of Interest (ROI) tool and Geographical Information System (GIS) software in order to extract information about the OW speed assessment of the Samothraki island area. The primary results of this study show that the southwest area of Samothraki island has good potential for future OW farms installation (bottom fixed and floating version) in near and offshore areas. This study shows the OW energy potential per location, as well as the trend of OW speed, which has changed over the past 40 years in the Mediterranean Sea.

1. Introduction

The current forecasts indicate a rapid growth of the GHG (Greenhouse Gases) emissions in the world [1], which has very significant effects on climate change and the environment [2]. Also, concerns of the human societies about energy security issues in industrialized countries should not be forgotten either. Indeed, energy self-sufficiency is central in the political agenda in order to avoid, for instance, an unbridled rise in energy prices due to geopolitical issues as the two oil crises of 1973 and 1980 [3]. To address these acute problems, countries around the world face severe energy and environmental challenges and expanding the use of different Renewable Energy Sources (RESs) can be a particular solution to overcome the current situation. Wind energy is one of the safest and most well-known types of RESs.

Wind energy can be considered as an environmentally friendly and cost-effective source, which can help to solve problems related to environmental pollution, such as reducing the emissions of CO_2, SO_x and NO_x [4]. In recent years, the construction and design cost of wind turbines has decreased significantly due to the significant growth of the new technologies. This has attracted attention for further use of wind energy to reduce air pollution and energy security. This is especially true in the countries that are heavily

* Corresponding author.
E-mail addresses: meysam.majidinezhad@uniroma1.it (M.M. Nezhad), mehdi.neshat@adelaide.edu.au (M. Neshat), daniele.groppi@uniroma1.it (D. Groppi), pablo.marzialetti@uniroma1.it (P. Marzialetti), azim.heydari@uniroma1.it (A. Heydari), gsylaios@env.duth.gr (G. Sylaios), davide.astiasogarcia@uniroma1.it (D.A. Garcia).

https://doi.org/10.1016/j.renene.2021.03.045
0960-1481/

List of abbreviations

ACF	Auto Correlation Function
ASCII	American Standard Code for Information Interchange
DOE	Design of Experiments
ECMWF	European Centre for Medium-Range Weather Forecasts
ECs	European Countries
ERA	ECMWF Interim reanalysis
ERA-5	ECMWF fifth-generation global atmospheric reanalysis
GHG	Greenhouse Gases
GIS	Geographical Information System
GRIB	GRIdded Binary or General Regularly-distributed Information in Binary form
JRA-55	Japanese 55-year Reanalysis
LiDAR	Light Detection and Ranging
MERRA-2	Modern-Era Retrospective analysis for Research and Applications, Version-2
NetCDF	Network Common Data Form
NCEP	National Centers for Environmental Prediction
NCAR	National Center for Atmospheric Research
NARR	North American Regional Reanalysis
NASA	The National Aeronautics and Space Administration
OW	Offshore Wind
PACF	Partial Autocorrelation Function
RS	Remote Sensing
ROI	Region Of Interest
RESs	Renewable Energy Sources
SODAR	SOnic Detection And Ranging
SAR	Synthetic Aperture Radar
WEC	Wave Energy Converter
WTG	Wind Turbine Generator

dependent on imported fossil fuels, such as Greece.

Evaluating the wind energy potential should take precedence over the utilization of sources in wind farm construction projects [5]. Therefore, identifying and evaluating suitable site locations for a successful wind farm installation is very important and necessary [5]. Indeed, a few meters per second (m/s) difference of the wind speed potential can make the difference from a suitable and an unsuitable site location for a wind farm. There are different criteria for selecting optimal locations for RESs plants, especially for OW (Offshore Wind) farms site selection [6]. In order to optimally identify suitable locations, many parameters of OW must be evaluated, for example, wind speed, wind direction, wind shear, wind power density [6]. Therefore, local data collected by measuring devices must be used to evaluate suitable locations. Wind data collection is usually done near the shore and/or offshore using wind towers or buoys for a short period. Although such data are very valuable and highly accurate, those cannot be considered as representative for large sea areas, because they only have the ability to measure the wind speed at the point where they are installed. Nevertheless, these devices are very expensive and they also need to be installed on-site for more than a year and thus are very time consuming [7]. In this regard, basic, fast and cost-free measurement methods could help to identify unobserved areas with suitable potential and can reduce the overall OW farm construction project cost. There are many different tools and techniques for wind energy potential assessment, analysis, detection and reporting, for instance, cup anemometers, SOnic Detection And Ranging (SODAR) [8], Light Detection And Ranging (LiDAR) [9], Synthetic Aperture Radar (SAR) satellite data [10], numerical simulation and reanalysis dataset [11,12].

The ERA (ECMWF Interim reanalysis)-Interim reanalysis dataset has been designed and developed by the European Center for Medium-Range Weather Forecast (ECMWF). The ECMWF uses predicted models and data capture techniques, including (4D-Var) analysis with a 12-h analysis window. ERA-Interim is an ongoing project that includes a large dataset of marine and atmospheric parameters such as wind speed. In ECMWF dataset, the wind speed at 10 m standard height is available from 1979 to present time. The data cover a spatial resolution (approximately 80 km) of $0.75^{\circ}-0.75^{\circ}$ and a time resolution of 3-hourly time steps (00:00, 03:00, 06:00, 12:00) intervals for each day per month [13].

These types of reanalysis dataset can be used to research various parameters of the RESs field. It is quite clear that the clarity of data is the main factor in measuring RESs potential and allows for more appropriate and accurate results [14]. Recent studies shows the widespread use of the "reanalysis" dataset for long-term analysis focusing on monthly and annual average production values [15]. It should be noted that the reanalysis dataset is made by merging several global climate-forecasting models that gather their data observations from a wide range of the sources in different regions, including surface stations, cub anemometers, buoys and balloons, aircraft, ships and satellites. This feature made this type of dataset very accurate in wind speed measuring even in small areas [16,17]. For example, wind speed, wave height, wavelength, tidal, thermal and ocean water depth can be measured using this kind of dataset. Table 1 shows the reanalysis source available to the present time.

There are five main factors that can increase the ERA-Interim dataset popularity in universities, industries and companies, a) the reanalysis products include many parameters, such as wind speed and wave height, b) the data available from 1979 (long-term historical dataset was available) [18], c) the reanalyses dataset are generally free, open-source and supported by unlimited policy, d) the reanalysis products received from the global observation system and made up by different observations tools to cover a large area of all world [19], of course it should be noted that wind observations are strongly influenced by local conditions, such as local topography and natural and human elevations. Therefore, it is natural that it does not show the correct values in these conditions, but it has shown a very good ability to measure wind speed in large areas [17]; e) Reanalysis dataset do not have gaps because they are fed using data collected from large number of sources [20].

Wind speed estimation by means of the different reanalysis dataset has been used more often every day, as proved by several studies of the ocean and sea that have been conducted, such as Sweden [19,21], Djibouti [22], Germany [23], Black Sea [24], Danish part of the North Sea [25], East China Sea [26], the Latin American and European coastal environments [27]. Onea et al. [28], provides a nearshore wind potential analysis in the vicinity of the Mediterranean Sea using 15-year long RS (Remote Sensing) data from ECMWF and the National Centers for Environmental Prediction (NCEP) dataset and presented two numerical models. Then, the wind velocity at 10 m height was evaluated knowing the wind velocity at 80 m height concluding that interesting wind energy conditions exist in the northern and southern parts of the Mediterranean Sea.

Rusu and Onea [27], using a reanalysis database covering 17 years, provided a comprehensive picture of the wind and wave energy in Latin America and the European coastlines. Firstly, the

Table 1
List of the global reanalysis datasets available to present time.

Source	Name	Start to Record	Resolution	Formats
ECMWF	ERA-Interim	1979	0.75 ° × 0.75 ° x 60 lev 0.1 hPA top	NetCDF (Network Common Data Form), GRIB (GRIdded Binary or General Regularly-distributed Information in Binary form)
ECMWF	ERA-5 (ECMWF fifth-generation global atmospheric reanalysis)	1979	~31 km, 137 levels to 1 Pa	NetCDF, GRIB
Japanese Meteorological Agency	JRA-55 (Japanese 55-year Reanalysis)	1957	T319 × 60 levels, 0.1 hPA top	GRIB
NARR (North American Regional Reanalysis)	NCEP (National Centers for Environmental Prediction) NARR	1979	32 km	GRIB
NCEP, DOE	NCEP Reanalysis (R2)	1979	2.5 ° × 2.5 °28 levels 3 hPA top	NetCDF, GRIB
NCEP, NCAR (National Center for Atmospheric Research)	NCEP-NCAR (R1)	1948	2.5 ° × 2.5 °; 3 hPA top	NetCDF, GRIB
NASA (The National Aeronautics and Space Administration)	MERRA-2 (Modern-Era Retrospective analysis for Research and Applications, Version-2)	1980	~56 km × 70 km	NetCDF, GRIB

most interesting sites are selected, and then, the performance of five different Wind Turbine Generators (WTGs) and Wave Energy Converter (WECs) are investigated. By looking at most of the studies focused on the wind energy potential analysis in the Mediterranean Sea [29,30], it is possible to split them in two main categories, i) analysis on marine RESs mapping, and ii) evaluation of the performance corresponding to bottom and floating WTGs [31].

The assessment of feasible location for OW installation is particularly relevant for islands. Due to their remoteness from the mainland, islands are heavily dependent on fossil fuels for meeting their needs and are thus dependent on importing fuels and many other goods at high prices [32]. Most of these islands, due to their location in the open sea and ocean areas, have excellent conditions with suitable climatic potential for the installation of energy converters to achieve energy self-sufficiency [33].

Several methods have been suggested for the self-healing of small islands around the world: Azores [34], Maldives [35], Faroe Islands [36], El Hierro [37], Gran Canaria [38], Ireland [39], Sri Lanka [40], Taiwan [41], New Zealand and Madagascar [42,43], New Guinea and Tasmania [44]. Given that many of these islands are geographically located in developed or developing countries, this causes them to be directly exposed to international oil markets fluctuations and to suffer from a very fragile, small scale local economy [45]. However, more than 85,000 islands can be found around the world, of which approximately 13% are inhabited and have a population of about 740 million people [33,46]. Islands belonging to developing countries have four distinct characteristics, a) severe dependence on imported fossil fuels, b) power plants used to generate electricity, c) high operating and maintenance costs in the entire energy sector, d) high local RESs potential [45].

The scope of this study is to analyse the OW energy potential of the Samothraki island to evaluate the possibility for the OW farms development by means of ERA-Interim reanalysis dataset. The Mediterranean islands represent perfect areas to assess, detect, report and analyse OW potential by means of reanalysis datasets. The Samothraki island will largely benefit from the adoption of the OW farms since it mostly relies on fossil fuels, but given their geographical location, they have the potential to use RESs to meet their energy needs. The present study aims at assessing the OW energy potential in the Samothraki island by means of a methodology, applicable both near and offshore, based on ERA-Interim from ECMWF reanalysis dataset. In this case, the Region Of Interest (ROI) tool enables to improve results from automatic detection and analysing OW speed by ERA-Interim reanalysis dataset around the small island.

2. Case study

Greece is located in southeastern Europe, in the Balkan Peninsula, bordering Albania and Bulgaria to the north and Turkey to the east. Greece has a long coastline with the Aegean Sea and the Ionian Sea. Greece is one of the countries that due to its geographical location can use a variety of energy converters, especially wind turbines. A country like Greece has the potential to use onshore, nearshore and offshore wind farms [47]. Greece has 6000 islands in the Aegean and Ionian Seas, of which only 227 are inhabited. This number of islands has made Greece a unique phenomenon among European Countries (ECs). It should be noted that this country, with about 16,000 km of coastline, has a high wind potential in the Aegean and Ionian seas, which can be used as endless energy to supply electricity to these areas.

The Mediterranean Sea has been analysed by several studies, it includes several big and small islands that have high wind energy potential and can be considered “hot spots area” such as Sicily and Sardinia [48], Malta [49], Iberian Mediterranean coast and the Balearic islands [50], Greek islands [51]. Given that more than 70% of near and offshore areas have significant wind capacity, it is expected that the wind industry will have a significant growth in the next future even though nowadays the operation of offshore winds in these areas are relatively new [52].

Before the commissioning and installation of renewable energy converters important issues need to be considered, for instance, the social acceptance is one of the crucial ones; indeed, public trust in decision-makers and consideration of the views of different segments of society is crucial in the decision. One aspect that may be strongly influenced by the energy converters installation around islands is tourism activities. This is despite the fact that the Greece islands attract thousands of tourists every year and play an important role in the country and local economy [53].

Since islands are located in sea areas, the number of obstacles for the OW are reduced. This translates in higher wind speed and more stable winds with low fluctuations compared to the mainland, thus they are more suitable and safer for the OW farm installation. Higher and more continuous winds mean more electricity and more stable production with less issue at grid level for energy management [54]. However, it should be borne in mind that the wind farm installations are strongly related to specific local/national characteristics and laws [55].

In this regard, to better understand the wind speed potential in Greek islands, the Samothraki island has been selected as a case study. The Samothraki island is located (40.4477° N, 25.5918° E) in the northeast part of the Aegean archipelago within the

Mediterranean Sea and has a 178 km^2 surface [56]. Fig. 1 shows the location of the island and the surrounding area (i.e. a 40 km radius has been considered) under study including also the Gökçeada island. Studies show that the island has good wind potential for use of near and OW turbines [3] and also the water depth around the island is between 0 and 35 m, which is suitable for installing fixed and floating turbines [57].

3. Materials and methods

In this study, the ERA-Interim reanalysis dataset covering the period between January 1979 and July 2019 (478 monthly average ERA-Interim reanalysis dataset) has been used for identifying wind speed in the Samothraki island surrounding area. To this aim, wind speed ERA-Interim datasets have been processed to extract monthly means of daily means maps for 40 years. The method uses NetCDF format data processing and mapping of the studied areas and is based on the use of two main software in two main steps.

In the first step, after downloading all ERA-Interim reanalysis datasets into different layers using the GIS (Geographical Information System) software, all the collected data were used to prepare a map of the Mediterranean Sea (Fig. 2a). Then by focusing on the OW speed potential in the pixels covering the area of Samothraki island (Fig. 2b), the potential of each interested region was identified for the second phase of studies. Furthermore, at this stage, near and OW speed data extracted from the Mediterranean Sea and around the Samothraki island has also been used as a reference for error evaluation.

In the second step, all of the NetCDF files have been merged and displayed as one layer, by means of the Steak Layer tool, to extrapolate OW speed in each pixel of the case study area. Two areas with the highest potential around the island have been identified (i.e. ROI 1 (West of Samothraki), ROI 2 (East of Samothraki)) in addition to the whole surrounding area of the Samothraki island (i.e. ROI 3). The ERA-Interim reanalysis processing by means of the ROI tool has been used to find OW characteristics in the specific two interested areas. The second step can be used to identify the most powerful sites in a small area to identify the average OW speed potential of two different interested areas (ROIs) located in the west and east part of the Samothraki island.

Finally, the wind speed from ERA-Interim reanalysis dataset obtained for the three different interested areas (i.e. ROI 1, ROI 2 and ROI 3) at 10 m height has been compared with the wind speed recorded by a cup anemometer installed on the Samothraki island weather station at 90 m height. The meteorological station of the Samothraki island is located in the western part of the island (latitude: 40.46200° N, longitude: 25.50109° E).

In order to compare the extrapolated wind speed V at heights of 10 m with the one measured by the cup anemometer at 90 m Equation (1) has been used.

$$V_{90} = V_{10} \frac{LOG(Z_{90}) - \text{LOG}\ (Z_{10})}{\text{LOG}\ (Z_{10}) - \ \text{LOG}\ (Z_0)} \tag{1}$$

where, V_{90} is wind speed at 90 m hub height, V_{10} is wind speed at 10 m standard high from sea water surface, Z_0 is the roughness of the sea surface water is 0.0002 m, Z_{10} and Z_{90} are as reference heights [58,59].

3.1. Time series data analysis

Time-series data analysis considers the fact that data samples taken over a specific period may hold an internal linear or nonlinear structure such as autocorrelation and seasonal variation that should be made the scene [60]. In this research, we investigate to detect both autocorrelation and seasonality (periodic fluctuations) properties.

3.1.1. Autocorrelation

Autocorrelation signifies a mathematical representation of the similarity rate between an assigned time series data and a lagged

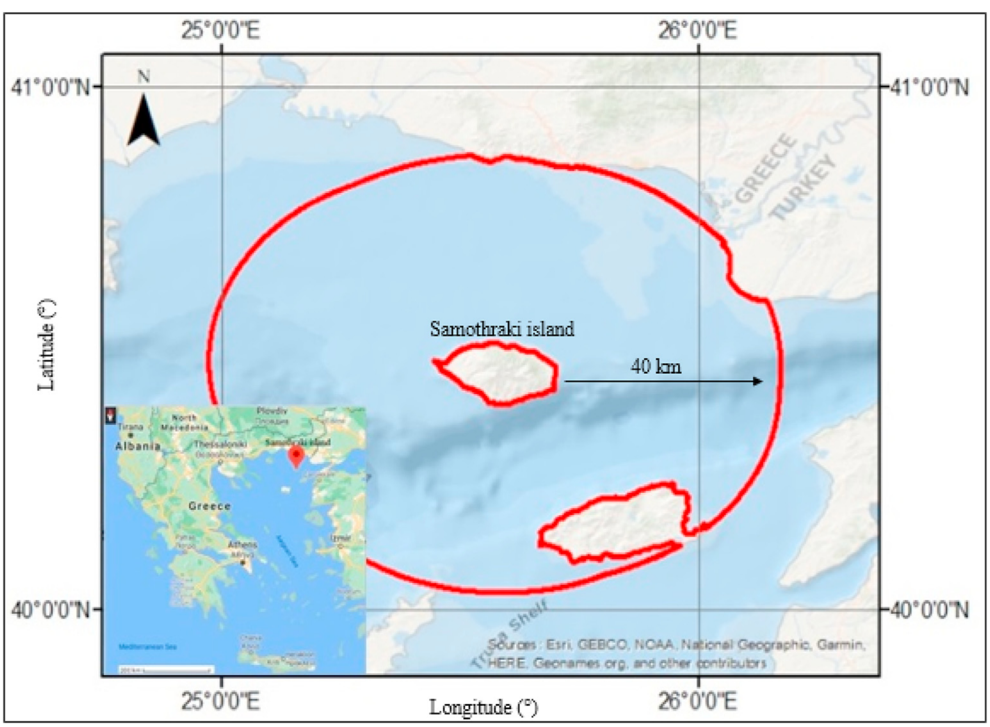

Fig. 1. Showed the Samothraki island location.

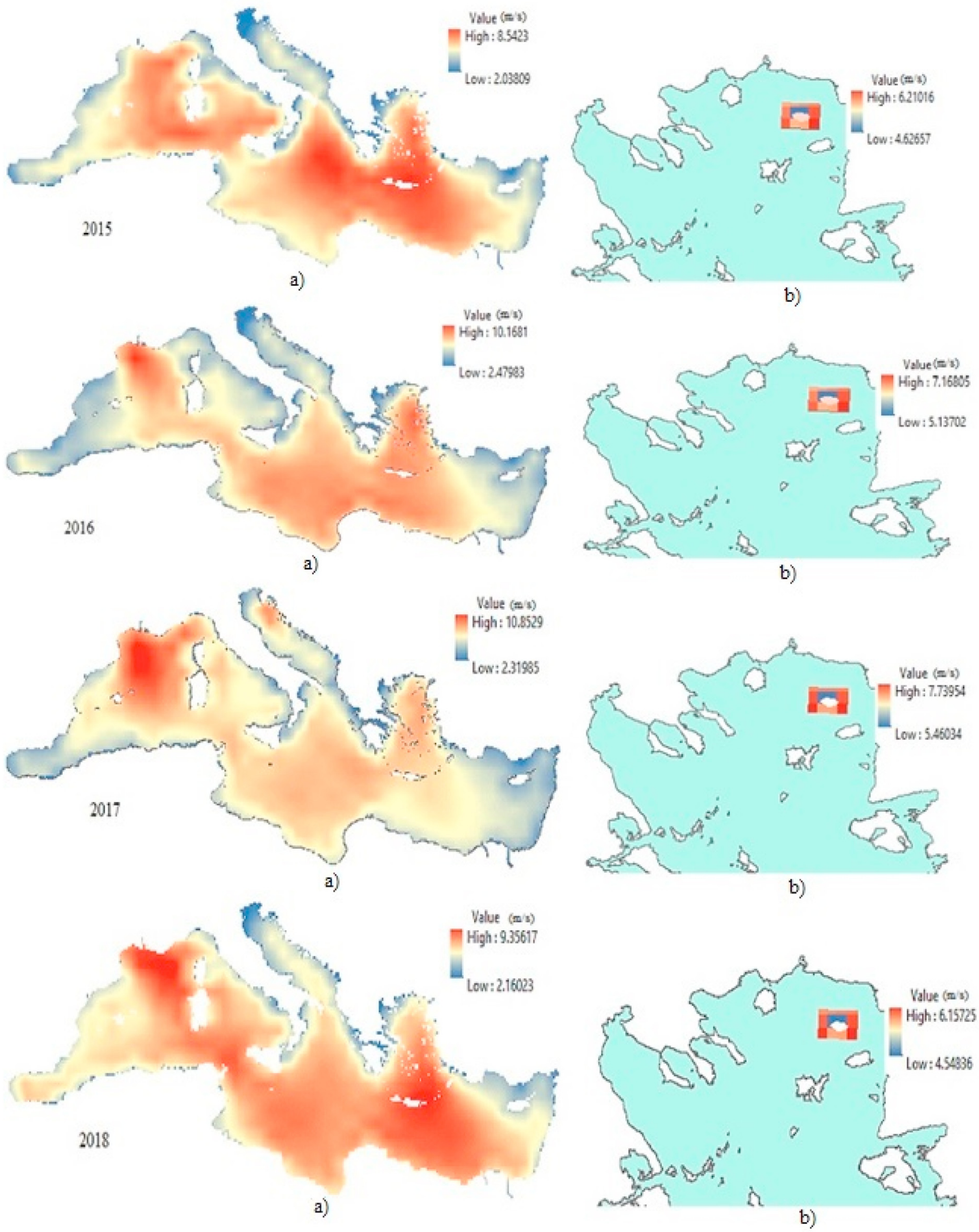

Fig. 2. Shows wind speed per (m/s) of a) the Mediterranean Sea and b) focused of interested area around the Samothraki island.

tale of itself across consecutive time intervals [61]. It is calculated similarly to the correlation between two various time series. However, autocorrelation applies the equivalent time series twice: earlier in its initial order and once lagged one or more periods. Indeed, the autocorrelation function (ACF) estimates the correlation between y_t and $y_t + k$, where $k = \{0, \ldots, K\}$ and y_t is a stochastic procedure. Thus, the measure of autocorrelation for lag k is computed as follows:

$$r_k = \frac{c_k}{c_0} \tag{2}$$

Where c_0 is the initial sample variance of the applied time series, and c_k is calculated using Eq. (3):

$$c_k = \frac{1}{T}\sum_{t=1}^{T-k}(y_t - y')(y_{t+1} - y') \tag{3}$$

It is assumed that q is the lag beyond where the AFC is effectively zero in theory. Therefore, the measured standard error of the autocorrelation at lag $k > q$ is summarised as follows:

$$SE(r_k) = \sqrt{\frac{1}{T}\left(1 + 2\sum_{j=1}^{q} r_j^2\right)} \tag{4}$$

If the distribution of the time series is quite random, then the standard error decreases to $1/\sqrt{T}$.

3.1.2. Seasonality

When a time-sequential data has a trend, generally autocorrelations for short lags incline to be a positive and high value. This is because observations near in periods are likewise close in size. An iterative pattern in each year is recognised as seasonal variation. However, the phrase is employed more commonly to repeating patterns in any fixed term. In order to apply a seasonal filter to measure the seasonal elements of a time series data, it is assumed that all observations recorded during the time interval k, $k = 1, \ldots, s$ where s can be known as the periodicity of the seasonality [62]. A seasonal filter made of a weighted convolution and observations recorded during the previous and next periods k. As an example, given monthly time series data where $s = 12$, a smoothed January observation can be a symmetric and weighted average of January recorded data. Therefore, for a general time series x_t, $(t = 1, \ldots, N)$, the seasonally smoothed sample at each time step $k + js$, $j = 1, \ldots, N/s - 1$, is calculated by Eq. (5).

$$s'_{k+js} = \sum_{l=-r}^{r} a_l x_{k+(j+l)s} \tag{5}$$

Where a_l is the weights and computed as follows:

$$\sum_{l=-r}^{r} a_l = 1 \tag{6}$$

With regard to applying a S_n *m seasonal filter, we should define a symmetric n-term moving average of m-term averages. This computation is matched with using a symmetric and weighted moving average that is unequal to $n + m - 1$ terms. Here we assume that $r = (n + m - 1)/2$. The applied weights in a S_3 *3 filter is listed as $\left\{\frac{1}{9}, \frac{2}{9}, \frac{1}{3}, \frac{2}{9}, \frac{1}{9}\right\}$. Consequently, if the time series data collected during the 10 years per month from 2005 to 2015, the defined S_3 *3 filter value for January 2005 will be:

$$Jan'_{05} = \frac{1}{3}\left[\frac{1}{3}(Jan_{03} + Jan_{04} + Jan_{05}) + \frac{1}{3}(Jan_{04} + Jan_{05} + Jan_{06}) + \frac{1}{3}(Jan_{05} + Jan_{06} + Jan_{07})\right] \tag{7}$$

Furthermore, we will have seven terms for a S_3 *5 filter including $\left\{\frac{1}{15}, \frac{2}{15}, \frac{1}{5}, \frac{1}{5}, \frac{1}{5}, \frac{2}{15}, \frac{1}{15}\right\}$. The observations will be lost at the initial and end of the time series data, if we use a symmetric filter obviously. To figure out this issue, we can apply asymmetrical weights at the end of time series data.

In this work, we used a 5-term $S_{3\times3}$ seasonal convolutional filter in order to deform the seasonal trend in the dataset. Initially, it is applied a moving average to January's values (at records 1, 13, 25, …, end), and then implement a convolutional to the column for February (at indices 2, 14, 26, …, end), and in the following for the resting months. Next, an asymmetric weight after the convolutional filter is applied using conv2 function. In order to keep the seasonal component around one, approximately, and then split by, a 13-term convolutional window of the expected seasonal component.

4. Results

Fig. 2 shows the yearly average wind speed (m/s) in the period 2015–2018 evaluated from ERA-Interim datasets produced by ECMWF for the Mediterranean (Fig. 2a) and the focus on the Samothraki island (Fig. 2b). The ERA-Interim reanalysis dataset has been analysed to map the wind speed potential in the Samothraki island, the result showed that the southeast and the west parts of the island have a promising wind speed potential and might justify further analysis.

Fig. 2 shows the wind speed (in m/s) for these two cases to better understand the OW potential in a large and small area. By using this step, the user can focus on the Hot Spot pixels around the island.

In Fig. 3, the 40 years ERA-Interim reanalysis dataset has been analysed in two regions using the ROI tool. Firstly, a total area (Mediterranean Sea) and then, the Samothraki island has been analysed considering an area of 40 km distance around the island. Considering all the above mentioned about the advantage of using and why the popularity and efficiency of reanalysis dataset source of the description below of Table 1 can be used as a reliable reference in various academic and governmental studies.

Fig. 4 (correlogram) represents the sample ACF and Partial Autocorrelation Function (PACF) to qualitatively evaluate the autocorrelation between both time series data including the average wind speed in Mediterranean Sea and Samothraki island surrounding area.

Observing closely, we can recognise that the 1st, 12th, and the 24th observations are highly correlated. This indicates that a very similar pattern of the wind speed value at every 12 months in both locations will be encountered. Fig. 5 shows the estimation of wind speed seasonal component in Mediterranean Sea. It is noticed that the seasonal level alters over the scope of the wind speed data.

Fig. 6 is an example of using this data to show the monthly wind speed in the Mediterranean Sea, which is processed for the period of August 2018 to July 2019.

In Fig. 7, the monthly average wind speed (m/s) in the Mediterranean Sea and the Samothraki island with a period between (1979–2019) for 40 years reanalysis dataset was shown.

Fig. 8 shows the monthly wind speeds obtained from the two study areas in the western and eastern parts of the island. The analysis suggests that wind speed in the west is higher than in the east region. The fact that the main wind direction is from west to east and the existence of mountainous areas with the 1400 m high from sea level on the Samothraki island can be the main cause of the lesser average wind speed in the eastern part (i.e. ROI 2). Another very important factor that can be noticed is the trend of wind speed change in the past years. Fig. 9, illustrates how wind

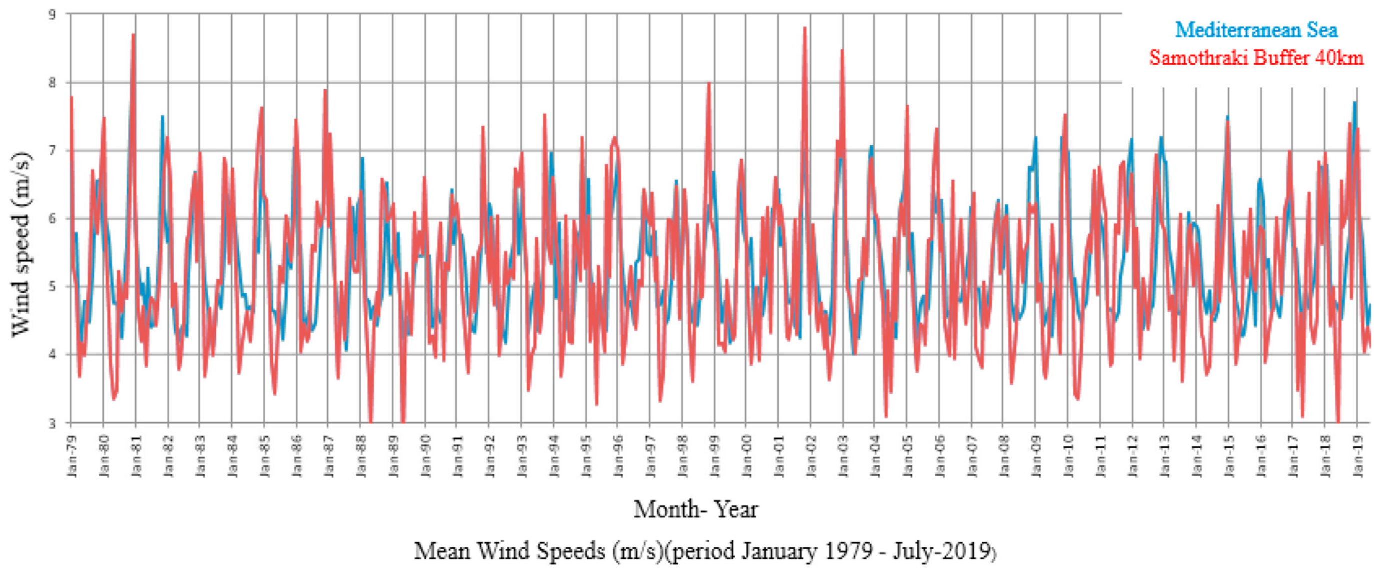

Fig. 3. The monthly mean wind speed in Mediterranean Sea (blue) and the Samothraki island around with 40 km distance from the coastlines (red) in the period between 1979 and 2019.

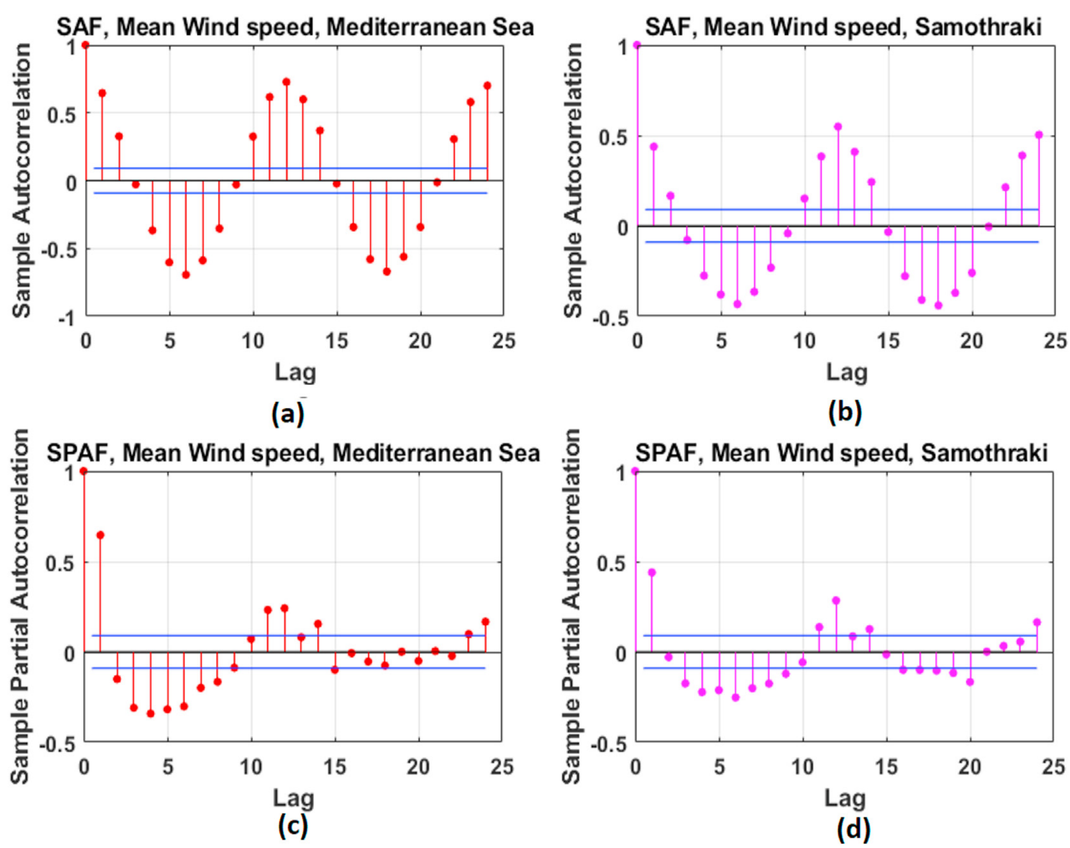

Fig. 4. The standard and partial sample autocorrelation function of the mean wind speed in Mediterranean Sea and Samothraki island. (a) Standard observations autocorrelation function in Mediterranean Sea, (b) Standard observations autocorrelation function in Samothraki Island, (c) Partial observations autocorrelation function in Mediterranean Sea, (d) Partial observations autocorrelation function in Samothraki Island. The horizontal lines display the upper and lower confidence bounds.

speed changes in these two areas of the island over the past 40 years.

Finally, the RMSE and R values of the selected ROIs have been evaluated versus the measured values from the cup anemometers installed on the island. Fig. 10 a) shows the RMSE and R value for ROI1; Fig. 10 b) shows the RMSE and R values in the eastern region (i.e. ROI2). This difference in the amount of error can be attributed to the difference in the distance between the two areas under studies and the meteorological station. Of course, the effect of the surface roughness of the island (natural and man-made heights and

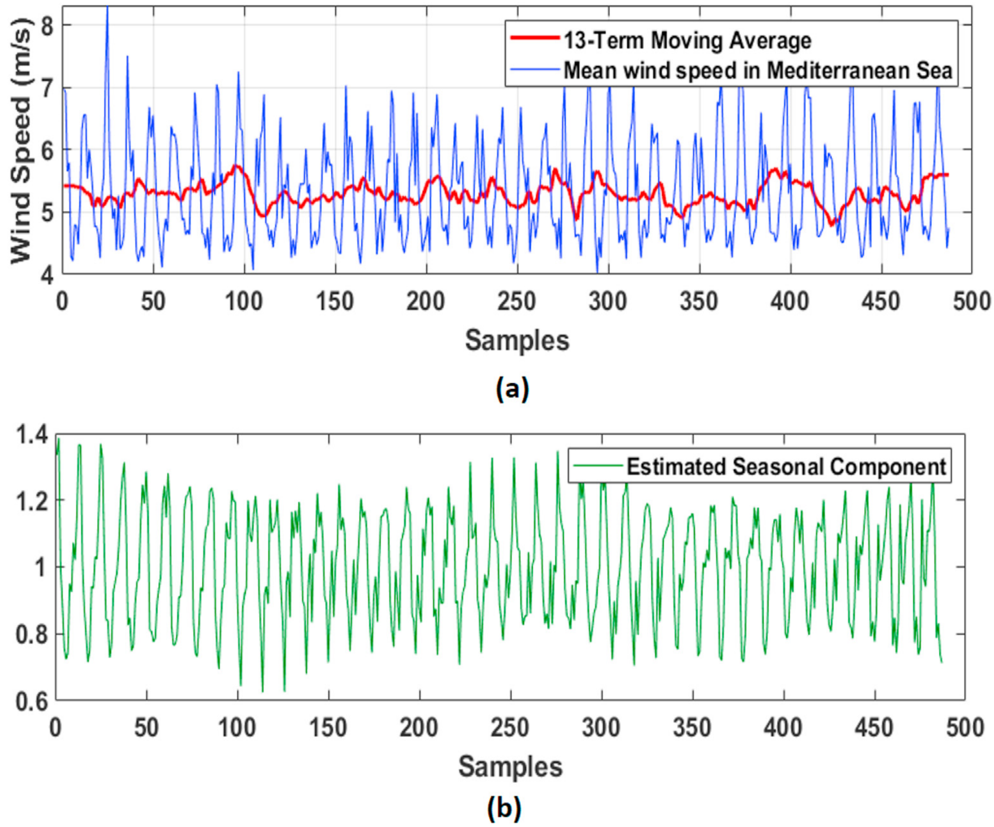

Fig. 5. The estimation of wind speed seasonal component in Mediterranean Sea. (a) The mean and the 13-term moving average observations from the time series data of Mediterranean Sea, (b) Extracted the estimated seasonal component from Mediterranean Sea observations.

elevations) on wind speed in the eastern region cannot be ignored. Fig. 10 c) also generally shows the amount of RMSE and R for the entire study area at a distance of 40 km from around the island.

5. Discussion

It can be said that OW energy is developing and expanding with a very significant trend in the world, which is directly related to the needs of human societies and the growth of technology. The growing development of OW energy is a good sign of this dramatic trend in wind energy use around the world. Proving the effectiveness of offshore sites is not very easy. A few metres per second difference in wind speed can turn a good site into a bad site, and because of the high and constant wind speeds that occur in the sea and oceans, OW farms can generate more electricity. OW source assessment in a specific area requires the availability of high quality and accurate wind data over a long time period. To this purpose, ground measuring devices have been traditionally used in the past. This type of data is often scarce for offshore areas and does not cover large areas and can only represent a small area.

In addition, collecting them requires time, money, and manpower to maintain them, which further limits these devices, especially in offshore areas. However, these devices have good accuracy for collecting spatial data, if they are calibrated at the right time. Considering all the above, it can be understood that the use of this type of tools alone cannot be associated with a significant increase in OW energy. Proper location of the OW project sites plays a key role in their economic, technical, environmental and social success [63]. In the first stage, these sites should have two parameters of high and continuous wind speed and low deep water in an area with a minimum distance to the shoreline. Considering these parameters can significantly reduce the installation and commissioning cost in the primary OW farm site assessment steps and the wind farms maintenance cost of the next steps.

Although suitable sites with a minimum distance to the shoreline can be very convenient, they can cause noise during the setup and operation stages. On the other hand, the Mediterranean Sea islands, especially the Greek islands of Aegean Sea, are very famous due to their natural landscapes, thus, during the planning and design phases it is very important to analyse the impact on the landscape of these areas so as to avoid dissatisfaction of residents [3]. It should be considered the impact on marine and aerial species. Many countries around the world today face many limitations in evaluating optimal sites for developing OW farms. These criteria must be compatible with the interests of the investment companies that finance this sector, and on the other hand, they must be compatible with national and environmental laws. In this regard, more research that can increase the understanding of the human societies in selecting appropriate criteria for better use of RESs can lead to the selection of more compatible sites with all sectors.

This reanalyses dataset have the ability to address large areas wind potential assessment as well as focus on small areas with appropriate accuracy. It can be said that the data obtained from the projects of well-known operational centers such as ECMWF, NCEP can be widely used to conduct initial assessments of suitable areas for wind farms installation and operation. In addition to having the advantage of extensive and long-term spatial coverage with a reasonable resolution, this dataset can be made available to researchers free of charge. The error rate of these datasets can be reduced to a minimum and time and cost consuming measurement campaigns can be avoided using this dataset.

The shape files, maps, atlas, vector point and polygon with

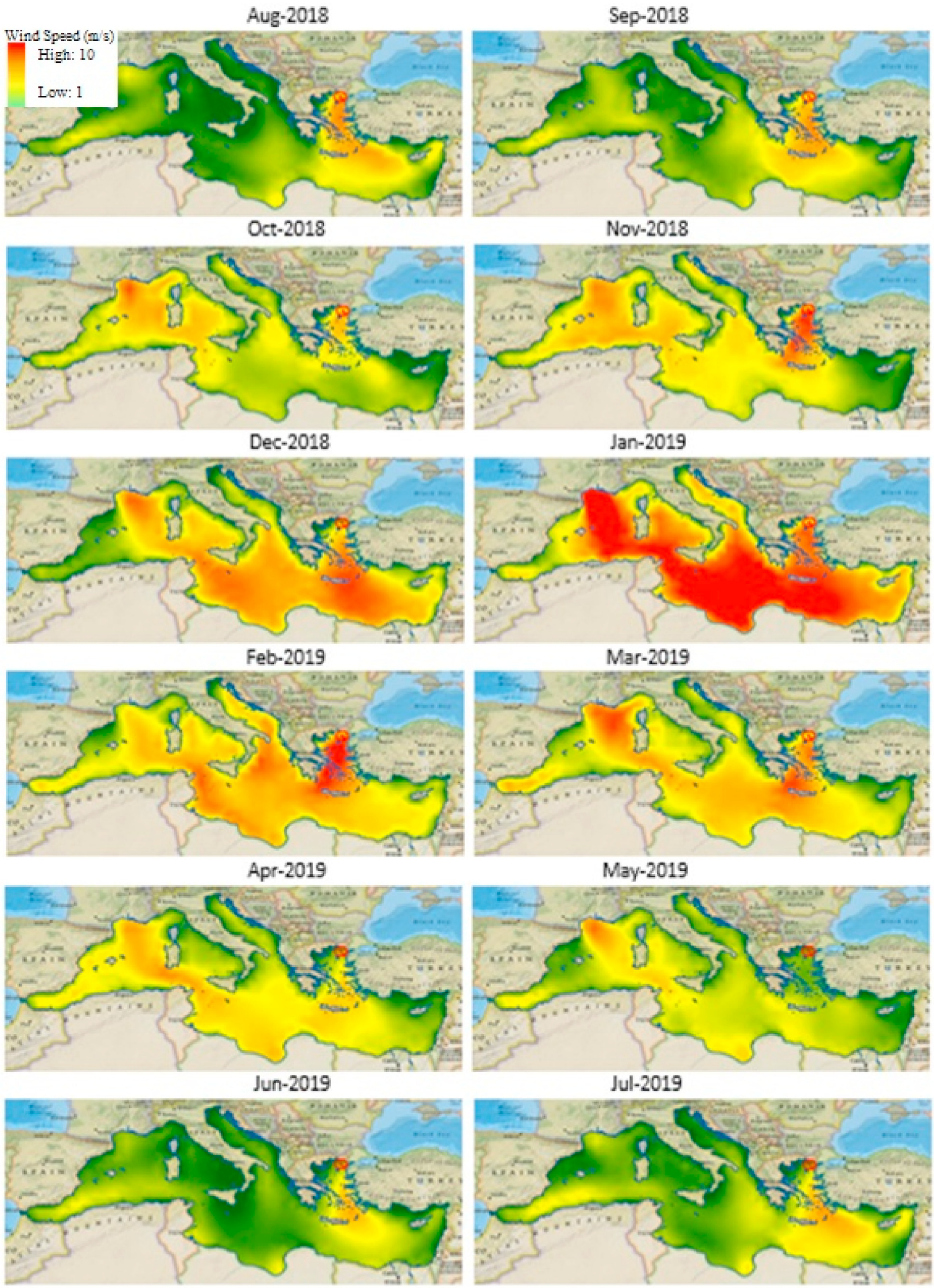

Fig. 6. Monthly wind speed evaluated from ERA-Interim datasets produced by ECMWF for the Mediterranean Sea in the period Aug 2018–Jul 2019.

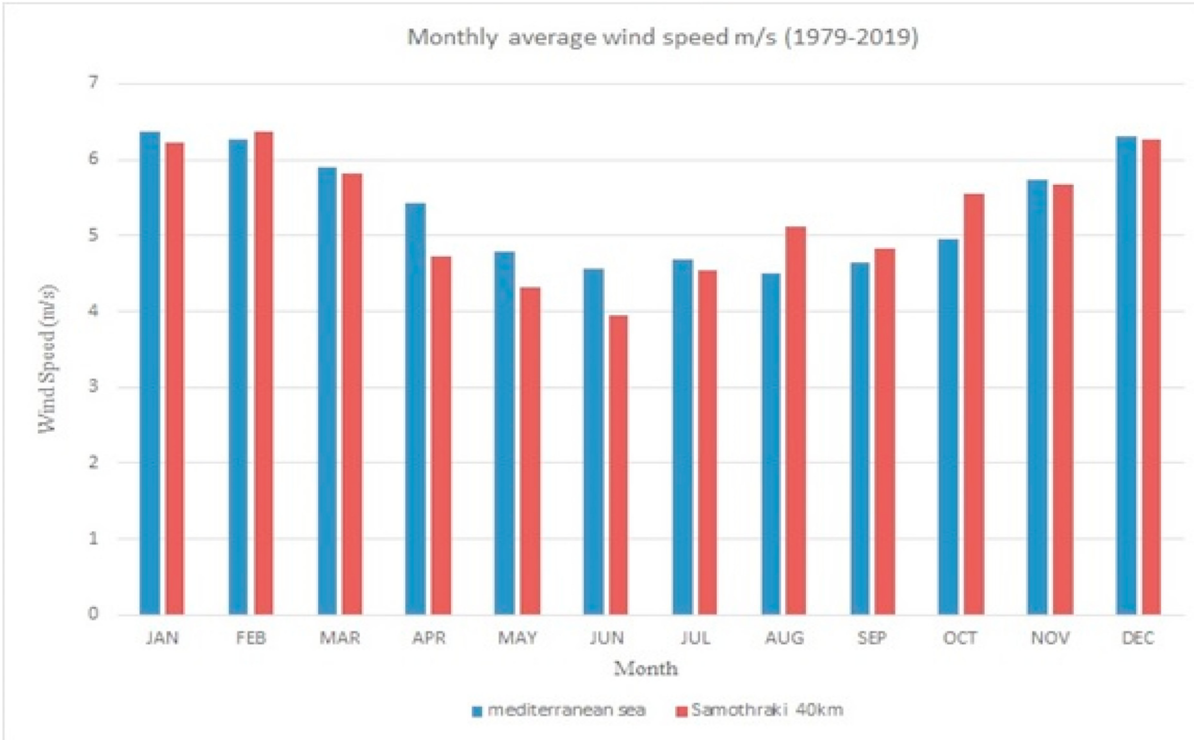

Fig. 7. Monthly average wind speed in the Mediterranean Sea (blue) and the Samothraki island with period (1979–2019).

Fig. 8. Monthly average wind speed in the ROI 1 and ROI 2 located in the west and east of Samothraki island with period (1979–2019).

NetCDF, ASCII (American Standard Code for Information Interchange) data and datasets format generated by these centers can be considered a variable and dynamic material. Gaining an overview of data from Earth observation systems with the aim of identifying temporal and geographic data gaps can make a significant difference in the offshore renewable energy development. On the other

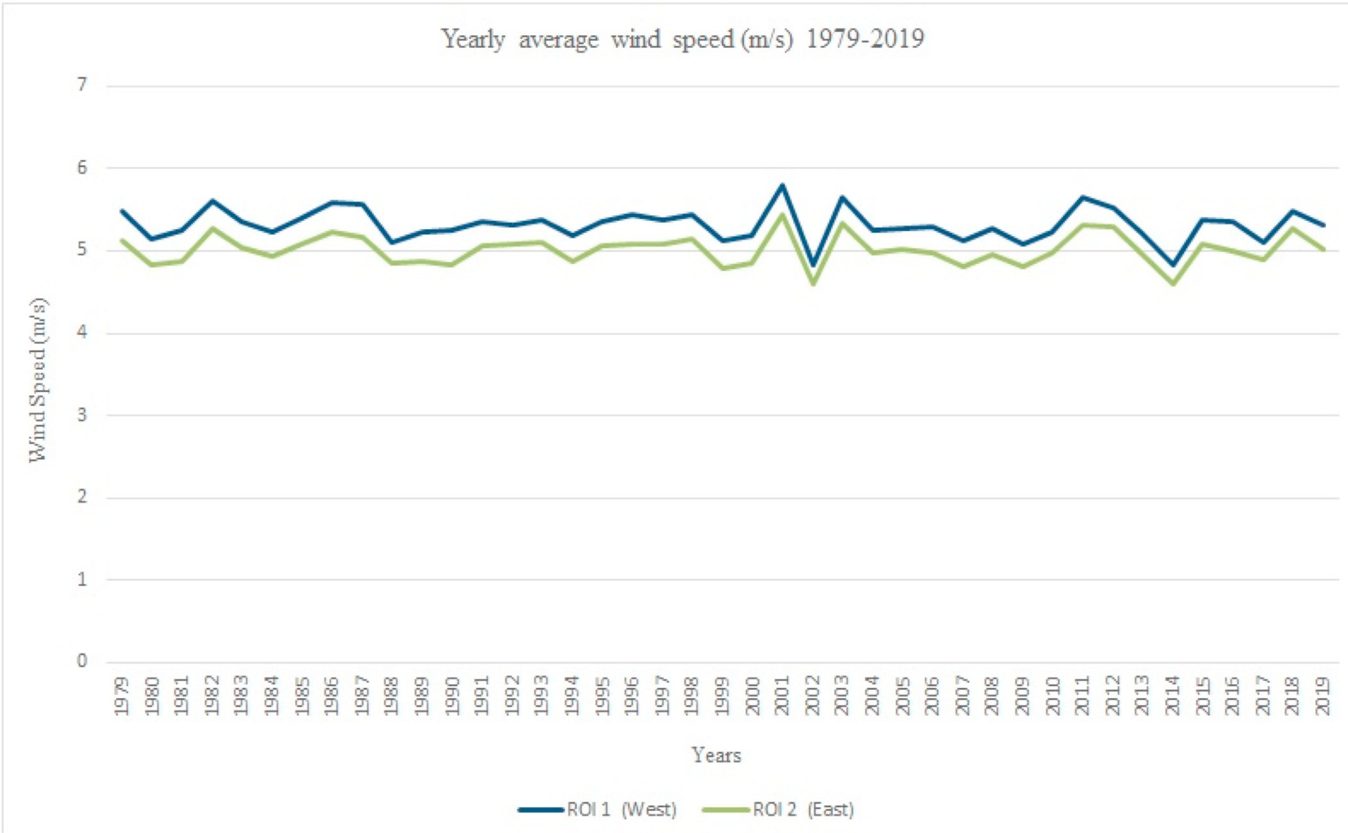

Fig. 9. Yearly trend average wind speed of sea surface water in the ROI 1 and ROI 2 located in the west and east of Samothraki island with period (1979–2019).

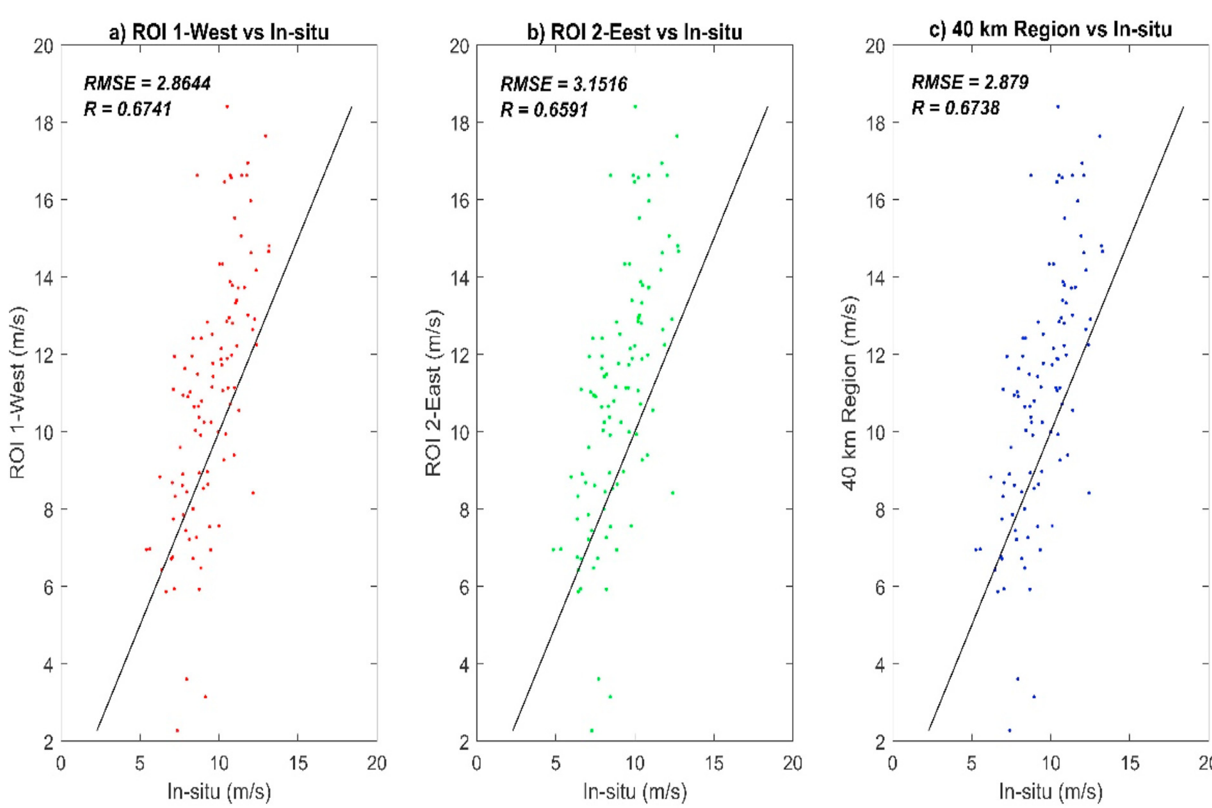

Fig. 10. Comparison between wind speed data retrieved with ERA-Interim reanalysis datasets vs in-situ data (m/s) of a) ROI 1– West; b) ROI 2– East; c) 40 km region around the Samothraki island.

hand, the development and research of innovative methods that can use remote sensing data analysis should be studied and identified to reduce the data gap in the forgotten areas. The proposed methods in the first place can have various advantages, but the most important of them are the following: a) it is easy to work with shortest possible time; b) significantly reduce the computational error of the project; c) can easily cover forgotten study areas and existing gaps; d) according to different group and platform goals can provide facilities to developed and expanded in the next stages of projects.

6. Conclusions

To make a preliminary assessment of offshore wind energy at the sites under study, researchers need long-term wind data, while facing limitations on ground-based devices for data collection. Therefore, long-term wind data are easily obtained from atmospheric numerical models or satellite products. The purpose of this study is to present a fast method for analysing the initial wind speed in the OW region to identify high wind power areas. The ERA-Interim reanalysis dataset has been used to analyse OW speed around the Samothraki island for 40 years. The ERA-Interim reanalysis dataset is free and supported by an unlimited source policy. In this research, all data has been presented as a single layer, we began to identify specific sites for WTGs installation. Then, two interesting areas of the island are investigated to identify the areas with the highest potential.

The results show that the wind speed in ROI 1 in the west of the island has a greater potential than ROI 2 in the east of the island. This is an effective and fast method that can help identify areas suitable for the OW turbine installations. This way it is possible to simultaneously analyse and compare a large number of areas of interest. A preliminary assessment method has been introduced for the initial identification of OW sites around islands that can help bridge the gap created by terrestrial data constraints and assess forgotten marine areas. This method can easily analyse the initial results of rapid OW assessment of the desired site in large areas in a few steps. This method can save time with high replicability and reduce the cost of identifying the desired sites. It can be said that this method can help us to better understand forgotten areas wind potential for the development of OW sites farm in different parts of the world.

CRediT authorship contribution statement

M. Majidi Nezhad: Conceptualization, Software, Investigation, Methodology, Data processing, Writing and Reviewing. **M. Neshat:** Methodology, Writing, Data processing. **D. Groppi:** Writing – original draft, Methodology, Visualization. **P. Marzialetti:** Methodology. **A. Heydari:** Methodology, Data processing, Visualization. **G. Sylaios:** Supervision, Reviewing and Editing. **D. Astiaso Garcia:** Methodology, Writing – original draft, Data processing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This research has been carried out within ODYSSEA project that received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727277. A shorten version of this research has been presented during the 1st Asia Pacific Conference on Sustainable Development of Energy Water and Environment System (SDEWES) held in Gold Coast, Australia, April 06–09, 2020. The title of the conference paper was "*Wind energy potential reported by ERA-Interim Re-analysis dataset: A case study Samothraki Small Island*".

References

[1] P.A. Østergaard, N. Duic, Y. Noorollahi, H. Mikulcic, Sustainable development using renewable energy technology, Renew. Energy 146 (2020) 2430–2437, https://doi.org/10.1016/j.renene.2019.08.094.
[2] P.A. Østergaard, N. Duic, Y. Noorollahi, H. Mikulcic S. Kalogirou, Sustainable Development using renewable energy technology, Renew. Energy 146 (2020) 2430–2437, https://doi.org/10.1016/j.renene.2020.09.124.
[3] I. Spiropoulou, D. Karamanis, G. Kehayias, Offshore wind farms development in relation to environmental protected areas, Sustain. Cities Soc. 14 (2014) 305–312, https://doi.org/10.1016/j.scs.2014.05.006.
[4] S. Moradi, H. Yousefi, Y. Noorollahi, D. Rosso, Multi-criteria decision support system for wind farm site selection and sensitivity analysis: case study of Alborz Province, Iran, Energy Strateg. Rev. 29 (2020) 100478, https://doi.org/10.1016/j.esr.2020.100478.
[5] C. Zheng, C. Li, J. Xu, Micro-scale classification of offshore wind energy resource dd A case study of the New Zealand, J. Clean. Prod. 226 (2019) 133–141, https://doi.org/10.1016/j.jclepro.2019.04.082.
[6] H.S. Ramadan, Wind energy farm sizing and resource assessment for optimal energy yield in Sinai Peninsula, Egypt, J. Clean. Prod. 161 (2017) 1283–1293, https://doi.org/10.1016/j.jclepro.2017.01.120.
[7] T.H. Soukissian, A. Papadopoulos, Effects of different wind data sources in offshore wind power assessment, Renew. Energy 77 (2015) 101–114, https://doi.org/10.1016/j.renene.2014.12.009.
[8] K.S. Khan, M. Tariq, Wind resource assessment using SODAR and meteorological mast – a case study of Pakistan, Renew. Sustain. Energy Rev. 81 (2017) 2443–2449, https://doi.org/10.1016/j.rser.2017.06.050.
[9] J. Li, X. Bill Yu, LiDAR technology for wind energy potential assessment: demonstration and validation at a site around Lake Erie, Energy Convers. Manag. 144 (2017) 252–261, https://doi.org/10.1016/j.enconman.2017.04.061.
[10] M.M. Nezhad, A. Heydari, D. Groppi, F. Cumo, D.A. Garcia, Wind source potential assessment using Sentinel 1 satellite and a new forecasting model based on machine learning : a case study Sardinia islands, Renew. Energy 155 (2020) 212–224, https://doi.org/10.1016/j.renene.2020.03.148.
[11] C.W. Frank, C.W. Frank, B. Pospichal, S. Wahl, J.D. Keller, The added value of high resolution regional reanalyses for wind power applications the added value of high resolution regional reanalyses for wind power applications, Renew. Energy 148 (2019) 1094–1109, https://doi.org/10.1016/j.renene.2019.09.138.
[12] P. Bechtle, M. Schelbergen, R. Schmehl, U. Zillmann, S. Watson, Airborne wind energy resource analysis, Renew. Energy 141 (2019) 1103–1116, https://doi.org/10.1016/j.renene.2019.03.118.
[13] D. Ganea, E. Mereuta, L. Rusu, Estimation of the near future wind power potential, Energies 11 (2018) 3198, https://doi.org/10.3390/en11113198.
[14] N. Jadidoleslam, M. Ozger, Wave Power Potential Assessment of Aegean Sea with an Integrated 15-year Data, vol. 86, 2016, pp. 1045–1059, https://doi.org/10.1016/j.renene.2015.09.022.
[15] M. Decker, M.A. Brunke, Z. Wang, K. Sakaguchi, X. Zeng, Evaluation of the reanalysis products from GSFC , NCEP , and ECMWF using flux tower observations, J. Clim. (2012) 1916–1944, https://doi.org/10.1175/JCLI-D-11-00004.1.
[16] D.P. Dee, S.M. Uppala, A.J. Simmons, P. Berrisford, P. Poli, et al., The ERA-Interim reanalysis : configuration and performance of the data assimilation system, R. Meteorol. Soc. (2011) 553–597, https://doi.org/10.1002/qj.828.
[17] D.J. Cannon, D.J. Brayshaw, J. Methven, P.J. Coker, D. Lenaghan, Using reanalysis data to quantify extreme wind power generation statistics: a 33 year case study in Great Britain, Renew. Energy 75 (2015) 767–778, https://doi.org/10.1016/j.renene.2014.10.024.
[18] S. Rose, J. Apt, What can reanalysis data tell us about wind power ? Renew. Energy 83 (2015) 963–969, https://doi.org/10.1016/j.renene.2015.05.027.
[19] J. Olauson, ERA5: the new champion of wind power modelling ? Renew. Energy 126 (2018) 322–331, https://doi.org/10.1016/j.renene.2018.03.056.
[20] W. Früh, Long-term wind resource and uncertainty estimation using wind records from Scotland as example, Renew. Energy 50 (2013) 1014–1026, https://doi.org/10.1016/j.renene.2012.08.047.
[21] J. Olauson, J. Olauson, M. Bergkvist, Modelling the Swedish wind power production using MERRA reanalysis data, Renew. Energy 76 (2015) 717–725, https://doi.org/10.1016/j.renene.2014.11.085.
[22] O. A. Dabar, M. O. Awaleh, D. Kirk-davidoff, J. Olauson, L. Söder, S. I. Awaleh, Wind resource assessment and economic analysis for electricity generation in three locations of the Republic of Djibouti, Energy, https://doi.org/10.1016/j.energy.2019.07.107,
[23] E. Rusu, F. Onea, Wind and Wave Energy Resource of Germany Reported by ERA- Interim Reanalysis Data, E3S Web Conf, 2019, https://doi.org/10.1051/e3sconf/201912204003.

[24] F. Onea, Evaluation of some state-of-the-art wind technologies in the nearshore of the Black Sea, Energies 11 (2018) 9–2452, https://doi.org/10.3390/en11092452.
[25] U. Henfridsson, V. Neimane, K. Strand, R. Kapper, H. Bernhof, Wave energy potential in the baltic sea and the Danish part of the North Sea, with reflections on the Skagerrak 32 (2007) 2069–2084, https://doi.org/10.1016/j.renene.2006.10.006.
[26] H. He, J. Song, Y. Bai, Y. Xu, J. Wang, F. Bi, Climate and extrema of ocean waves in the East China Sea, Sci. China Earth Sci. 61 (7) (2018) 980–994.
[27] E. Rusu, F. Onea, A parallel evaluation of the wind and wave energy resources along the Latin American and European coastal environments, Renew. Energy 143 (2019) 1594–1607, https://doi.org/10.1016/j.renene.2019.05.117.
[28] F. Onea, L. Deleanu, L. Rusu, C. Georgescu, Evaluation of the wind energy potential along the Mediterranean Sea coasts, Energy Explor. Exploit. 34 (5) (2016) 766–792, https://doi.org/10.1177/0144598716659592.
[29] L.F. Assis Tavares, M. Shadman, L.P. Freitas Assadad, C. Silva, L. Landau, Assessment of the offshore wind technical potential for the Brazilian Southeast and South regions, Energy 196 (2020) 117097, https://doi.org/10.1016/j.energy.2020.117097.
[30] J.M. Espada, M. Ortega, V. Negro, What about marine renewable energies in Spain ? J. Mar. Sci. Eng. 7 (8) (2019) 249, https://doi.org/10.3390/jmse7080249.
[31] F. Onea, E. Rusu, The expected shoreline effect of a marine energy farm operating close to the expected shoreline effect of a marine energy farm operating close to Sardinia island, Water. doi:10.3390/w11112303.
[32] X. Costoya, F. Santos, M.C. Sousa, Projections of wind energy resources in the Caribbean for the 21st century, Energy 178 (2019) 356–367, https://doi.org/10.1016/j.energy.2019.04.121, 2019.
[33] H. Meschede, P. Holzapfel, F. Kadelbach, J. Hesselbach, Classification of global island regarding the opportunity of using RES, Appl. Energy 175 (2016) 251–258, https://doi.org/10.1016/j.apenergy.2016.05.018.
[34] M. Alves, R. Segurado, M. Costa, On the road to 100 % renewable energy systems in isolated islands, Energy 198 (2020) 117321, https://doi.org/10.1016/j.energy.2020.117321.
[35] J. Liu, C. Mei, H. Wang, W. Shao, C. Xiang, Powering an island system by renewable energy — a feasibility analysis in the Maldives, Appl. Energy 227 (2017) 18–27, https://doi.org/10.1016/j.apenergy.2017.10.019.
[36] D. Al, B. Thomsen, I. Dakanali, K. Tzirakis, Faroe Islands: towards 100 % R . E . S . penetration, Renew. Energy 135 (2019) 473–484, https://doi.org/10.1016/j.renene.2018.12.042, 2020.
[37] C. Bueno, J.A. Carta, Technical – economic analysis of wind-powered pumped hydrostorage systems, Part II : model application to the island of El Hierro 78 (2005) 396–405, https://doi.org/10.1016/j.solener.2004.08.007.
[38] C. Bueno, J.A. Carta, Wind powered pumped hydro storage systems, a means of increasing the penetration of renewable energy in the Canary Islands 10 (2006) 312–340, https://doi.org/10.1016/j.rser.2004.09.005.
[39] A. Singlitico, et al., Can thermal energy recovery from digestate make renewable gas from household waste more cost effective ? A case study for the Republic of Ireland, J. Clean. Prod. 261 (2020) 121198, https://doi.org/10.1016/j.jclepro.2020.121198, 2020.
[40] H. Sun, M. Mohsin, M. Alharthi, Q. Abbas, Measuring environmental sustainability performance of South Asia, J. Clean. Prod. 251 (2020) 119519, https://doi.org/10.1016/j.jclepro.2019.119519.
[41] W. Lin, K. Chang, K. Chung, The impact of subsidy programs for solar thermal Applications : a case study for a remote island, Energies 12 (20) (2019) 3944, https://doi.org/10.3390/en12203944.
[42] E. Bustaffa, L. Cori, A. Manzella, D. Nuvolone, F. Minichilli, et al., The health of communities living in proximity of geothermal plants generating heat and electricity : a review, Sci. Total Environ. 706 (2020) 135998, https://doi.org/10.1016/j.scitotenv.2019.135998.
[43] D. Surroop, P. Raghoo, Renewable energy to improve energy situation in African island states, Renew. Sustain. Energy Rev. 88 (2017) 176–183, https://doi.org/10.1016/j.rser.2018.02.024.
[44] T. Duke, et al., Solar Powered Oxygen Systems in Remote Health Centers in Papua New Guinea : a Large Scale Implementation Effectiveness Trial, vol. 7, 2017, p. 1, https://doi.org/10.7189/jogh.07.010411.
[45] D. Curto, V. Franzitta, M. Trapanese, M. Cirrincione, A preliminary energy assessment to improve the energy sustainability in the small islands of the Mediterranean Sea, J. Sustain. dev. energy water environ. syst. (2005), https://doi.org/10.13044/j.sdewes.d7.0314 ABS.
[46] E. Rusu, F. Onea, An assessment of the wind and wave power potential in the island environment, Energy 175 (2019) 830–846, https://doi.org/10.1016/j.energy.2019.03.130.
[47] E.I. Konstantinidis, P. Botsaris, Viability Analysis of an Offshore Wind Farm in North Aegean Sea, Greece, 2018, https://doi.org/10.1063/1.4871484.
[48] M.M. Nezhad, R.U. Shaik, A. Heydari, A. Razmjoo, N. Arslan, D. Astiaso Garcia, A SWOT analysis for off shore wind energy assessment using remote-sensing potential, Appl. Sci. 10 (18) (2020) 6398, https://doi.org/10.3390/app10186398.
[49] V. Franzitta, D. Curto, D. Milone, D. Rao, Assessment of renewable sources for the energy consumption in Malta in the Mediterranean Sea, Energies 9 (12) (2016) 1034, https://doi.org/10.3390/en9121034.
[50] A. Ulazia, J. Sáenz, G. Ibarra-berastegui, S.J. González-rojí, Using 3DVAR data assimilation to measure offshore wind energy potential at different turbine heights in the West Mediterranean, Appl, Energy 208 (2017) 1232–1245, https://doi.org/10.1016/j.apenergy.2017.09.030, 15.
[51] D. Ganea, V. Amortila, E. Mereuta, E. Rusu, A joint evaluation of the wind and wave energy resources close to the Greek islands, Sustain. Times 9 (2017) 1025, https://doi.org/10.3390/su9061025, doi: 10.3390/su9061025.
[52] V. Kotroni, K. Lagouvardos, S. Lykoudis, High-resolution model-based wind atlas for Greece, Renew. Sustain. Energy Rev. 30 (2014) 479–489, https://doi.org/10.1016/j.rser.2013.10.016.
[53] E. Riva, R. Riva, S. Favuzza, V. Vaccaro, Near zero energy islands in the Mediterranean : supporting policies and local obstacles, Energy Pol. 66 (2014) 592–602, https://doi.org/10.1016/j.enpol.2013.11.007.
[54] M. Deveci, E. Özcan, R. John, C. Covrig, D. Pamucar, A study on offshore wind farm siting criteria using a novel interval-valued fuzzy-rough based Delphi method, J. Environ. Manag. 270 (2020) 110916, https://doi.org/10.1016/j.jenvman.2020.110916.
[55] M. Christoforaki, T. Tsoutsos, Sustainable siting of an offshore wind park a case in Chania , Crete,", Renew. Energy 109 (2017) 624–633, https://doi.org/10.1016/j.renene.2017.03.063, 2017.
[56] Y. Panagopoulos, E. Dimitriou, N. Skoulikidis, Vulnerability of a northeast mediterranean island to soil loss, Can Grazing Management Mitigate Erosion?, water 11 (2019) 1491, https://doi.org/10.3390/w11071491.
[57] D.G. Vagiona, M. Kamilakis, Sustainable Site Selection for Offshore Wind Farms in the South Aegean — Greece, 2018, https://doi.org/10.3390/su10030749.
[58] X. Costoya, D. Carvalho, M. Gómez-gesteira, On the suitability of offshore wind energy resource in the United States of America for the 21st century, Appl. Energy 262 (2019) 114537, https://doi.org/10.1016/j.apenergy.2020.114537, 2020.
[59] J. Jang, K. Park, A. Aur, B. Chapron, J. Lee, Validation of sea surface wind from sentinel-1A/B SAR data in the coastal, Regions of the Korean Peninsula 12 (7) (2019) 2513–2529.
[60] D. Machiwal, M. K. Jha, Hydrologic Time Series Analysis: Theory and Practice. 2554. https://link.springer.com/book/10.1007/978-94-007-1861-6
[61] Y. Xie, S. Liu, H. Fang, J. Wang, Global autocorrelation test based on the Monte Carlo method and impacts of eliminating nonstationary components on the global autocorrelation test, Stoch. Environ. Res. Risk Assess. 34 (2020) 1645–1658, https://doi.org/10.1007/s00477-020-01854-5, 10.
[62] S. Ryu, H. Choi, H. Lee, H. Kim, Convolutional autoencoder based feature extraction and clustering for customer load analysis, IEEE Trans. Power Syst. 35 (2) (2020) 1048–1060, https://doi.org/10.1109/TPWRS.2019.2936293.
[63] U. Cali, N. Erdogan, S. Kucuksari, M. Argin, Techno economic analysis of high potintial offshore wind farm locations in Turkey, 22, https://doi.org/10.1016/j.esr.2018.10.007, 2018, 325-336.