Modelling the cross-shore profiles of sand beaches using Artificial Neural Networks

Journal:	Marine Georesources & Geotechnology
Manuscript ID	UMGT-2018-0074.R1
Manuscript Type:	Original Article
Date Submitted by the Author:	19-May-2018
Complete List of Authors:	López, Isabel; Universitat d'Alacant, Aragonés, Luis; Universitat d'Alacant Villacampa, Yolanda; Universitat d'Alacant
Keywords:	Artificial Neural Network, sand, beach profile, profile slope, Posidonia oceanica
Note: The following files were submitted by the author for peer review, but cannot be converted to PDF. You must view these files (e.g. movies) online.	
Figure_5.jpg	

SCHOLARONE™
Manuscripts

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

Modelling the cross-shore profiles of sand beaches using Artificial Neural Networks

Isabel López^(a,*), Luis Aragonés^(b), Yolanda Villacampa^(c)

^(a,*) Isabel López. Corresponding Author. Email: isalopu.il@gmail.com. Department of Civil Engineering. University of Alicante. 03690, San Vicente del Raspeig, Spain.

^(b) Luis Aragonés. Email: laragones@ua.es. Department of Civil Engineering. University of Alicante. 03690, San Vicente del Raspeig, Spain.

^(c) Yolanda Villacampa. Email: villacampa@ua.es. Department Applied Mathematics. University of Alicante. 03690, San Vicente del Raspeig, Spain.

ABSTRACT

Artificial Neural Networks (ANN) have been widely used successfully to solve coastal engineering problems. In this article they are used to model the cross-shore profile of sandy beaches taking into account the possible effect of marine vegetation (*Posidonia oceanica*). Sixty ANNs were generated by modifying both the inputs and the number of neurons in the hidden layer. The best results were obtained with the following inputs: wave height perpendicular to the coast and the associated period and probability of occurrence, median sediment size, profile slope, and energy reduction factor due to *Posidonia oceanica*. With these inputs and 10 neurons in the hidden layer, a mean absolute error of 0.22 m during training and 0.21 m during the test was obtained, which represents an improvement of 81.2% and 55.5% compared to models without and with *Posidonia oceanica*.

Keywords: Artificial Neural Network; Sand; Beach Profile; Profile slope; *Posidonia oceanica*

1. Introduction

Beach erosion is a very serious problem around the world (Allen 1981; Semeoshenkova and Newton 2015; Pranzini, Wetzel, and Williams 2015). To address this problem, it is important to know the morphology and morphodynamics of the area of study (Larson and Kraus 1995), which is mainly controlled by wave climate, tide and sediment characteristics (Bernabeu, Medina, and Vidal 2003; Boon and Green 1988). Therefore, numerical simulations of hydrodynamics, sediment transport and morphological changes is essential for coastal management, planning and maintenance (Chen et al. 2015; Keshtpoor et al. 2015). Because of the influence of tidal currents, freshwater discharge, waves and the interaction between them on the hydrodynamics of tidal inlets, they are often highly dynamic environment sand have complex hydrodynamics, resulting in equally complex sediment transport and morphological changes (Sedigh et al. 2016).

Another important factor in determining the cross-shore beach profile is the presence of marine vegetation. In the case of the Mediterranean, the marine phanerogamous *Posidonia oceanica* stands out (Medina, Tintore, and Duarte 2001), and cover about 1.5% of the total Mediterranean Sea surface (Pasqualini et al. 1998). *Posidonia oceanica* meadows are usually recorded from near the surface to 40 m depth, but living plants have been found as deep as 48 m in particularly clear waters (Boudouresque et al. 1994; Pergent-Martini et al. 2005). This species loses leaves in autumn that form large litter patches in the surf zone and huge litter banks on adjacent beaches, resulting in wedge and layered structures of few centimetres to several meters in thick (Gómez-Pujol et al. 2013). This marine plant affects the profile due to its capacity to reduce wave energy by friction between the water and the beams (Méndez, Losada, and Losada 1999; Koftis and Prinos 2012), as well as by the retention and stabilization of sediments causing a more vertical transverse profile (Gacia,

1
2 48 Granata, and Duarte 1999). Several experiments have confirmed that the *Posidonia*
3
4 49 *oceanica* meadows reduce wave energy, especially for low energy, low amplitude waves,
5
6 50 which improves sediment stabilization in relation to areas without vegetation (Manca et al.
7
8
9 51 2012). However, during storms (high energy), they offer almost no protection (Vacchi et al.
10
11 52 2017).

12
13
14 53 The modelling of coastal profiles began in the 1950s with simple mathematical equations
15
16 54 (Bruun 1954; Dean 1977; Vellinga 1983; Vellinga 1984). While mathematical and numerical
17
18 55 process-based models are now used that can incorporate a large number of parameters and
19
20 56 even hydrodynamic models (Masselink and Li 2001; Stive and de Vriend 1995; Aragonés et
21
22 57 al. 2016; Neill, Elliott, and Hashemi 2008; Ranasinghe et al. 2004). However, due to
23
24 58 uncertainties in understanding nearshore processes (wave breaking, wave reflection,
25
26 59 refraction, diffraction and sediment transport) there are still important discrepancies
27
28 60 between model results and measured data (Iglesias et al. 2009). Accordingly, other methods
29
30 61 such as Artificial Intelligence (AI) have been introduced in this area, which are less expensive
31
32 62 compared with physical-based numerical models (Hashemi, Ghadampour, and Neill 2010).

33
34
35
36
37 63 AI is based on learning through data, that is, it is necessary to know the variables (wind,
38
39 64 waves, sediment, etc.) but not the processes precisely, so it is a useful tool in coastal
40
41 65 applications (Bernabeu, Medina, and Vidal 2003; Hashemi, Ghadampour, and Neill 2010). In
42
43 66 recent years, AI techniques such as artificial neural networks (ANNs) have been successfully
44
45 67 applied to coastal engineering problems (Iglesias et al. 2009; Huang et al. 2003; Ghorbani et
46
47 68 al. 2010; López, Aragonés, Villacampa, and Serra 2017; Demirci, Üneş, and Aköz 2015).

48
49
50
51 69 In addition, some authors have used neural networks to determine the submerged (López,
52
53 70 Aragonés, Villacampa, and Compañ 2017; van Rijn et al. 2003) or surfaced (Hashemi,
54
55 71 Ghadampour, and Neill 2010) profile of a beach under different conditions. However, these

authors have not taken into consideration the possible effect that marine vegetation can have on both waves and profile. Although other authors have taken it into account in other cases, such as planview evolution (Alvarez-Ellacuria et al. 2011). Therefore, the purpose of this study is to investigate the potential of an ANN to predict the cross-shore beach profile of sand beaches in areas with and without *Posidonia oceanica*. To this end, first, the variables that may influence the formation of the profile were studied and then different ANNs were generated (different input variables and number of hidden layers) and the architecture that best represents the cross-shore beach profiles in the study area was selected.

2. Study area

The study area is located in the western Mediterranean. Specifically, this work focuses on all sand beaches in the provinces of Valencia, Alicante and Murcia (Spain) (Figure 1). Valencia is a province located in the east of the Iberian Peninsula ($39^{\circ}28'30.7''\text{N}$, $00^{\circ}22'33''\text{W}$), within the Gulf of Valencia, which is the largest morphodynamic unit of the Spanish natural coastline. The 28 studied beaches have delta fans, dunes, lagoons, capes and ports in the coastal part and bars in the nearshore.

Meanwhile, the province of Alicante in the south of Valencia ($38^{\circ}20'43''\text{N}$, $0^{\circ}28'59''\text{W}$), is divided into two morphological zones: A zone formed by hills and riverside forests and mainly gravel beaches, comprising almost two thirds north (from the northern border of the province, until the Cape las Huertas). The southern third (from the Cape las Huertas to the southern border of the province) is made up of a large alluvial plain, and sandy beaches. In the province of Alicante, 38 beaches have been studied.

Figure 1. Location of the study area and the meadows of *Posidonia oceanica*. (no color is needed)

Murcia is located southeast of Spain (37°59'10"N, 1°07'49"W), and the north-south divides into two parts, separated by a series of hills that form the South Mountain range parts. These two areas are: i) Field of Murcia south, is the northern part of the coastal plain of the Campo de Cartagena; and ii) Huerta de Murcia north, consist of a flood plain. On its coast, we can find systems of coastal dunes and beaches, wetlands and coastal marine influence. Note the Mar Menor, a salt water lagoon, with a semicircular shape. It is separated from Mediterranean Sea by a strip of sand, 22 km in length and between 100 m and 1200 m in width. In Murcia, 37 beaches have been studied.

The beaches of the Province of Valencia are divided into three physiographic units: i) from the northern limit of the province to the Port of Valencia; ii) from the Port of Valencia to the Cabo de Cullera; iii) from the Cabo de Cullera to the southern limit of the province. In the three units, the predominant sediment transport is North-South, corresponding to the main currents. The dominant storms are from the ENE with a significant wave height of 3.9 m and a period of 11.6 s, while the most frequent waves in the area are from the E, with wave heights of 2.8 m in deep waters and a period of 10.5 s (Ecolevente 2006).

On the other hand, on the coastal front of Alicante and Murcia, the beaches are usually small and separated from each other, so in this case each of the beaches studied represents an independent physiographic unit. In the province of Alicante and up to Cabo de Palos (Murcia) the highest storms come from the E with wave heights of up to 4.5 m and periods of 10-12 s (Ecolevente 2006). According to López et al. (2016), the most frequent waves (ENE and E) produce North-South direction currents. In the southern part of the province of Murcia the predominant waves are those of the SE and SW with wave heights of up to 2.7 m and 4.2 m, respectively (EcoMAG 2009).

On the other hand, astronomical tides range between 20 cm and 30 cm in the area of Valencia and Alicante (Ecolevente 2006) and between 20 cm and 40 cm in Murcia (EcoMAG 2009), and when they are affected by meteorological factors, the tides surges can be up to 75 cm in Alicante and Valencia, and 1 m in Murcia.

3. Methodology

In the developed methodology, first the variables that may be related to the formation of the profile (climate, sedimentology and biocenosis) are analysed. Then, the process for the generation of neural networks and the selection of the optimal architecture is described.

3.1. Bathymetric profiles

To obtain the cross-shore profiles, the bathymetry of the “Estudio ecocartográfico de las provincias de Valencia y Alicante (Ecolevente 2006)” and “Estudio ecocartográfico de las provincias de Granada, Almería y Murcia (EcoMAG 2009)” conducted by the General Directorate of Coasts were used. This bathymetry was obtained using two multibeam and a single beam probe from the coastline to the depth of -40 m. The simplified point cloud of the data returned by the echo sounder has a spatial resolution of 5x5 m on the XY axis and $\pm$

1
2 134 0.15 m on the Z axis, from which a DTM (digital terrain model) was generated by TIN and,
3
4 135 from the TIN, the bathymetric and cross-shore profiles were generated. From the shoreline
5
6 136 to -2 m the data were completed with RTK survey (EcoMAG 2009; Ecolevante 2006). No
7
8 137 profile was discard because it was located in front of reefs or sand bars, but no profiles were
9
10 138 taken on gravel beaches, the study was only carried out for sand beaches.

13
14 139 Given the resolution of the bathymetry and the length of the beaches, by using a GIS
15
16 140 (Geographical Information System), profiles were obtained of the beaches (at least two),
17
18 141 with a total of 418 profiles (140 in Valencia, 138 in Alicante and 140 in Murcia;
19
20 142 Supplementary material 1). These profiles were divided into fifteen points (x, y), of which y_i
21
22 143 will be the outputs of the ANNs. The 15 points were chosen so that the x_i was constant for all
23
24 144 profiles, and reach, at least, the depth of closure (DoC), calculated according to Birkemeier
25
26 145 (1985). The x_i values considered are: $x_1 = 10$ m, $x_2 = 20$ m, $x_3 = 40$ m, $x_4 = 60$ m, $x_5 = 80$ m, $x_6 =$
27
28 146 100 m, $x_7 = 125$ m, $x_8 = 150$ m, $x_9 = 175$ m, $x_{10} = 200$ m, $x_{11} = 250$ m, $x_{12} = 300$ m, $x_{13} = 350$ m,
29
30 147 $x_{14} = 400$ m and $x_{15} = 450$ m. Following the criteria established by López, Aragonés,
31
32 148 Villacampa, and Compañ (2017), the points are closer at the landward edge of the profile
33
34 149 and further apart 100 m from the shoreline, to represent adequately the concave shape of
35
36 150 the profiles (Aragonés et al. 2016).

41 151 **3.2. Wave climate**

43
44 152 Wave data were obtained from directional buoys from the networks "REDEXT" and
45
46 153 "REDCOST" of Public Agency Puertos del Estado (www.puertos.es). For Northern domain
47
48 154 (from the northern boundary of the province of Valencia to Cape Nao), the Valencia 2630
49
50 155 buoy (39°30'57.6"N, 0°12'17.9"E, 260 m deep) was used. For beaches from Cabo Nao to
51
52 156 Cape Santa Pola, the Alicante 1616 buoy (38°15'0.0"N, 0°24'35.9"W, 52 m deep), was used.
53
54 157 And for southern domain, the Cabo de Palos 2610 buoy (37°39'3.6"N, 0°09'37.2"W, 230 m
55
56
57
58
59
60

deep) was used. Since Alicante buoy is in intermediate water, data were carried to deep water using the function, $H_o = H_R \cdot K_\alpha / K_R$, given by the ROM_0.3-91 (1991), where K_α is the coefficient of directional distribution and K_R is the coefficient of refraction-shoaling, H_o is the wave height in deep water and H_R the wave height at the buoy.

For the study, different wave heights, periods, directions, and probability of occurrence (p) were accounted for, to determine the most influential in the profile. The different wave heights, and their associated periods, occurrence probabilities and directions used are: waves of highest frequency (MF), waves of the highest energy (highest wave height, ME), and waves associated with the direction perpendicular to the coast (PC). All the data were obtained using the software AMEVA v1.4.3 (IHCantabria 2013), and are referred to as the wave height exceeded 12 hours a year ($H_{s,12}$).

Moreover, the wave height at breaking (H_b) was obtained by two methods: i) using the methodology proposed by the Recommendation for Marine Works (ROM_0.3-91 1991), which considers refraction and shoaling, and ii) using the formulation proposed by Goda (2010).

3.3. Sediment characteristics

Sediment samples were obtained from a survey conducted by the University of Alicante in 2012 (Alicante), 2013 (Valencia) and 2014 (Murcia). For the 103 studied beaches, 453 samples were analysed (4 to 5 samples per beach evenly distributed along the shoreline). Samples were taken in the swash zone, and were saved in a bucket to be labelled. Sediment was collected by dragging on the bottom a plastic bag inserted in an oval metallic frame, giving a vertical penetration in the sediment of about 2–4 cm. The weight of samples ranged from 200 to 500 g. After being packed into bags the samples were transported in an icebox to the laboratory.

1
2 182 For each sample, the median sediment size (D_{50}), real sample density (ρ_m), the material
3
4 183 density (ρ_s) and the porosity (p) were obtained following the UNE 103 101: 1995, the UNE
5
6 184 7050-2: 1997 and the UNE 103 100: 1995. Also the following scientific literature was taken
7
8 185 into account: Syvitski (2007); Román-Sierra, Muñoz-perez, and Navarro-Pons (2013). For the
9
10 186 characterization of the cross-shore profiles, the data obtained from the nearest sample to
11
12 187 each profile were used.

15
16 188 **3.4. *Posidonia oceanica***

17
18 189 In the provinces of Alicante and Murcia, there is an extensive presence of *Posidonia oceanica*
19
20 190 meadows (Figure 1). This marine phanerogama plays an important role in the beach profile.
21
22 191 Some of the most important effects are: i) Improvement of retention of suspended particles
23
24 192 (Terrados and Duarte 2000; Gacia and Duarte 2001), ii) consolidates the sediment, acting as
25
26 193 a reef profile, generating a profile more vertical than unprotected ones (Fonseca 1996;
27
28 194 Muñoz-Perez and Medina 2010). That is why the profile slope will be studied from the
29
30 195 shoreline to the beginning of the *Posidonia* meadow. iii) the friction of the plant leaves with
31
32 196 water produces a reduction in the incident wave energy (Gambi et al. 1989; Gacia and
33
34 197 Duarte 2001), so the energy reduction coefficient K_v will be studied. And iv) Protection of the
35
36 198 erosion of beaches by the accumulation of leaves on the coast (Boudouresque and de
37
38 199 Grissac 1983). Although the protection role of seagrass banquettes should be reconsidered,
39
40 200 since seagrass cast accumulations are continuously built up and destroyed and rarely persist
41
42 201 before the arrival of new sea storms (Gómez-Pujol et al. 2013).

43
44 202 **3.4.1. Energy reduction coefficient (K_v)**

45
46 203 For obtaining energy reduction coefficient K_v , the function proposed by Mendez and Losada
47
48 204 (2004) for variable depth (Eq. 1) was used, because all the meadows are on sloping bottoms.

49
50
51
52
53
54
55
56
57 205
$$K_v = \frac{1}{1+\lambda x} \quad (1)$$

Where K_V is the reduction coefficient, λ is a parameter related to the characteristics of the plant and swell (Eq. 2), and x is the distance along meadow (m).

$$\lambda = \frac{4}{9\pi} \cdot C_D \cdot b_v \cdot N \cdot H_0 \cdot k \cdot \frac{\sinh^3(k \cdot \delta \cdot h) + 3 \cdot \sinh(k \cdot \delta \cdot h)}{(\sinh(2 \cdot k \cdot h) + 2 \cdot k \cdot h) \cdot \sinh(k \cdot h)} \quad (2)$$

where b_v is the plant area per unit height of vegetation in the direction normal to speed, N is the plant density (stems/ m^2), δ is the relative plant height with respect to the water depth (h), k is the wave number, and C_D is the drag coefficient (Eq. 3).

$$C_D = \alpha + \left(\frac{\beta}{Re}\right)^\gamma \quad (3)$$

where Re is the Reynolds number and α , β and γ are empirical parameters proposed by Méndez, Losada, and Losada (1999); Cavallaro et al. (2011); Koftis and Prinos (2012); Maza, Lara, and Losada (2013) (Table 1). Because of the diversity of the proposed values, it was decided that C_D be determined through values proposed by each of the authors and see which was better suited for the study area. The required data (plant density, stem height, leaf length, depth, and width of *P. oceanica*, which lies in front of each of the beaches) were obtained from EcoMAG (2009) and Ecolevante (2006). In order to take into account only the energy reduction due to *Posidonia oceanica* meadows, those beaches with bare sandy bottom were assigned a value of $K_V=0$.

Table 1. Parameters α , β and γ , to calculate drag coefficient (C_D), according to the literature

Studies	α	β	γ	Range R_e
Méndez et al. (1999)	0.4	4600	2.9	2300 – 20000
Cavallaro et al. (2011)	0	2100	1.7	200 – 15500
Koftis and Prinos (2012)	0.1	2100	1	1000 – 3200
Maza et al. (2013)_01	0.87	2200	0.88	4000 – 6000
Maza et al. (2013)_02	1.61	4600	1.9	2000 – 7000

3.4.2. Slope

The slope of each of the profiles from the coastline to the beginning of the *Posidonia* meadow or the depth of closure of Birkemeier (1985) was studied. It is observed that the

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

226 slope of the profiles located in *Posidonia oceanica* zones is larger than the profiles located in
227 naked sandy bottoms (Figure 2). The mean slope of the profiles without *Posidonia oceanica*
228 is 0.015 ± 0.003 , while the slope of the profiles with *Posidonia oceanica* is 0.026 ± 0.009 . In
229 addition, it has been observed that in the analysed beaches the DoC estimated from the
230 formulation proposed by Birkemeier (1985) is always within the meadow of *Posidonia*.

231
232 **Figure 2. A)** Comparison of profiles with and without the presence of *Posidonia oceanica* to two
233 beaches with similar characteristics (D_{50} and incident wave energy). The straight line is on the Caseta
234 de la Mare de Deu Beach (Alicante) and has *Posidonia*. The dashed line belongs to El Saler beach
235 (Valencia), without the presence of *Posidonia*. **B)** Average value and standard deviation of the slope,
236 on the beaches with and without seagrass. (no color is needed)

237 **3.5. Artificial neural networks modelling**

238 An artificial neural network system (ANNS) is a system made up of artificial neurons that
239 emulates the concepts of the nervous system. An artificial neuron is an elemental processor
240 so that from an input vector coming from the outside or from other neurons it provides a
241 single response or output. In addition, the neurons will be organized in structural units called
242 layers; several layers will constitute a neural network, and finally, a neural network (or set of
243 them), along with the input and output interfaces, plus the necessary additional modules,
244 will constitute the overall process system.

245 In the set of layers that constitute a neural network, three types are distinguished: i) Input
246 layer. It consists of neurons that receive data or signals from the environment (where
247 independent variables are introduced); ii) Hidden Layer(s). It is the one that does not have a

248 direct connection with the environment (a number of neurons is selected in the layer, the
249 allocation of weights is produced and the computational process is carried out); iii) Output
250 layer. It is the layer whose neurons provide neuronal network response (where the results
251 are shown).

252 For this work, the methodology described by López, Aragonés, Villacampa, and Compañ
253 (2017) was followed. To obtain neural networks, MATLAB code-generated
254 software/software (MathWorks, Inc., Natwick, MA) and the Neural Network Toolbox
255 libraries were used. In which the backpropagation (BP) algorithm was applied together with
256 the Levenber-Marquardt (LMA) algorithm, as it improves the calculation speed by using the
257 second derivative approach method (Wang 2004). In order to avoid over-adjustment and
258 obtain a good predictive model, the validation set is used to monitor the performance of the
259 model during the training phase and to minimize over fitting, and 50 models were generated
260 in each architecture selected in the hidden layer, i.e. 50 models were run independently, to
261 avoid the effects caused by the automatic selection of the initial weights given to each
262 neuron, as well as the selection of the profiles used for training or testing.

263 In order to determine the variables that would be used as input variables, in the input layer,
264 the correlations between each of the analysed variables and each of the points of the
265 profiles (outputs) were first studied using the SPSS statistical software.

266 The results show that the variables D_{50} , H_o (PC), p (PC) and T (PC) are the variables that best
267 define the profile, which is consistent with the results obtained by López, Aragonés,
268 Villacampa, and Compañ (2017). However, it can be seen that at the intermediate points of
269 the profile (125 - 250 m), the K_v factor of Koftis (hereafter K_v) and the slope have an
270 important influence. This is why three types of network models with different variables have
271 been generated, one using the same variables as López, Aragonés, Villacampa, and Compañ

1
2 272 (2017) and two more progressively adding the variables K_v and slope, to see the influence of
3
4 273 these two variables on the results. The three types of generated networks have in the input
5
6 274 layer the following variables:

- 7
8
9 275 1) ANN1: D_{50} , H_o (PC), T (PC), and p (PC)
10
11
12 276 2) ANN2: D_{50} , H_o (PC), T (PC), p (PC) and K_v
13
14
15 277 3) ANN3: D_{50} , H_o (PC), T (PC), p (PC), K_v , and slope (m)
16

17 278 In each case, for the identification of ANN the input data were divided into three groups.
18
19 279 Thus, the training, validation and test groups have dimensions of 313 (75%) profiles, 42
20
21 280 (10%) profiles and 63 (15%) profiles, respectively. Since the profiles used in each of the
22
23 281 groups are randomly selected by the program, each model was run 50 times, to rule out the
24
25 282 influence of the variability of the input data in each group (training, validation, testing). The
26
27 283 outputs correspond to the 15 points that define the profiles ($y_1, y_2, \dots, y_{15}$).
28
29

30
31 284 For network optimization, the number of neurons in the hidden layer ranged from 1 to 20.
32
33 285 The optimal ANN architecture was determined based on the Pearson's coefficient (R^2) of
34
35 286 training, validation and testing sets. Therefore, the criterion for selecting the optimal model
36
37 287 was to obtain the maximum value of R^2 with the lowest dispersion of results in the 50
38
39 288 executions during test and training.
40
41

42
43 289 To determine the performance of the selected network model, three different criteria were
44
45 290 used: absolute error (Eq. 4), mean absolute percentage error (MAPE, Eq. 5) and percentage
46
47 291 relative error (Eq. 6).
48
49

50
51 292
$$e = |r_i - o_i| \quad (4)$$

52

53
54 293
$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{r_i - o_i}{r_i} \right| \quad (5)$$

55
56
57
58
59
60

$$\delta = \sqrt{\frac{\sum_{i=1}^n (r_i - o_i)^2}{(n-p) \frac{1}{n} \sum_{i=1}^n (r_i)^2}} \quad (6)$$

Where r_i corresponds to the measured values, o_i are the values obtained from the network, n is the number of values and p is the number of free parameters of expression.

Finally, the results obtained are compared with the model for the equilibrium transverse profile proposed by Dean (1977), since it is the most used by coastal engineers in coastal regeneration. In addition, it is also compared with the numerical model developed by Aragonés et al. (2017) to obtain the equilibrium profile in areas with *Posidonia oceanica*.

4. Results

First, the results of the study of the correlations between the different analysed variables and each of the points of the profile that are part of the output of the neural network are shown (Table 2). As can be seen, the correlation values are generally low in the points closer to the shoreline, although they are quite high in the endpoints. The variables that have greater relationship with all points are: D_{50} , H_o (PC) T (PC) and p (PC), with an average in absolute value of 0.645, 0.550, 0.549 and 0.546. Also highlight the slope (m) and the coefficient K_v . Although, the correlation mean values are between 0.3 and 0.4, correlations with intermediate points of the profile (125–250 m) are greater than 0.5 in all cases. The correlations indicate the linear relationships between two variables, but this does not mean that in non-linear models, such as ANN, the combination of variables which present the highest correlations obtain the best results. Therefore, it was decided to generate several neural networks with different input variables.

Figure 3 shows the R^2 value obtained for each ANN (ANN1, ANN2 and ANN3) for training and test. As can be seen results at training and test are similar. Among the architectures, ANN [6–10–15] (inputs, neurons in hidden layer, outputs) was selected, since presents the highest

1
2 317 value of the mean R^2 with the lowest dispersion (0.907 ± 0.019 for test and 0.901 ± 0.019 for
3
4 318 training). Although, there are other architectures with high values of R^2 such as [6–16–15],
5
6 319 whose results are very similar (0.897 ± 0.022 for test and 0.907 ± 0.017 for training), the
7
8 320 architecture [6–10–15] has lower number of neurons in the hidden layer.
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

321
322 **Figure 3.** Mean values of R^2 for each of the analysed architectures in test (a) and training (b). (no
323 color is needed)

Table 2. Correlations between the study variables and the cross-shore profile.

Variables	Y (x=10)	Y (x=20)	Y (x=40)	Y (x=60)	Y (x=80)	Y (x=100)	Y (x=125)	Y (x=150)	Y (x=175)	Y (x=200)	Y (x=250)	Y (x=300)	Y (x=350)	Y (x=400)	Y (x=450)	Average (ABS)
D ₅₀	-0.334	-0.365	-0.431	-0.513	-0.606	-0.682	-0.739	-0.765	-0.770	-0.773	-0.764	-0.753	-0.731	-0.729	-0.722	0.645
T (PC)	-0.251	-0.304	-0.362	-0.435	-0.511	-0.543	-0.585	-0.614	-0.628	-0.644	-0.660	-0.653	-0.668	-0.693	-0.704	0.550
H _o (PC)	-0.245	-0.301	-0.376	-0.459	-0.540	-0.570	-0.602	-0.619	-0.627	-0.636	-0.645	-0.635	-0.643	-0.664	-0.673	0.549
p (PC)	-0.219	-0.281	-0.339	-0.414	-0.496	-0.533	-0.579	-0.608	-0.623	-0.645	-0.672	-0.671	-0.686	-0.710	-0.719	0.546
Porosity	-0.183	-0.234	-0.280	-0.338	-0.384	-0.388	-0.427	-0.457	-0.478	-0.510	-0.525	-0.531	-0.555	-0.583	-0.602	0.432
Dir (PC)	0.236	0.241	0.239	0.268	0.292	0.318	0.386	0.461	0.501	0.533	0.542	0.534	0.561	0.567	0.584	0.418
H _{b,ROM}	0.249	0.281	0.298	0.305	0.318	0.350	0.425	0.468	0.491	0.498	0.481	0.447	0.441	0.476	0.502	0.402
T (MF)	0.185	0.181	0.184	0.220	0.248	0.276	0.346	0.426	0.471	0.511	0.529	0.528	0.556	0.561	0.579	0.387
Slope	-0.110	-0.121	-0.123	-0.143	-0.199	-0.253	-0.521	-0.682	-0.513	-0.650	-0.510	-0.304	-0.402	-0.425	-0.350	0.354
K _v Koftis	0.059	0.063	0.015	-0.048	-0.153	-0.232	-0.616	-0.501	-0.550	-0.589	-0.557	-0.457	-0.336	-0.419	-0.494	0.339
H _o (ME)	0.114	0.104	0.102	0.127	0.161	0.186	0.270	0.361	0.422	0.452	0.446	0.443	0.341	0.245	0.443	0.281
Dir (ME)	-0.034	-0.015	-0.020	-0.061	-0.127	-0.177	-0.246	-0.312	-0.358	-0.417	-0.481	-0.515	-0.512	-0.516	-0.536	0.288
K _v Cavallaro	-0.172	-0.216	-0.251	-0.301	-0.345	-0.366	-0.423	-0.464	-0.487	-0.515	-0.531	-0.540	-0.565	-0.595	-0.617	0.426
K _v Mendez	-0.023	-0.087	-0.117	-0.186	-0.254	-0.288	-0.330	-0.344	-0.354	-0.379	-0.396	-0.358	-0.324	-0.296	-0.283	0.268
K _v Maza_01	-0.298	-0.342	-0.302	-0.282	-0.301	-0.311	-0.306	-0.292	-0.288	-0.269	-0.215	-0.176	-0.152	-0.149	-0.149	0.255
K _v Maza_02	-0.289	-0.328	-0.286	-0.256	-0.273	-0.292	-0.296	-0.284	-0.263	-0.237	-0.203	-0.192	-0.196	-0.209	-0.219	0.255
T (ME)	0.033	0.055	0.045	0.019	-0.047	-0.111	-0.177	-0.247	-0.292	-0.348	-0.416	-0.462	-0.469	-0.475	-0.492	0.246
H _{b,Godá}	-0.027	-0.038	-0.034	-0.111	-0.182	-0.227	-0.270	-0.278	-0.290	-0.306	-0.343	-0.304	-0.265	-0.238	-0.214	0.208
Real density	0.330	0.318	0.307	0.268	0.216	0.206	0.183	0.135	0.097	0.090	0.116	0.121	0.114	0.106	0.126	0.182
Dir (MF)	0.009	0.022	0.058	0.064	0.013	-0.025	-0.087	-0.170	-0.225	-0.272	-0.289	-0.332	-0.368	-0.376	-0.372	0.179
Material density	-0.145	-0.142	-0.158	-0.133	-0.131	-0.117	-0.119	-0.126	-0.128	-0.154	-0.187	-0.223	-0.208	-0.189	-0.187	0.156
p (ME)	0.118	0.094	0.108	0.081	0.029	0.014	-0.033	-0.093	-0.134	-0.164	-0.181	-0.171	-0.205	-0.237	-0.233	0.126
p (MF)	0.142	0.112	0.108	0.126	0.168	0.193	0.175	0.163	0.154	0.131	0.116	0.095	0.059	0.037	0.017	0.120
H _o (MF)	0.020	0.042	0.061	0.089	0.065	0.023	0.022	0.038	0.048	0.028	-0.046	-0.082	-0.098	-0.096	-0.091	0.057

Figure 4 shows the absolute error for each of the profiles (sum in absolute value of the error in each point of the profile) and the mean value for the selected architecture [6–10–15] during training and test. The mean error is 0.22 m in training and 0.21 m in test, with a maximum of 0.74 m in the profile 183 in training (Alicante) and 0.52 m in the profile 405 in test (Murcia), and a minimum of 0.04 m in the profile 136 in training (Valencia) and 0.05 m in the profile 79 in test (Valencia). While in the Dean's and Aragonés' model the mean errors are 1.16 m and 0.49 m, reaching a maximum of 7.02 m in the profile 353 and 3.85 m in the profile 352, respectively. In Figure 4c, this same error for each of the studied beaches is displayed (average of the sum in absolute value of the error in each point of the profiles belonging to each beach). In the case of Valencia, the mean error is 0.12 m, the maximum error is 0.27 m in the beach 1. In the provinces of Alicante and Murcia, the error increases until 0.28 m. The maximum error is 6.30 m for Dean's formulation and 3.24 m for the Aragonés' model, producing on the beaches 82 and 81, respectively.

Figure 5 shows the MAPE and percentage relative error (δ) for each beach (see supplementary material 2 for errors in each of the profiles). The MAPE and the percentage relative error for training and test data sets are very similar. The mean MAPE is 9.5 for training data set, while for test data set the mean is 8.1%. The mean percentage relative error is 10.4% for training and 8.4% for test. By provinces the mean value of MAPE (for all profiles, training and tests data together) is 9.3%, being 6.6% in the province of Valencia, 11.2% in Alicante and Murcia. Four beaches are remarkable for having values over 20% (32, 33, 65 and 71). While for the models of Dean and Aragonés, the MAPE is tripled, with mean values of 20.0% and 14.3% in Valencia, 34.8% and 25.4% in Alicante, and 53.6% and 39.6% in Murcia, respectively. As for the percentage relative error, the mean values are 4.4%, 7.6% and 6.9% in Valencia,

1
2 351 Alicante and Murcia, respectively. If the data for each of the beaches (Figure 5) is
3
4 352 closely examined, it can be seen that only six beaches present values over 15%
5
6 353 (beaches 1, 2, 30, 35, 42 and 44). The percentage relative error for the Aragonés model
7
8 354 remains relatively low (28.5% in Valencia, 26.2% in Alicante and 14.2% in Murcia),
9
10 355 however for Dean's function this error shows large values above 1500% in some
11
12 356 beaches (average in Valencia 510.5%, in Alicante 259.3% and 57.8% in Murcia).
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

Figure 4. a) Absolute error (m) of each profile of the ANN [6–10–15] during training and, **b)** during test. **c)** Absolute error (m) on each beach of the ANN [6–10–15] ANN, Dean's function and Aragonés' model. (no color is needed)

Figure 5. MAPE (a) and δ (b) for beach [6–10–15]. (no color is needed)

5. Discussion

A key factor in a beach nourishment is the cross-shore beach profile, since it is used for the design of different elements: i) volume of sand required in beach nourishment (Davison, Nicholls, and Leatherman 1992; Hinton and Nicholls 1998; Stive et al. 1992; Hallermeier 1981), ii) design of coastal defence structures (Jiménez and Sánchez-Arcilla 1993), or iii) the calculation of the sedimentary balance (Capiobianco et al. 2002). However, most of the models or formulations proposed so far do not take into account the presence of marine biocenosis acting consolidating the ground and increasing the profile slope (among others). As a result, large volume errors are often committed when calculating the volume of sand needed in beach nourishment, or locating the coastal defence elements. Therefore, models must be more and more precise, and to achieve this, it is necessary to take into account all those local factors that can affect

1
2 375 the profile. The objective of this article is to check whether the inclusion of variables
3
4 376 related to marine vegetation (energy reduction coefficient or slope) improve the
5
6 377 results obtained by López, Aragonés, Villacampa, and Compañ (2017) when modelling
7
8 378 the transverse beach profile.
9

10
11 379 First, an analysis of linear correlations shows (Table 2) that the factors most correlated
12
13 380 with the cross-shore profile are those related to the waves perpendicular to the coast,
14
15 381 namely, the period, the wave height and the frequency ($R = 0.550, 0.549$ and 0.546 ,
16
17 382 respectively). Regarding sedimentology, most formulations concerning beach profile
18
19 383 are related to the median sediment size (D_{50}) (Kriebel, Kraus, and Larson 1991; Vellinga
20
21 384 1984; Dean 1991), which is also justified in this study, in which D_{50} is the one with the
22
23 385 greatest correlation among the sedimentological parameters studied ($R = 0.645$).
24
25 386 Finally, among the variables related with *Posidonia oceanica*, the slope and the
26
27 387 coefficient K_v obtained using data from Ecolavante (2006) and the parameters
28
29 388 proposed by Koftis and Prinos (2012), is the one that has a greater relation to the
30
31 389 profile, which agrees with the result obtained by Aragonés et al. (2017). Although they
32
33 390 do not show large correlations with the profile, if look at each of the studied points, it
34
35 391 can be seen that for the intermediate points ($125 < x < 250$ m) the correlations are
36
37 392 greater than 0.5. Therefore, it was decided to generate 60 neural networks (using
38
39 393 different input variables and numbers of neurons in the hidden layer), in order to
40
41 394 determine the individual influence of each of the variables, and choose the
42
43 395 combination that gives best results.
44
45
46
47
48
49

50
51 396 The results of R^2 (Figure 3) confirm the importance of *Posidonia oceanica* in the beach
52
53 397 profile, being the architecture [6-10-15] which offers the best results ($R^2=0.907\pm0.019$
54
55 398 for test and $R^2=0.901\pm0.019$ for training), with results 7.3% better than ANN 1 (López,
56
57
58
59
60

399 Aragonés, Villacampa, and Compañ (2017) model) which does not present any variable
400 related to *Posidonia*, and 5.3% better than ANN 2, which includes only the coefficient
401 K_v . Therefore, if this model were to be extrapolated to other study areas with the same
402 characteristics, it would only be necessary to check the optimal number of neurons in
403 the hidden layer to obtain the best results. However, it would not be necessary to
404 check the input variables, as the results are much better when using slope and K_v
405 coefficient.

406 On the other hand, for evaluating the performance of the model, various statistical
407 parameters were studied (Eq. 4, 5 and 6). By analysing these parameters, it was
408 observed that the neural network improves the results compared to actual models
409 (Dean and Aragonés). Thus, it was observed that the mean absolute error of the ANN
410 (for all profiles, training and test data together) is 81.2% and 55.5% lower than Dean
411 (0.22 m vs 1.16 m) and Aragonés (0.22 m vs. 0.49 m) models, respectively. The MAPE
412 and the percentage relative error also exhibit an improvement over the numerical
413 model of Aragonés; these errors were 64.0% and 71.3% lower. By analysing in detail
414 the errors, it could be seen that the greatest errors occur mainly on the beaches 30,
415 33, 42, 65, 81 and 102. After the study of the inputs used in the profiles of these
416 beaches (sediment, slope, morphology of the *Posidonia* meadow, etc.) no anomalous
417 value was observed or that stood out with respect to the average of values used in the
418 rest of the profiles (Table 3). However, these beaches presented the following
419 singularities: i) Beaches with important nourishments (Figure 6a and 6c), therefore,
420 perhaps the profile has not yet stabilized. ii) Beaches with rock reefs or islets in front of
421 their coasts so the bathymetry is considerably altered, and therefore also the profiles
422 are (Figure 6b and 6d). These kinds of profiles represent only 5.5% (23/418) of the
423 studied profiles, so the network is not able to learn effectively their singularities. In

order to correct this problem, there are two options: a) remove these profiles from the ANN, and b) increase the sample size of data by Monte-Carlo simulations or by perturbing the input by say 5/10 % or similar, however given the extent of the work this is left for future work. Nevertheless, the results obtained by the ANN in this area are lower than both Dean's formulation (72.7% absolute error, 65.4% MAPE and 88.3% percentage relative error) and Aragonés model (36.9% absolute error, 30.0% MAPE and 82.5% percentage relative error) (Figure 5). The improvement in the accuracy of the profile results in a smaller volume error when calculating the amount of sand needed in beach nourishment, and therefore a lower economic cost, about 5.3 – 9.8 €/m of beach (assuming a cost of 11.5 €/m³ (López, Aragonés, Villacampa, and Compañ 2017)). This cost savings certainly compensate the largest computational cost of the ANN versus the simplicity of the numerical models and the formulations.

Table 3. Average value and standard deviation of each of the variables studied and of the beaches with the greatest errors (30, 33, 42, 65, 81 and 102).

	D ₅₀	H _o (PC)	T (PC)	p (PC)	Kv	Slope
Average	0.326±0.272	3.01±0.88	11.0±1.9	0.2559±0.1400	0.819±0.226	0.017±0.010
30	0.338	1.90	8.3	0.1977	0.584	0.019
33	0.240	2.13	12.3	0.2200	0.616	0.008
42	0.242	1.99	8.7	0.2326	0.974	0.025
65	0.259	3.00	10.0	0.3095	0.409	0.013
81	0.313	2.41	12.5	0.1782	1.000	0.029
102	0.315	2.40	10	0.2197	0.844	0.030

Finally, the ANN developed here is not over-adjusted because, as can be seen from the results, the errors made during the training are very similar to those of the test. In addition, if the relationship between the number of data for training and the number of network parameters is analysed, a value of 52.2 is obtained that is much higher than the 5-20 value suggested in the literature to avoid overlearning (Hair et al. 2004). Furthermore, this ANN is based on the definition of the cross-shore beach profile in

445 fifteen points separate so that its characteristics are defined generally. However, given
 446 the good results provided by the network, if the profile was very irregular it could
 447 increase the number of points that define the profile to improve the accuracy,
 448 although this would increase the computation time, provided that the areas where the
 449 model is applied have the same characteristics as the area studied here. If the new
 450 area of application presents different characteristics, such as tides, it should be
 451 checked whether the model is valid or whether it would be improved by adding the
 452 new variable (tide).

453
 454 **Figure 6. a)** Poniente beach before and during the 1991 nourishment. **b)** Mojón beach with
 455 rock reefs. **c)** Portman beach with fillings from mining. **d)** Higuericas beach. (no color is
 456 needed)

6. Conclusions

458 For modelling the cross-shore profile of sand beaches with presence of *Posidonia*
 459 *oceanica*, different artificial neural networks were considered, with different input
 460 variables and different number of neurons in the hidden layer. The criterion for
 461 selection of the best model was getting the highest R^2 with the smallest dispersion of
 462 results in the 50 executions carried out for each model. Thus, it was found that the

network [6–10–15] offered the best results (for test $R^2 = 0.907 \pm 0.019$ and for training $R^2 = 0.901 \pm 0.019$), where the input variables were formed by D_{50} , H_o (PC), T (PC), p (PC), slope (m) and K_v Koftis.

From results it was observed that the mean absolute error committed by the ANN during test was 0.21 m (0.22 m for training) while the Dean formulation and the Aragonés model amounted to 1.16 m and 0.49 m, respectively. Also the MAPE and relative error rate values (for training 9.5% and 10.4% and for test 8.1% and 8.4%, respectively) are much lower in the network compared to the Dean formulation (65.4% and 88.3%, respectively) and Aragonés model (30.0% and 82.5%, respectively). In addition, the network offered better results in beaches with very particular singularities (large non-stabilized anthropic fills and points that alter the bathymetry as rock reefs or islets), although errors were high because these beaches only represent the 5.5% of the studied profiles and therefore the learning of these profiles by the network was complex. To improve the results, a greater number of profiles with similar characteristics or eliminate these singular beaches from the model would be necessary.

7. Acknowledgements

The authors want to thanks the Jefatura Provincial de Costas de Alicante and Organismo Público Puertos del Estado for the information provided has enabled this study.

This research has been partially funded by Universidad de Alicante through the project “Estudio sobre el perfil de equilibrio y la profundidad de cierre en playas de arena” (GRE15-02).

8. References

- Alvarez-Ellacuria, A, A Orfila, L Gómez-Pujol, G Simarro, and N Obregon. 2011. "Decoupling spatial and temporal patterns in short-term beach shoreline response to wave climate." *Geomorphology* no. 128 (3-4):199-208.
- Allen, James R. 1981. "Beach erosion as a function of variations in the sediment budget, Sandy Hook, New Jersey, U.S.A." *Earth Surface Processes and Landforms* no. 6 (2):139-150. doi: 10.1002/esp.3290060207.
- Aragonés, L., I. López, Y. Villacampa, and F. J. Navarro-González. 2017. "Using the presence of seagrass *Posidonia oceanica* to model the equilibrium profile parameter A of sandy beaches in Spain." *Journal of Coastal Research* no. 33 (3):642-652.
- Aragonés, L., J. C. Serra, Y. Villacampa, J. M. Saval, and H. Tinoco. 2016. "New methodology for describing the equilibrium beach profile applied to the Valencia's beaches." *Geomorphology* no. 259:1-11. doi: <http://dx.doi.org/10.1016/j.geomorph.2015.06.049>.
- Bernabeu, A. M., R. Medina, and C. Vidal. 2003. "Wave reflection on natural beaches: an equilibrium beach profile model." *Estuarine, Coastal and Shelf Science* no. 57 (4):577-585. doi: [http://dx.doi.org/10.1016/S0272-7714\(02\)00393-1](http://dx.doi.org/10.1016/S0272-7714(02)00393-1).
- Birkemeier, William A. 1985. "Field data on seaward limit of profile change." *Journal of waterway, port, coastal, and ocean engineering* no. 111 (3):598-602.
- Boon, J. D., and M. O. Green. 1988. Caribbean beachface slopes and beach equilibrium profiles. Paper read at 21st Conference on Coastal Engineering, at Torremolinos, Spain.
- Boudouresque, CF, and A Jeudy de Grissac. 1983. "L'herbier à *Posidonia oceanica* en Méditerranée: les interactions entre la plante et le sédiment." *Journal de recherche océanographique* no. 8 (2-3):99-122.
- Boudouresque, CF, A Meinesz, M Ledoyer, and P Vitiello. 1994. *Les herbiers à phanérogames marines, Les biocénoses marines et littorales de Méditerranée, synthèse, menaces et perspectives*.
- Bruun, P. 1954. Coast Erosion and the Development of Beach Profiles. In *Vicksburg: Beach Erosion Board Technical Memorandum*: U.S. Army Engineer Waterway.
- Capiobianco, M., H. Hanson, M. Larson, H. Steetzel, M. J. F. Stive, Y. Chatelus, and T. Karambas. 2002. "Nourishment design and evaluation: Applicability of model concepts." *Coastal Engineering* no. 47 ((2)):113-135.
- Cavallaro, Luca, Carlo Lo Re, Giovanni Paratore, Antonino Viviano, and Enrico Foti. 2011. Response of *Posidonia oceanica* to wave motion in shallow-waters-preliminary experimental results. Paper read at 32nd Conference on Coastal Engineering, at Shanghai, China.
- Chen, Jia-Lin, Tian-Jian Hsu, Fengyan Shi, Britt Raubenheimer, and Steve Elgar. 2015. "Hydrodynamic and sediment transport modeling of New River Inlet (NC) under the interaction of tides and waves." *Journal of Geophysical Research: Oceans* no. 120 (6):4028-4047. doi: 10.1002/2014jc010425.
- Davison, A.T., R.J. Nicholls, and S.P. Leatherman. 1992. "Beach nourishment as a coastal management tool: An annotated bibliography on developments associated with the artificial nourishment of beaches." *Journal Coastal Research* no. 8:984-1022.
- Dean, R. G. 1977. Equilibrium Beach Profiles: U.S. Atlantic and Gulf Coasts. Department of Civil Engineering. In *Ocean Engineering Technical Report*. Newark, Delaware.: University of Delaware.
- Dean, R.G. 1991. "Equilibrium beach profiles: characteristics and applications." *Journal of Coastal Research* no. 7 (1):53-84.
- Demirci, Mustafa, Fatih Üneş, and M. Sami Aköz. 2015. "Prediction of cross-shore sandbar volumes using neural network approach." *Journal of Marine Science and Technology* no. 20 (1):171-179. doi: 10.1007/s00773-014-0279-9.
- Ecolevante. 2006. *Estudio ecocartográfico del litoral de las provincias de Alicante y Valencia*: Dirección General de Costas, Ministerio de Medio Ambiente, Spain, [Available online: <http://www.mapama.gob.es/es/costas/temas/proteccion-costa/ecocartografias/ecocartografia-alicante.aspx>].

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

540 EcoMAG. 2009. *Estudio ecocartográfico de las provincias de Granada, Almería y Murcia.*:
541 Dirección General de Costas, Ministerio de Medio Ambiente, Spain [Available online:
542 <http://www.mapama.gob.es/es/costas/temas/proteccion->
543 [costa/ecocartografias/ecocartografia-murcia.aspx](http://www.mapama.gob.es/es/costas/temas/proteccion-costa/ecocartografias/ecocartografia-murcia.aspx)].
544 Fonseca, MARK S. 1996. "The role of seagrasses in nearshore sedimentary processes: a
545 review." *Estuarine Shores: Hydrological, Geomorphological and Ecological Interactions*.
546 Blackwell, Boston, MA:261-286.
547 Gacia, E., T. C. Granata, and C. M. Duarte. 1999. "An approach to the measurement of particle
548 flux and sediment retention within seagrass (*Posidonia oceanica*) meadows." *Aquatic*
549 *Botany* no. 65:255–268.
550 Gacia, Esperança, and Carlos M Duarte. 2001. "Sediment Retention by a Mediterranean
551 *Posidonia oceanica* Meadow: The Balance between Deposition and Resuspension."
552 *Estuarine, Coastal and Shelf Science* no. 52 (4):505-514.
553 Gambi, MC, MC Buia, E Casola, and M Scardi. 1989. Estimates of water movement in *Posidonia*
554 *oceanica* beds: a first approach. Paper read at International workshop on *Posidonia*
555 beds.
556 Ghorbani, Mohammad Ali, Rahman Khatibi, Ali Aytek, Oleg Makarynsky, and Jalal Shiri. 2010.
557 "Sea water level forecasting using genetic programming and comparing the
558 performance with artificial neural networks." *Computers & Geosciences* no. 36 (5):620-
559 627.
560 Goda, Yoshimi. 2010. "Reanalysis of regular and random breaking waves statistics." *Coastal*
561 *Engineering Journal* no. 52 (01):71-106. doi: 10.1142/s0578563410002129.
562 Gómez-Pujol, Lluís, Alejandro Orfila, Amaya Álvarez-Ellacuría, Jorge Terrados, and Joaquin
563 Tintoré. 2013. "Posidonia oceanica beach-cast litter in Mediterranean beaches: a
564 coastal videomonitoring study." *Journal of Coastal Research* no. 65 (sp2):1768-1773.
565 Hair, Joseph F, William C Black, Barry J Babin, Rolph E Anderson, and Ronald L Tatham. 2004.
566 *Multivariate data analysis*. Vol. 5: Prentice hall Upper Saddle River, NJ.
567 Hallermeier, R. J. 1981. "A profile zonation for seasonal sand beaches from wave climate."
568 *Coastal Engineering* no. 4 (3):253-277.
569 Hashemi, M. R., Z. Ghadampour, and S. P. Neill. 2010. "Using an artificial neural network to
570 model seasonal changes in beach profiles." *Ocean Engineering* no. 37 (14–15):1345-
571 1356. doi: <http://dx.doi.org/10.1016/j.oceaneng.2010.07.004>.
572 Hinton, C., and R. J. Nicholls. 1998. "Spatial and temporal behaviour of depth of closure along
573 the Holland coast." *Proceedings of 26th International Conference on Coastal*
574 *Engineering, ASCE*:2913-2925.
575 Huang, Wenrui, Catherine Murray, Nicholas Kraus, and Julie Rosati. 2003. "Development of a
576 regional neural network for coastal water level predictions." *Ocean Engineering* no. 30
577 (17):2275-2295.
578 Iglesias, G, I López, A Castro, and R Carballo. 2009. "Neural network modelling of planform
579 geometry of headland-bay beaches." *Geomorphology* no. 103 (4):577-587.
580 Análisis Matemático y Estadístico de Variables Medioambientales (AMEVA), Cantabria, Spain.
581 Available online: <http://ihameva.ihcantabria.com/>.
582 Jiménez, J. A., and A. Sánchez-Arcilla. 1993. "Medium-term coastal response at the Ebro Delta,
583 Spain." *Marine Geology* no. 114(1):105-118.
584 Keshtpoor, Mohammad, Jack A. Puleo, Fengyan Shi, and Nicholas R. DiCosmo. 2015.
585 "Numerical Simulation of Nearshore Hydrodynamics and Sediment Transport
586 Downdrift of a Tidal Inlet." *Journal of Waterway, Port, Coastal, and Ocean Engineering*
587 no. 141 (2):04014035. doi: doi:10.1061/(ASCE)WW.1943-5460.0000273.
588 Koftis, Theoharris, and Panayotis Prinos. 2012. "Estimation of wave attenuation over *Posidonia*
589 *Oceanica*." *Mitteilungen des Lehrstuhls und Instituts für Wasserbau und*
590 *Wasserwirtschaft der Rheinisch-Westfälischen Technischen Hochschule Aachen* no.
591 165.
592 Kriebel, David L, Nicholas C Kraus, and Magnus Larson. 1991. Engineering methods for
593 predicting beach profile response. Paper read at Coastal Sediments (1991).

- Larson, M., and N Kraus. 1995. "Prediction of cross-shore sediment transport at different spatial and temporal scales." *Marine Geology* no. 126 (1):111-127.
- López, Isabel, L. Aragonés, Y. Villacampa, and P. Compañ. 2017. "Artificial neural network modeling of cross-shore profile on sand beaches: The coast of the province of Valencia (Spain)." *Marine Georesources & Geotechnology*:1-11. doi: 10.1080/1064119x.2017.1385666.
- López, Isabel, Luis Aragonés, Yolanda Villacampa, and José C. Serra. 2017. "Neural network for determining the characteristic points of the bars." *Ocean Engineering* no. 136:141-151. doi: <https://doi.org/10.1016/j.oceaneng.2017.03.033>.
- López, M., I. López, L. Aragonés, J. C. Serra, and V. Esteban. 2016. "The erosion on the east coast of Spain: Wear of particles, mineral composition, carbonates and *Posidonia oceanica*." *Science of The Total Environment* no. 572:487-497. doi: <https://doi.org/10.1016/j.scitotenv.2016.08.076>.
- Manca, E, I Cáceres, JM Alsina, Vicky Stratigaki, I Townend, and CL Amos. 2012. "Wave energy and wave-induced flow reduction by full-scale model *Posidonia oceanica* seagrass." *Continental Shelf Research* no. 50:100-116.
- Masselink, Gerhard, and Ling Li. 2001. "The role of swash infiltration in determining the beachface gradient: a numerical study." *Marine Geology* no. 176 (1-4):139-156. doi: [http://dx.doi.org/10.1016/S0025-3227\(01\)00161-X](http://dx.doi.org/10.1016/S0025-3227(01)00161-X).
- Maza, Maria, Javier L. Lara, and Inigo J. Losada. 2013. "A coupled model of submerged vegetation under oscillatory flow using Navier–Stokes equations." *Coastal Engineering* no. 80 (0):16-34. doi: <http://dx.doi.org/10.1016/j.coastaleng.2013.04.009>.
- Medina, J. R., Joaquín Tintore, and Carlos M Duarte. 2001. "Praderas de *Posidonia oceánica* y la regeneración de playas." *Revista de Obras Públicas* no. 3.409:31-43.
- Mendez, Fernando J, and Inigo J Losada. 2004. "An empirical model to estimate the propagation of random breaking and nonbreaking waves over vegetation fields." *Coastal Engineering* no. 51 (2):103-118.
- Méndez, Fernando J, Iñigo J. Losada, and Miguel A. Losada. 1999. "Hydrodynamics induced by wind waves in a vegetation field." *Journal of Geophysical Research: Oceans* no. 104 (C8):18383-18396. doi: 10.1029/1999jc900119.
- Muñoz-Perez, J. J., and R. Medina. 2010. "Comparison of long-, medium- and short-term variations of beach profiles with and without submerged geological control." *Coastal Engineering* no. 57 (3):241-251. doi: <http://dx.doi.org/10.1016/j.coastaleng.2009.09.011>.
- Neill, Simon P., Alan J. Elliott, and Mohammad R. Hashemi. 2008. "A model of inter-annual variability in beach levels." *Continental Shelf Research* no. 28 (14):1769-1781. doi: <http://dx.doi.org/10.1016/j.csr.2008.04.004>.
- Pasqualini, V., C. Pergent-Martini, P. Clabaut, and G. Pergent. 1998. "Mapping of *Posidonia oceanica* causing Aerial Photographs and Side Scan Sonar: Application off the Island of Corsica (France)." *Estuarine, Coastal and Shelf Science* no. 47 (3):359-367. doi: <https://doi.org/10.1006/ecss.1998.0361>.
- Pergent-Martini, C., V. Leoni, V. Pasqualini, G. D. Ardizzone, E. Balestri, R. Bedini, A. Belluscio, T. Belsher, J. A. Borg, C. F. Boudouresque, S. Boumaza, J. M. Bouqueneau, M. C. Buia, S. Calvo, J. Cebrian, E. Charbonnel, Cossu A. Cinelli F, Di Maida G., B. Dural, P. Francour, S. Gobert, G. Lepoint, A. Meinesz, H. Molenaar, H. M. Mansour, P. Panayotidis, A. Peirano, G. Pergent, L. Piazzzi, M. Pirrotta, G. Relini, J. Romero, J. L. Sanchez Lizaso, R. Semroud, P. J. Schembri, A. Shili, A. Tomasello, and B. Velimirov. 2005. "Descriptors of *Posidonia oceanica* meadows: Use and application." *Ecological Indicators*:213-230.
- Pranzini, Enzo, Lilian Wetzel, and Allan T. Williams. 2015. "Aspects of coastal erosion and protection in Europe." *Journal of Coastal Conservation* no. 19 (4):445-459. doi: 10.1007/s11852-015-0399-3.
- Ranasinghe, Roshanka, Graham Symonds, Kerry Black, and Rob Holman. 2004. "Morphodynamics of intermediate beaches: a video imaging and numerical modelling

study." *Coastal Engineering* no. 51 (7):629-655. doi:
http://dx.doi.org/10.1016/j.coastaleng.2004.07.018.

ROM_0.3-91. 1991. Recommendation for Marine Works, Climate Action: Swell. Madrid, Spain: Puertos del Estado, Ministerio de Fomento.

Román-Sierra, Jorge, Juan j Muñoz-perez, and Marina Navarro-Pons. 2013. "Influence of sieving time on the efficiency and accuracy of grain-size analysis of beach and dune sands." *Sedimentology* no. 60 (6):1484-1497. doi: 10.1111/sed.12040.

Sedigh, Mahnaz, Rodger Tomlinson, Nick Cartwright, and Amir Etemad-Shahidi. 2016. "Numerical modelling of the Gold Coast Seaway area hydrodynamics and littoral drift." *Ocean Engineering* no. 121:47-61. doi: https://doi.org/10.1016/j.oceaneng.2016.05.002.

Semeoshenkova, Vera, and Alice Newton. 2015. "Overview of erosion and beach quality issues in three Southern European countries: Portugal, Spain and Italy." *Ocean & Coastal Management* no. 118:12-21. doi: https://doi.org/10.1016/j.ocecoaman.2015.08.013.

Stive, Marcel J. F., H. J. de Vriend, R. J. Nicholls, and M. (1993) Capobianco. 1992. Shore nourishment and the active zone: A time scale dependent view. Paper read at Proceedings of the 23rd Coastal Engineering Conference, at Venice, Italy.

Stive, Marcel J. F., and Huib J. de Vriend. 1995. "Modelling shoreface profile evolution." *Marine Geology* no. 126 (1-4):235-248. doi: http://dx.doi.org/10.1016/0025-3227(95)00080-I.

Syvitski, James PM. 2007. *Principles, methods and application of particle size analysis*. Edited by James PM Syvitski. Cambridge, UK: Cambridge University Press.

Terrados, Jorge, and Carlos M Duarte. 2000. "Experimental evidence of reduced particle resuspension within a seagrass *Posidonia oceanica* meadow." *Journal of Experimental Marine Biology and Ecology* no. 243 (1):45-53.

Vacchi, Matteo, Giovanni De Falco, Simone Simeone, Monica Montefalcone, Carla Morri, Marco Ferrari, and Carlo Nike Bianchi. 2017. "Biogeomorphology of the Mediterranean *Posidonia oceanica* seagrass meadows." *Earth Surface Processes and Landforms* no. 42 (1):42-54.

van Rijn, L. C., D. J. R. Walstra, B. Grasmeijer, J. Sutherland, S. Pan, and J. P. Sierra. 2003. "The predictability of cross-shore bed evolution of sandy beaches at the time scale of storms and seasons using process-based Profile models." *Coastal Engineering* no. 47 (3):295-327. doi: http://dx.doi.org/10.1016/S0378-3839(02)00120-5.

Vellinga, P. 1984. "A tentative description of a universal erosion profile for sandy beaches and rock beaches." *Coastal Engineering* no. 8 (2):177-188. doi: http://dx.doi.org/10.1016/0378-3839(84)90012-7.

Vellinga, Pier. 1983. "Predictive computational model for beach and dune erosion during storm surges." *Delft Hydraulics Laboratory*.

Wang, Q.H. 2004. "Improvement on BP algorithm in artificial neural network." *Journal of Qinghai University* no. 22 (3):82-84.