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Zaimes, George N, Gounaridis, Dimitrios and Symeonakis, Elias (2019) Assessing the impact of dams on riparian and deltaic vegetation using remotely-sensed vegetation indices and Random Forests modelling. *Ecological Indicators*, 103. pp. 630-641. ISSN 1470-160X

DOI: <https://doi.org/10.1016/j.ecolind.2019.04.047>

Publisher: Elsevier BV

Version: Accepted Version

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Assessing the impact of dams on riparian and deltaic vegetation using remotely-sensed vegetation indices and Random Forests modelling

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Abstract: Riparian and deltaic areas exhibit a high biodiversity and offer a number of ecosystem services but are often degraded by human activities. Dams, for example, alter the hydrologic and sediment regimes of rivers and can negatively affect riparian areas and deltas. In order to sustainably manage these ecosystems, it is, therefore, essential to assess and monitor the impacts of dams. To this end, site-assessments and in-situ measurements have commonly been used in the past, but these can be laborious, resource demanding and time consuming. Here, we investigated the impact of three dams on the riparian forest of the Nestos River Delta in Greece by employing multi-temporal satellite data. We assessed the evolution in the values of eight vegetation indices over 27 years, derived from 14 dates of Landsat data. We also employed a modelling approach, using a machine learning Random Forests model, to investigate potential linkages between the observed changes in the indices and a host of climatic and topographic parameters. Our results show that low density vegetation (0-25%) is more affected by the construction of the dams due to its proximity to anthropogenic influences and the effects of hydrologic regime alteration. In contrast, higher density vegetation cover (50-75%) appears to be largely unaffected, or even improving, due to its proximity to the river, while vegetation with intermediate coverage (25-49%) exhibits no clear trend in the Landsat-derived indices. The Random Forests model found that the most important parameters for the riparian vegetation (based on the Mean Decrease Gini and the Mean Decrease Accuracy) were the distance to the dams, the sea

29 and the river. Our results suggest that management plans of riparian and deltaic areas need to
30 incorporate and take into consideration new innovative management practices and monitoring studies
31 that employ multi-temporal satellite data archives.

32 **Keywords:** remote sensing, vegetation alterations, Landsat images, anthropogenic impacts, riparian
33 forest

34 **1. Introduction**

35 Riparian and deltaic areas are unique in that they are both semi-aquatic and ecotones: transition
36 zones between terrestrial and aquatic ecosystems (Naiman et al., 2005). Both ecosystems are
37 disturbance-driven, with frequent flood and drought cycles, a greater soil water availability and higher
38 water table year around, which leads to the presence of tall and dense hydrophyllic vegetation and
39 represent a nexus of high biodiversity and increased ecosystem services (Sabo et al., 2005; Zaimes et
40 al., 2011a).

41 Approximately 25% of the world's population lives on deltaic coastlines and wetlands with this
42 percentage expected to increase in the future (Syvitski et al., 2005), which means that anthropogenic
43 activities will continue to alter them (Corbacho et al., 2003). The numerous threats they face, along
44 with the many ecosystem services they offer, have led to their protection status by the Ramsar
45 Convention (Ramsar, 2009) and the Natura 2000 Network (European Commission, 2007); their
46 conservation or re-establishment, especially in human-modified environments, has become a
47 worldwide priority (National Research Council, 2002).

48 The riparian and deltaic ecosystems are created, structured, maintained or destroyed by stream
49 water and the solutes and sediments (Naiman et al., 2005). Attempts to regulate the natural flow
50 regimes have direct effects on this equilibrium and consequently on the stream, river, adjacent
51 riparian areas and deltas. Dams regulate natural flow regimes and trap sediment, thus changing the
52 historical channel dynamics, fluvial geomorphology and vegetation disturbances downstream (Dunne
53 and Leopold, 1978; Simons and Li, 1980; Williams and Wolman, 1984; Chien, 1995; Brandt, 2000;
54 Shields et al., 2000). In most cases, these changes have major consequences on riparian vegetation
55 species, spatial and temporal structures and distributions (Williams and Wolman, 1984; Merritt and
56 Cooper, 2000; Shafroth et al., 2002; Zahar et al., 2008). In the Mediterranean region, rivers have
57 suffered a significant reduction in freshwater discharge with dam constructions one of the main
58 reasons (Ludwig et al., 2009). Consequently, the significant changes in the riparian vegetation
59 recorded in Mijares River, Spain and Avia, Homem and Lima Rivers in Portugal (Garófano-Gómez

60 et al., 2013; Aguiar et al., 2016) and the coastal erosion and delta degradation in the Po Delta in Italy
61 and Nile Delta in Egypt (Simeoni and Corbau, 2009; Stanley and Clemente, 2017) are to be expected.

62 The increases in extreme weather events due to climate change, particularly increased rainfall
63 intensity and extended drought periods compared to past conditions, should lead to higher surface
64 runoff and streamflows, higher sediment transport capacity and increased soil erosion (Giupponi and
65 Shechter, 2003). These changes in the hydrologic regimes should also impacts the process and
66 functionality of the riparian and deltaic ecosystems. In addition, the coastal areas where almost all
67 major deltas are located, face the adverse consequences of climate change such as coastal erosion and
68 sea-level rise that are expected to further degrade them (Blum et al., 2000; Nicholls et al., 2007).

69 To evaluate and monitor the impacts of anthropogenic activities on vegetation condition, site-
70 assessments and in-situ measurements have traditionally been undertaken (Parkes et al., 2003;
71 Gibbons and Freudenberger, 2006). These types of approaches can be laborious, resource demanding
72 and time consuming, especially when examining large areas (Garófano-Gómez et al., 2011).
73 Moreover, traditional approaches relying on field measurements are limited by topographic and
74 climatic conditions, as well as accessibility to remote areas. The technological advancements in the
75 field of Earth Observation (EO), has contributed to the widespread use of satellite remote sensing
76 approaches in the monitoring of the Earth's surface (Coppin et al., 2004; Rozenstein and Karnieli,
77 2011) including mapping and monitoring indicators of vegetation condition (Lausch et al. 2017;
78 Newell et al., 2006; Sheffield, 2006; Wallace et al., 2006). The increase is due to the more readily
79 available satellite data (Belward and Skøien, 2014) that can facilitate the growing demand for multi-
80 spectral and multi-temporal information over a wide range of spatial and temporal scales and data
81 types (e.g. Hansen et al., 2013; Zeng et al., 2008; Bellone et al., 2009; Zhu and Woodcock, 2013).

82 With the Landsat program running for more than four decades now, medium spatial resolution
83 satellite images have been widely used for monitoring land cover and associated changes (Hansen
84 and Loveland, 2012). These data have several advantages with the most prominent being the opening
85 of the Landsat archive in 2008, offering readily available data at no cost and making it the most cost-
86 effective option for studies that span decades and cover large extents (Wulder et al., 2012). The use
87 of remote sensing for assessing ecological properties of vegetation has been reviewed
88 comprehensively (Nagendra, 2001; Kerr and Ostrovsky, 2003; Turner et al., 2003; Gillespie et al.,
89 2008; Asner and Martin, 2009; Ustin and Gamon, 2010; Schimel et al., 2013). Commonly, vegetation
90 indices are used as proxies in the analysis of temporal trends in vegetation condition (Kerr and
91 Ostrovsky, 2003; Pettorelli et al. 2005; Higginbottom and Symeonakis, 2014). Vegetation indices

have been also used for riparian areas (Alphan, 2013; Carle and Sasser 2016; Wilson et al., 2016; Yang et al., 2018) and could be important tools for their sustainable management.

Prediction models can be used to explore the correlation between changes in vegetation condition and other environmental variables. Random Forests (Breiman, 2001) is a modelling framework that has been used, in combination with several environmental and climatic variables, for coastal and riparian vegetation studies to assess candidate bioindicators for ecological quality (Cortes et al., 2013), to assess and quantify riparian quality (Fernández et al., 2014) and species dynamics (Harper et al. 2011), to classify riparian vegetation (Chignell et al. 2017; Hayes et al., 2014; Nguyen et al. 2019; Tulbure et al. 2016; Woodward et al. 2018), to determine the wetland plant indices of biological integrity (Jones et al., 2016), and to assess the condition of freshwater wetlands (Miller et al., 2016).

The riparian vegetation of deltaic areas is the result of fluvio-deltaic and marine sedimentation processes (Trincardi et al., 2005), and therefore, climatic, sedimentary and tectonic processes (Overeem, 2005), along with natural and human-driven changes (Syvitski and Saito, 2007), are important for their formation conservation and functionality. Within this context, this study aims to investigate the impact of the dam constructions on riparian and deltaic vegetation along the Nestos Delta in Greece. It is hypothesized that since riparian and deltaic areas are dynamic, disturbance-driven ecosystems (e.g. affected by floods and droughts), any change from regulating or altering the natural flow and sediment regime would have a direct effect on the riparian and deltaic vegetation dynamics. A multi-temporal analysis is undertaken with data of eight Landsat-derived vegetation indices that span 27 years in order to capture the evolution of the spectral indices before and after the construction of the dams. The effect of the dams construction on the vegetation is also assessed with a modelling exercise (Random Forests) that was carried out to explore any associations between the changes observed in the vegetation indices and a suite of climatic and spatial variables. Models are tools that abstractly replicate complex interactions and nonlinear relationships, which are prevalent in heterogenous ecosystems, such as riparian. These tools are able to characterize parts of the complexity and delineate the factors of differing importance.

2. Material and methods

2.1 Study site

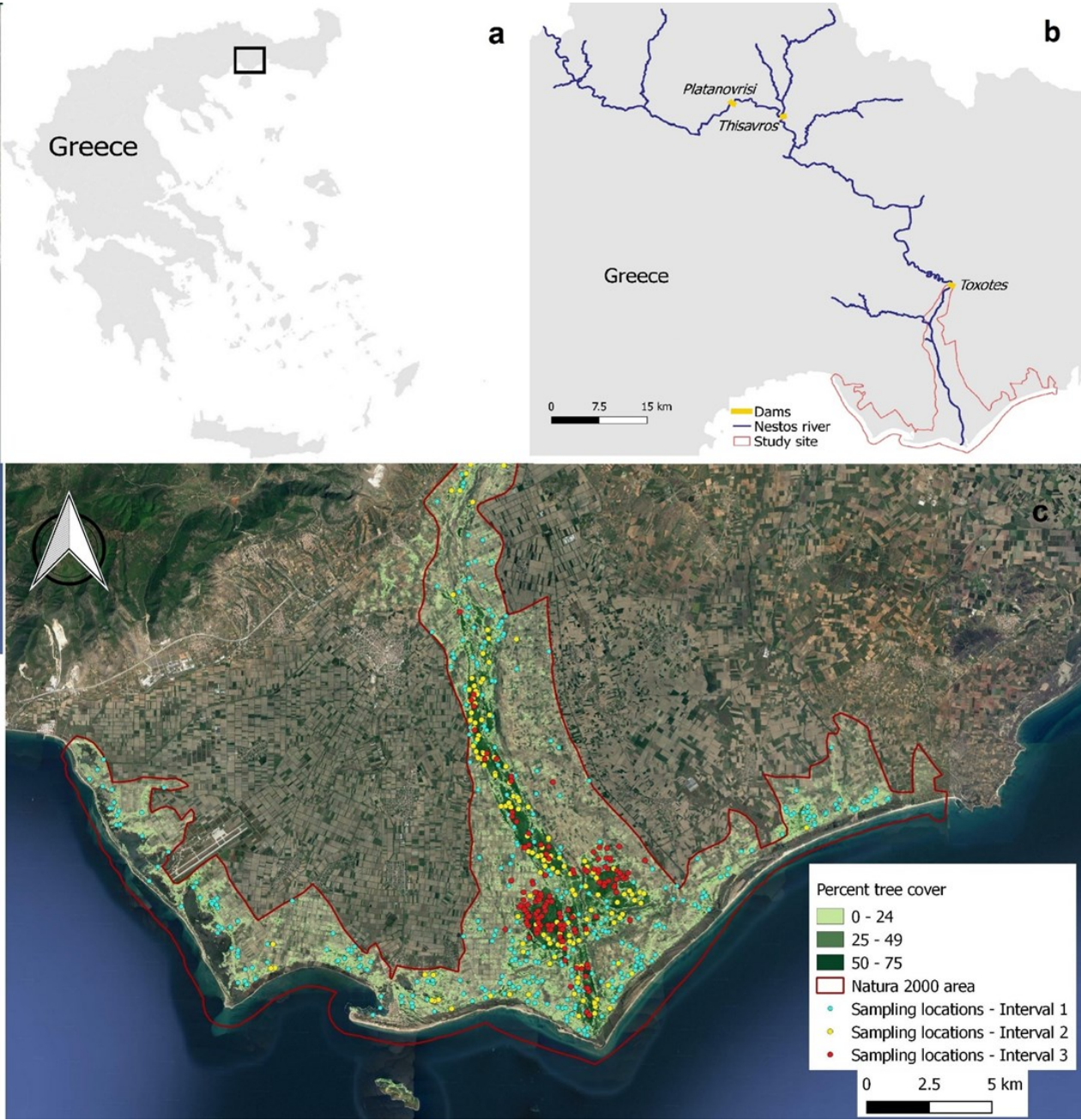
The riparian forest of the Nestos Delta (Figure 1) was one of the biggest in the Mediterranean (Sylaios and Kamidis, 2018). In the last century it has experienced significant Land-use Land-Change (LULC) transitions (Mallinis et al., 2011; Zaimes et al., 2011b). In the 1920s, it covered about 12,000

124 ha and was reduced to 7,000 ha in the 1940s, while today it covers only 800 ha. The forested area
125 was gradually converted to farmland after the 1930s while the river channels were straightened, and
126 dykes were constructed. In the 1970s, a significant policy change occurred, and legislation was passed
127 to protect the Delta and so its degradation was halted. Despite its significantly reduced area, the
128 Nestos Delta still hosts one of the most unique and highly ecologically significant riparian forests in
129 the Mediterranean region (Sylaios and Kamidis, 2018). It hosts four natural riparian forest habitat
130 types, as described in Annex I of Directive 92/43/EEC: a) a residual alluvial forest (*Alnionglutinoso-*
131 *incanae*); b) a mixed oak-elm-ash forest of great rivers; c) *Salix alba* and *Populus alba* gallery, and
132 d) a thermo-Mediterranean riparian gallery (*Nerio-Tamariceteae*) and south-west Iberian Peninsula
133 riparian gallery (*Securinegiontinctoriae*). The complexity and rare vegetation of the riparian forests
134 provides an excellent habitat for rare aquatic birds to breed and for migrating species to rest. The
135 Delta hosts 307 different bird species (34 of which are endangered based on the IUCN Red book), as
136 well as many species of mammals, reptiles and insects (Mallinis et al., 2011). This is why the Nestos
137 Delta is protected at the national, EU and international level¹.

138 While the entire Delta is in Greece the Nestos/Mesta River is transboundary. Specifically, the river's
139 length is 234 km (130 km in Greece) as it starts in the Rila Mountain of Bulgaria and ends in the
140 Aegean Sea on Greece (Ganoulis et al., 2008; Samaras and Koutitas, 2008). An international treaty
141 on the water use between Greece and Bulgaria in 1995 has entitled Greece with 29% of Nestos waters
142 (Mylopoulos et al., 2004). The main river and many of the tributaries of the Nestos River are used for
143 hydroelectricity, irrigation and eco-tourism. The Nestos Basin is mostly mountainous, while its
144 alluvial plain represents 18.2% of the total basin area and is cultivated by arable crops and includes
145 the Nestos Delta. The main crops grown are soft wheat (*Triticum aestivum*), durum wheat (*Triticum*
146 *durum*), sugar beet (*Beta vulgaris*), cotton (*Gossypium herbaceum*), rice (*Oryza sativa*), barley
147 (*Hordeum vulgare*), maize (*Zea mays*), asparagus (*Asparagus officinalis*), alfalfa (*Medicago sativa*)
148 and tobacco (*Nicotiana* spp). The Delta also has some of the most productive fish farms in Greece.
149 The largest urban area is the city of Chrisoupoli with approximately 8,000 people (Papachristou et
150 al., 2000). During periods of high streamflow, the channel width in the plain areas can reach up to 20
151 m, while the sandy bed of the river changes constantly. Finally, the minimum flow arriving to the
152 Delta was established legally at 6 m³/s.

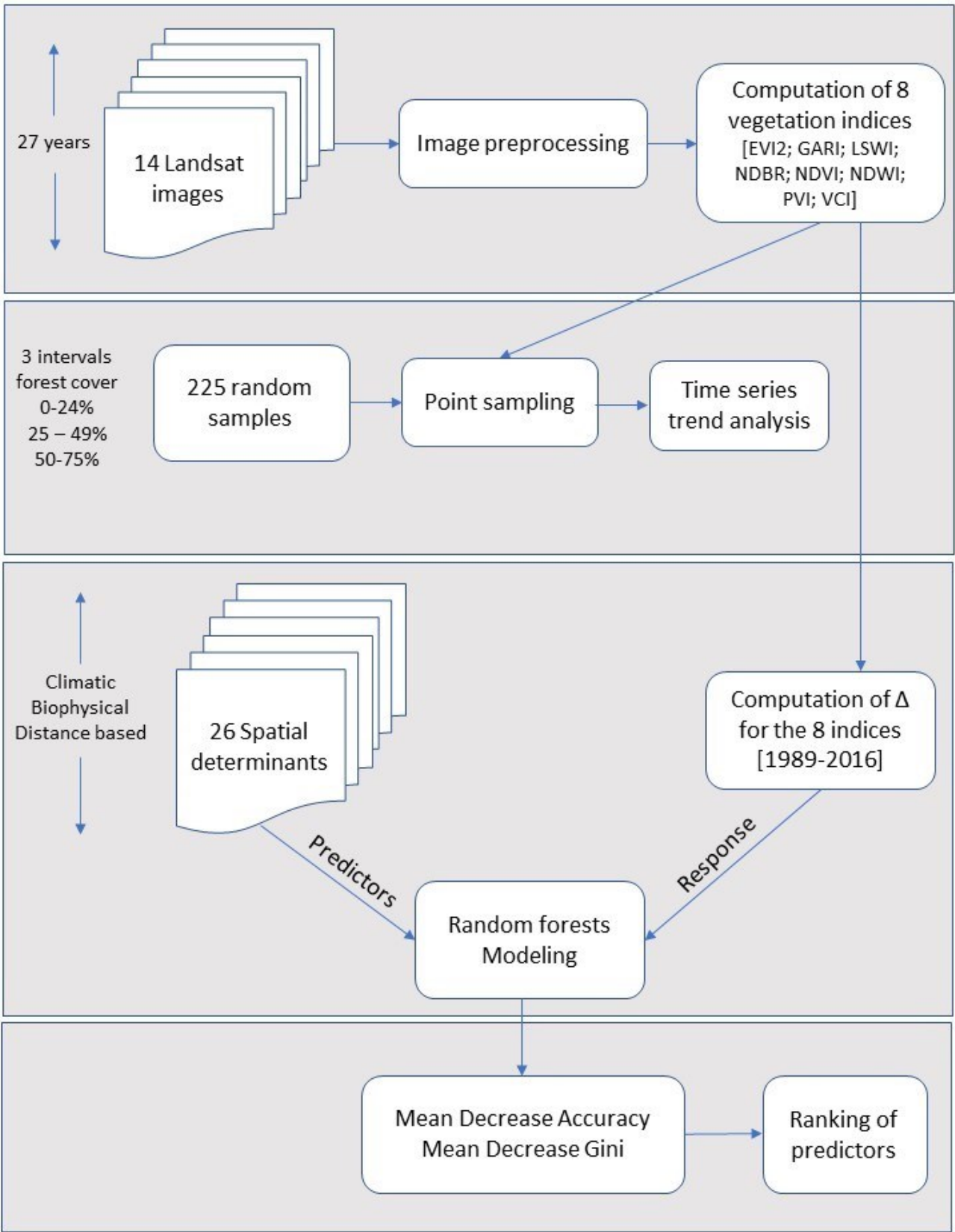
¹ The Delta is protected as: a) "Nestos Delta and adjacent lagoons" - Wetland of International Importance (Ramsar Convention); b) "Nestos Delta, Keramoti lagoons and island Thasopoula" - Special Protection Area (GR 1150001, Natura 2000 Network); c) "Nestos Delta, Keramoti Lagoons - surrounding region and coastal area" - Special Areas for Conservation (GR 1150010, Natura 2000 Network), d) Nestos Forest "Kotza Orman" - Wildlife Refuge, and e) Nestos Delta wetlands, Lake Vistonida with lagoonal and lacustrine features, Lake Ismarida and the wider region - National Park with Regional zone (JMD 44549/2008, Official Gazette 497/A/ 17-10-2008).

153 Of major importance for the functionality of the Delta, are two major hydropower dams, and a
 154 minor irrigation dam, located 30 km upstream from its mouth. The Platanovryssi hydropower dam
 155 that has been operating since 1997 has a height of 95 m and its reservoir capacity is 57,000,000 m³.
 156 Upstream is the Thissavros dam that has been operating since 1999, has a height of 172 m and a
 157 reservoir capacity of 705,000,000 m³. Finally, the Toxotes dam serves the irrigation network of the
 158 region and consists of two channels which distribute water to the east (11 m³/s) and west (9 m³/s)
 159 sections of the plain (Kamidis, 2011) (Figure 1).



161 Figure 1: Location of the study area, a) within Greece, b) the Nestos river and location of the three dams and
 162 c) the sampling locations.

165 The sequence of methodologies followed are depicted in detail in Figure 2.



166

167

Figure 2: Flowchart of the methodological steps followed throughout the study.

2.2.1 Evolution of vegetation indices

A total of 14 Landsat images (SM Table 1) spanning 27 years from 1989 to 2016 were acquired for the time series analysis. The acquisition strategy was designed in a way that met certain quality standards, namely, to have no cloud cover during the summer months (June, July, August), to avoid, as much as possible, phenological variation, and to exclude imagery with the scan line corrector malfunctioning of Landsat 7 ETM+ after 2003. The criteria led us to end up with images from three different sensors of Landsat with a spatial resolution of 30m.

Since our study involved spectral indices, the images needed to be corrected radiometrically and normalized atmospherically in order to avoid any discrepancies due to the multi-temporal and double-sensor type of analysis (Song et al. 2001). Following the approach implemented by Gounaridis et al. (2014), the first step was to convert the DN numbers into top-of-atmosphere reflectance using the dark-object subtraction method (Chavez, 1988). To obtain surface reflectance and achieve data normalization, we applied the 6S model originally introduced by Vermote et al. (1997). Topographic correction was not performed since the study area is a plain (elevation differences less than 20 m).

Eight spectral indices were selected to represent a range of spectral responses of vegetation condition over the study period (Table 1). This included the two-band version of the enhanced Vegetation Index (EVI2), which is a broadly used index for vegetation monitoring. This two-band version does not take into account the reflectance in the blue band and, in general, is preferred when the data are atmospherically corrected (Jiang et al., 2007). Complementary to EVI2, we also include the Normalized Difference Vegetation Index (NDVI), the modified Normalized Difference Water Index (NDWI), the Green Atmospherically Resistant Index (GARI) and the Normalized Difference Burning Ratio (NDBR), which are often used for monitoring forest disturbance (Hermosilla et al., 2015; Jarron et al., 2016). These indices take into account the shortwave infrared (SWIR) part of the wavelength, which is sensitive to moisture conditions that are important for the riparian vegetation. Similar to the modified NDWI, is the Land Surface Water Index (LSWI), which involves a band combination based on the SWIR part of the wavelength and appears to be useful in extracting the vegetation water status in the canopies (Chandrasekar et al. 2010). In addition, we included the Vegetation Condition Index (VCI), which is derived from an equation involving the minimum and maximum values of the NDVI. This index is often used to reflect relative changes in the moisture condition of vegetation and the values correspond to vegetation health and levels of stress (Pei et al., 2018). Finally, we also included the Perpendicular Vegetation Index (PVI), which is mainly used for the assessment of surface vegetation parameters, such as chlorophyll content, reducing the

disturbance of the soil background when extracting vegetation signals from multispectral bands (Richardson and Wiegand, 1987).

The evolution of the eight vegetation indices over the study period were captured at 573 random samples dispersed across the riparian forest of the Delta. We opted to split the initial sampling locations into three intervals according to the percentage of tree coverage (Figure 1). The three intervals were chosen based on the Global Forest Change Product (Hansen et al., 2013). Therefore, we allocated 299 random samples to areas with tree coverage between 0% and 24%, 150 random samples to areas with tree coverage between 25% and 49% and 124 samples to areas with tree coverage between 50% and 75% (which is the maximum tree coverage found in the area). The values of the eight vegetation indices for each of the 14 dates (SM Table 1) were sampled on the location of every training point.

Table 1. The eight Landsat-based vegetation indices used in this study

Abbreviation	Index name	Formula	Range	Reference
EVI 2	2 band Enhanced Vegetation Index (EVI)	$EVI2 = 2.5 * (NIR - RED) / (NIR + 2.4 * RED + 1.0)$	-1 to 1	Jiang et al. 2007
GARI	Green Atmospherically Resistant vegetation Index	$GARI = (NIR - (GREEN - (BLUE - RED))) / (NIR + (GREEN - (BLUE - RED)))$	-1 to 1	Gitelson et al. 1996
LSWI	Land Surface Water Index	$LSWI = (NNIR - SWIR) / (NIR + SWIR)$	-1 to 1	Chandrasekar et al. 2010
NDBR	Normalized Difference Burning Ratio	$NDBR = (NIR - SWIR) / (NIR + SWIR)$	-1 to 1	Key et al. 2002
NDVI	Normalized Difference Vegetation Index	$MDVI = (NIR - RED) / (NIR + RED)$	-1 to 1	Tucker, 1979
NDWI	Normalized Difference Water Index	$NDWI = (GREEN - NIR) / (GREEN + NIR)$	-1 to 1	Gao, 1996
PVI	Perpendicular Vegetation Index	$PVI = (NIR - \alpha RED - b) / (1 + \alpha^2)$ where $NIR = \alpha RED + b$	>0	Richardson and Wiegand, 1977
VCI	Vegetation Condition Index	$(NDVI - NDVI_{min}) / (NDVI_{max} - NDVI_{min})$	0-100	Liu and Kogan, 1996

2.2.2 Modelling of vegetation change

We explored any associations between the changes observed in the vegetation indices in the 27-year study period and a number of external variables. To do so, we processed a suite of 26 climatic and other distance-based spatial parameters (Table 2) that could potentially have an effect on the spatial configuration of changes in the values of the vegetation indices.

218 Table 2. List of data used as predictors in the Random Forest modelling (¹ Global Land Survey Digital Elevation
219 Model <http://glcf.umd.edu/data/glsdem/> ; ² Gounaridis et al. (2016), *Journal of Maps*, 12, 1055-1062; ³
220 <http://worldclim.org/version2> Fick, S.E., Hijmans, R.J. (2017). *International Journal of Climatology*, 37, 4302-
221 4315)

Acronym	Variable	Discription	Source	Time interval
<i>Territorial variables</i>				
dem	Elevation	Elevation in m	GLSDEM ¹	(-)
slope	Slope	Slope in degrees	"	(-)
dist_crops	Distance from croplands	Euclidean distance from croplands in m	Gounaridis et al. 2016 ²	2010
dist_sea	Distance from sea	Euclidean distance from the shoreline in m	(-)	(-)
dist_river	Distance from river	Euclidean distance from the Nestos river in m	(-)	(-)
dist_dams	Distance from dams	Euclidean distance from Thisavros and Platanovrissi dams in m	(-)	(-)
dist_resid	Distance from residential areas	Euclidean distance from residential areas in m	Gounaridis et al. 2016	2010
<i>Climatic variables</i>				
bioclim 01	Annual Mean Temperature	Annual Mean Temperature 1970 - 2000	WorldClim ³	1970-2000
bioclim 02	Mean Diurnal Range	(Mean of monthly (max temp - min temp))	"	"
bioclim 03	Isothermality	(bioclim 02 / bioclim 07)(*100)	"	"
bioclim 04	Temperature Seasonality	(standard deviation *100)	"	"
bioclim 05	Max Temperature of Warmest Month	Max Temperature of Warmest Month	"	"
bioclim 06	Min Temperature of Coldest Month	Min Temperature of Coldest Month	"	"
bioclim 07	Temperature Annual Range	(bioclim 05 - bioclim 06)	"	"
bioclim 08	Mean Temperature of Wettest Quarter	Mean Temperature of Wettest period of three months	"	"
bioclim 09	Mean Temperature of Driest Quarter	Mean Temperature of Driest period of three months	"	"
bioclim 10	Mean Temperature of Warmest Quarter	Mean Temperature of Warmest period of three months	"	"
bioclim 11	Mean Temperature of Coldest Quarter	Mean Temperature of Coldest period of three months	"	"
bioclim 12	Annual Precipitation	Annual Precipitation	"	"
bioclim 13	Precipitation of Wettest Month	Precipitation of Wettest Month	"	"
bioclim 14	Precipitation of Driest Month	Precipitation of Driest Month	"	"
bioclim 15	Precipitation Seasonality	(Coefficient of Variation)	"	"
bioclim 16	Precipitation of Wettest Quarter	Precipitation of Wettest period of three months	"	"
bioclim 17	Precipitation of Driest Quarter	Precipitation of Driest period of three months	"	"
bioclim 18	Precipitation of Warmest Quarter	Precipitation of Warmest period of three months	"	"
bioclim 19	Precipitation of Coldest Quarter	Precipitation of Coldest period of three months	"	"

222 Two parameters related with the relief were considered: elevation and slope that were based
223 on the Global Land Survey Digital Elevation Model (GLSDEM). Apart from the distance to the three

dams, the distance to cropland and residential areas were also chosen as factors that might affect the vegetation health and condition. The distance to the river was included as a potential spatial determinant of the soil moisture availability to the riparian vegetation. Finally, the distance to the sea was also included in the model to capture the geomorphological changes as we get closer to the coastline. All distances were computed using the Euclidean distance function. For the climatic parameters, the latest version of the WorldClim database (Fick et al. 2017) was employed. WorldClim v.2 is a set of 19 gridded climate layers at the global level, with a spatial resolution of $\sim 1 \text{ km}^2$. The dataset includes a wide range of temperature and precipitation data reported annually and quarterly spanning three decades (Table 2).

2.3 Model implementation

We opted to use Random Forests (RF) (Breiman, 2001), which is a robust non-parametric, machine learning algorithm. RF has several advantages that make it suitable for our approach. First, RF can efficiently handle heterogenous inputs with different nature (categorical, continuous) and scaling and from multiple sources (Gounaridis and Koukoulas 2016; Gounaridis et al. 2018; Wang et al. 2018). Second, the algorithm randomly selects a part of the training samples as well as a part of predictor variables, resulting in a number of independent to each other and identically distributed, regression trees. The randomness on the one hand and the independency of the regression trees on the other, makes RF insensitive to overfitting, to collinearity issues as well as to outliers and noise (Chan and Paelinckx, 2008). Based on these two advantages of the RF, we were able to incorporate in the model several predictors that were deemed to have an effect on the changes in vegetation condition. Another important advantage of the RF model is that it offers meaningful metrics that reflect the importance of each predictor variable (Gounaridis et al., 2019). This set of metrics was critical in our case in order to reveal any possible association between the external factors and the changes in vegetation indices.

The regression version of the Random Forests (RF) model (Breiman 2001) was implemented in R using the *RandomForest* package (Liaw and Wiener 2002). As a response variable, Δ was computed for each index, which is the difference between two subsequent dates. In our case, it was reasonable to compute Δ for each index between 1989 and 2016, in order to obtain the difference that occurred throughout the study period. These 26 territorial and climatic variables served as predictors to the RF models. To fine tune these models, five predictor variables (equal to the square root of the total number of predictor variables) were used for each tree split and 1000 trees for each run.

To quantify the actual importance and contribution for each of the 26 predictor variables, the analysis included two metrics: a) the Mean Decrease Accuracy and b) the Mean Decrease Gini. The

Mean Decrease Accuracy is a measure of how much the accuracy decreases if a variable is excluded from the model. Therefore, this metric can be considered as a proxy for the importance of a variable. The Mean Decrease Gini is a measure of each variable's contribution to the impurity of the resulting trees in the RF model: variables with a high value in Mean Decrease Gini contribute more to the model's homogeneity (Gounaridis et al., 2019).

3. Results

3.1 Evolution of vegetation indices

Our first step was to capture the evolution of the spectral indices before and after the construction of the dams. Eight complementary vegetation indices allowed for the comparison of vegetation trends during the 27-year period of the study. The fluctuations over the study period were captured at 573 random samples dispersed across the riparian forest of the Nestos Delta. Regarding the overall trend throughout the study period, it appears to be steady for the LSWI, NDWI and VCI, increasing for the PVI and NDVI and decreasing for the NDBR, EVI2 and GARI.

These comparisons were also carried out separately for the three classes depicting varying densities of tree coverage: 0-24%, 25-49% and 50-75% (Figure 3, 4 and 5 respectively). Specifically, for the first class (Figure 3) we see an increasing trend from 1989 to 1999 and a decreasing trend from 1999 to 2013 followed by an increase from 2013 to 2014 in all eight indices. The decreasing trend was more pronounced for the EVI2, NDVI and PVI. After 2014, the indices have different trends. Specifically from 2015 to 2016, the LSWI and NDBR decreased markedly while the NDWI only slightly. The other five indices decreased in 2015 but increased in 2016. The increase was more pronounced in 2016 for the GARI and VCI. However, the overall trend is a decrease for all eight indices, indicating slight degradation in the riparian vegetation of the delta. For the 25-49% class (Figure 4), the trends seem to differ more among them. Specifically, the EVI2, LSWI, NDVI and PVI showed a decreasing trend from 1989 to 1995 and only NDWI increased from 1989 to 2000. In general, most indices show an initial decreasing trend followed by a stabilizing or increasing trend in the later years. Only NDBR shows a general decreasing trend, especially in the last two years, while the NDWI has a stable trend after 2003 until the end of the study period. VI and PVI showed a decreasing trend from 1989 to 1995 and only NDWI increased from 1989 to 2000. In general, most indices show an initial decreasing trend followed by a stabilizing or increasing trend in the later years. Only NDBR shows a general decreasing trend, especially in the last two years, while the NDWI has a stable trend after 2003 until the end of the study period.

Percent Tree Cover: First interval 0 - 24

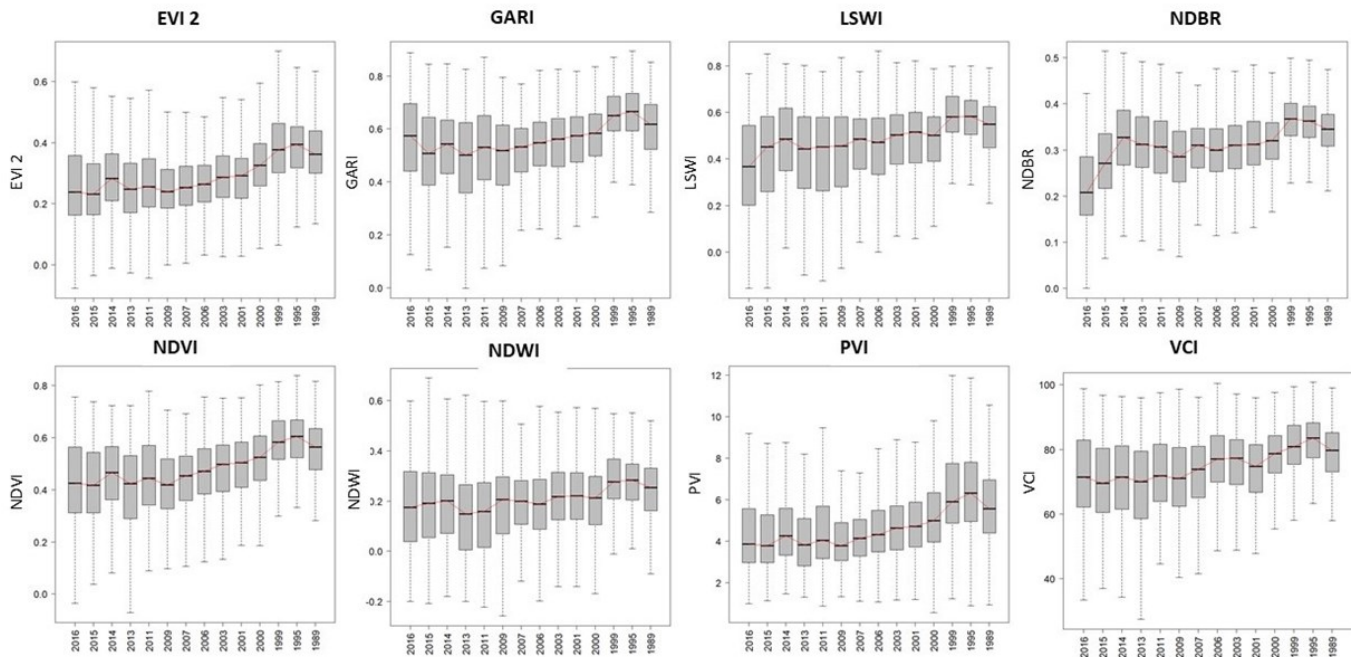


Fig. 3: Boxplots of the eight vegetation indices for the first percent tree cover interval (0-24%).

Percent Tree Cover: Second interval 25 - 49

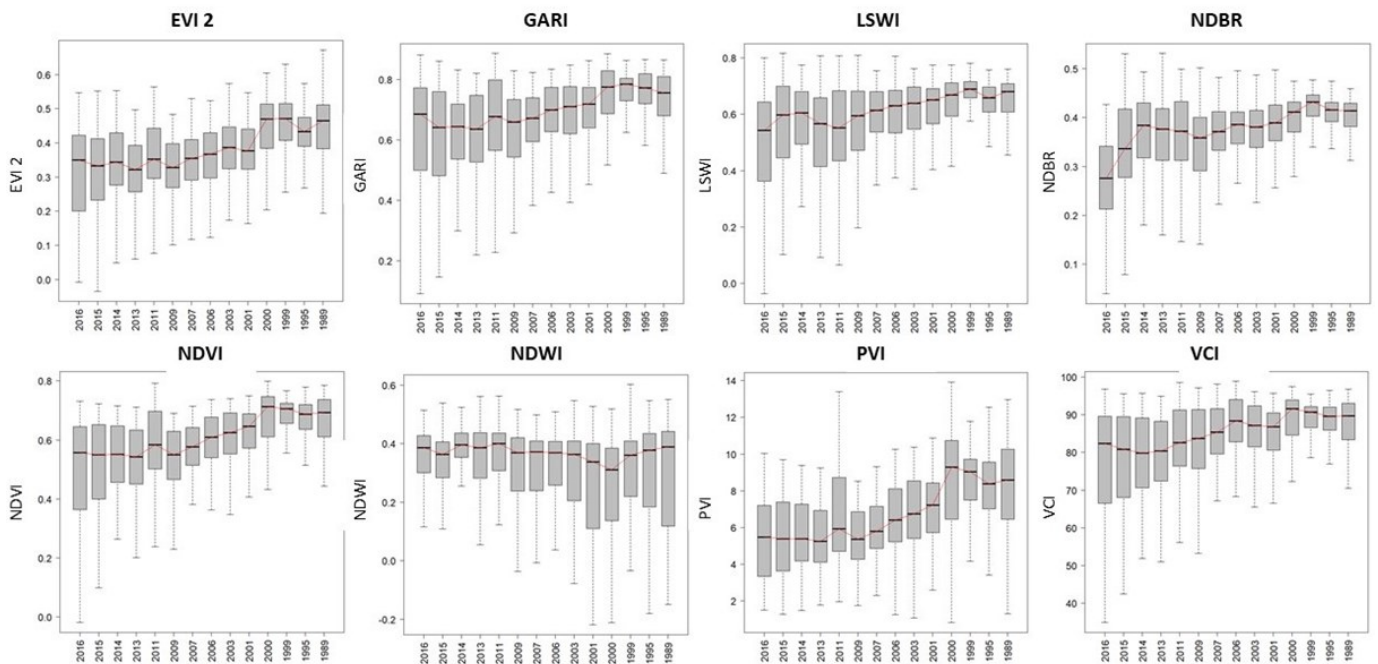
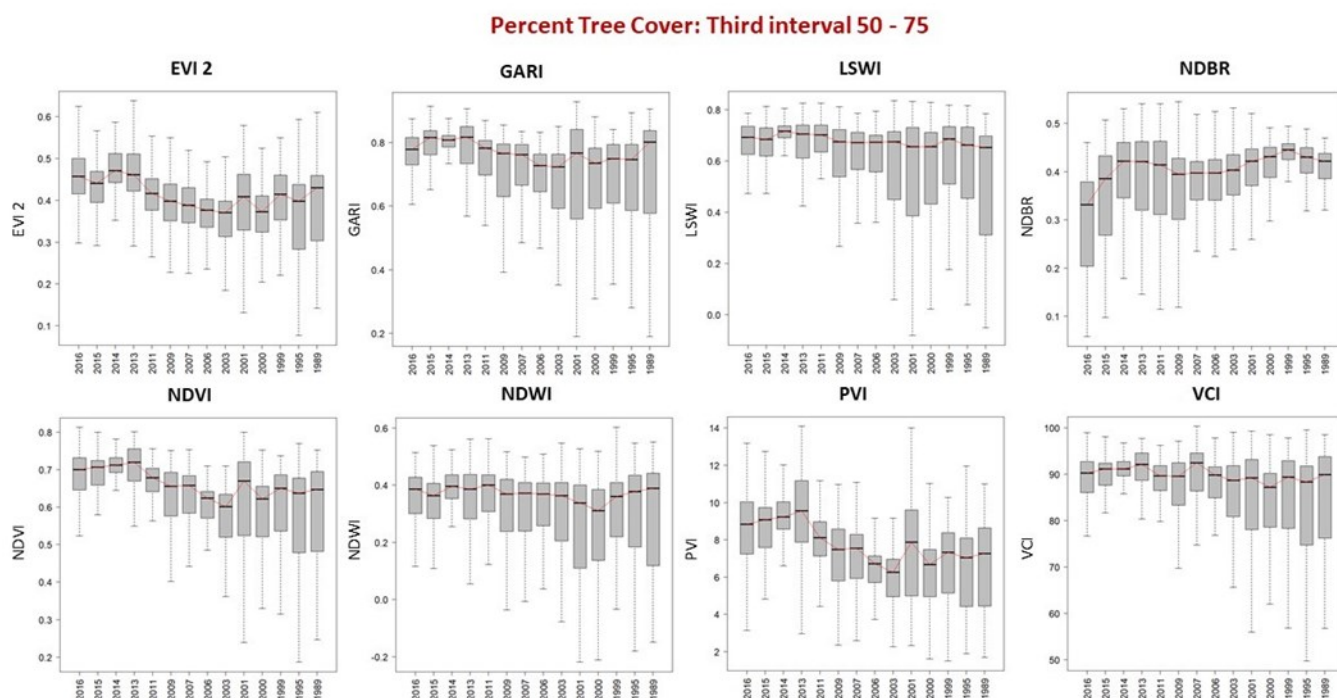


Fig. 4: Fig.2: Boxplots of the eight vegetation indices for the second percent tree cover interval (25-49%).

Regarding the 50-75% vegetation coverage class (Figure 5), the EVI2, GARI, NDVI, PVI and VCI had a rather unstable pattern (i.e. increase followed by a decrease in their values in every subsequent year) from 1989 till 2003. Following that, all five indices have an increasing trend: the EVI2 and GARI from 2003 to 2014, the NDVI from 2003 to 2013, and the PVI from 2003 to 2007. In the last years of the study, the pattern for four of the indices was again unstable: for the EVI2 and

297 GARI from 2014 to 2016, and for NDVI and PVI from 2013 to 2016. The remaining three indices
 298 (NDWI, NDBR and LSWI), followed their own, individual patterns during the entire period.



299
 300 Fig. 5: Boxplots of the eight vegetation indices for the third percent tree cover interval (50-75%).

301 3.2 Modelling of vegetation change

302 The modelling exercise was undertaken for the three different densities of tree coverage and
 303 the results were expressed with the Mean Decrease Accuracy and the Mean Decrease Gini. We
 304 focused on the top five descriptors based on the RF modelling results. For the Mean Decrease
 305 Accuracy of the 0-24% vegetation coverage (Figure 1-SM), the distance from the dams and the
 306 distance from the sea variables were in the top five for all vegetation indices, indicating that these
 307 factors were the most influential for the models. The mean temperature of the coldest quarter (in the
 308 top five of five indices), the distance from the river (in the top five of four indices) and the
 309 precipitation seasonality (in the top five of four indices) were also important (Figure 1-SM). When
 310 looking at the Mean Decrease Gini, distance from the croplands, distance from the sea, distance from
 311 the river, distance from the dams and distance from the residential areas were in the top 5 for all
 312 indices. Out of these four, the most important was the distance from the sea (always ranked first)
 313 followed by distance from the dams (mostly ranked second). Finally, the precipitation seasonality
 314 was also important since it was ranked in the top five in six occasions (Figure 1 SM).

315 For the 25-49% vegetation coverage, distance from the sea and distance from the dams were in
 316 the top five for all indices according to the Mean Decrease Accuracy (Figure 2 SM). The distance

317 from the sea was ranked first in most indices. The distance from the residential areas and the annual
318 precipitation were in the top five for five of the indices. Finally, the distance from the river was also
319 important since it was in the top five for four of the indices. In regard to the Mean Decrease Gini,
320 distance from the sea, distance from the river, and distance from the dams were in the top five for
321 five of the indices. The distance from the sea was ranked mostly first. The distance from the
322 residential areas (in the top five of 7 indices) and the distance from the croplands (in the top five of 6
323 indices) were also important descriptors.

324 The distance from the sea, distance from the river and distance from the dams were in the top
325 five for all indices for the Mean Decrease Accuracy for the vegetation coverage of 50-75% (Figure 3
326 SM). The distance from the sea was ranked first in all indices and the distance from the dams was
327 ranked second in most cases. Finally, the mean diurnal range (in the top five of 7 indices) and the
328 isothermality (in the top five of 6 indices) were also important. In regard to the Mean Decrease Gini,
329 distance from the croplands, distance from the sea, distance from the river, distance from the dams
330 and distance from the residential areas were in the top five for all indices. Most important descriptor
331 appears to be the distance from the river (ranked first in most cases), followed by the distance from
332 the sea (ranked second in most cases).

333 **4. Discussion**

334 **4.1 Effect of dams on riparian and deltaic vegetation**

335 The construction of dams on rivers can have major effects on riparian vegetation in deltas. The
336 bio-geomorphological dynamics of these ecosystems, which are not completely understood, are the
337 results of the interactions among river flows, sediment transport and the hydrophyllic vegetation
338 (Gurnell and Petts, 2002; Naiman et al., 2005; Magdaleno and Fernández, 2011). Several field studies
339 have shown how river regulation due to the artificial reservoirs of the dams can induce: a) vegetation
340 shifts with corresponding channel narrowing or widening (Williams and Wolman, 1984; Friedman et
341 al., 1996; Merritt and Cooper, 2000; Shafroth et al., 2002); b) declines in native species and the spread
342 of exotic ones (Merritt and Cooper, 2000; Shafroth et al., 2002); c) decrease in the overall habitat
343 heterogeneity (Naiman et al., 2005; Petts and Gurnell, 2005; New and Xie, 2008), and d) the
344 establishment of vegetation on islands (Gurnell and Petts, 2002). The random fluctuation of water
345 discharge that occurs in unregulated rivers (e.g. with no dams), leads to alternating periods of peak
346 flooding and very low flows (droughts) in the riparian areas. During floods, riparian areas are
347 submerged and vegetation takes advantage of the supply of nutrients, moisture and seeds (Naiman et
348 al., 2005), but vegetation can also be damaged (Yanosky, 1982) by: a) burial (Hupp, 1988; Friedman
349 and Auble, 1999), b) uprooting (Osterkamp and Costa, 1987), and c) anoxia (Kozlowski, 1984;

350 Naumburg et al., 2005). During droughts, vegetation grows and expands in new areas according to
351 the soil moisture content and the phreatic water table depth, as long as disturbances (e.g. floods) do
352 not occur (Liu and Ashton, 1995; Gurnell et al., 2001).

353 The regulation of stream flow, due to the presence of a dam(s), eliminates extreme events in
354 the hydrologic regimes that would have occurred otherwise. Specifically, discharges are significantly
355 reduced during the flood peak and in the wet-to-dry transition periods (Guo et al. 2018). In contrast,
356 discharges can slightly increase in the dry season (Guo et al. 2018), reducing drought occurrences.
357 The historical natural flows of the Nestos River, before the construction of the dams, ranged from 10
358 m³/s during the summer months, to 1.000 m³/s during the flood peaks. After the construction of the
359 dams, the downstream flow regime has changed and the suggested minimum environmental flow is
360 6 m³/s (Sylaios and Kamidis, 2018). These changes have different spatial impacts on the riparian
361 vegetation depending on its location in relation to the river channels. The samples selected in this
362 study, depending on their percentage tree coverage, represent a spatial gradient with respect to their
363 distance to the river channel. Typically, the samples with vegetation coverage of 50-75% were the
364 closest to the main river channel, the samples with 25-48% an intermediate distance and the samples
365 with 0-24% coverage the furthest from the main river channel. This spatial pattern determines the
366 differences in the trends for the samples based on the eight indices. Specifically for the 0-24%
367 vegetation coverage, we have an increasing trend from 1989 to 1999 for all indices. Both hydropower
368 dams were fully functional in 1999 so, potentially, their impacts were not fully experienced before
369 this period. After 1999, the riparian vegetation seems to be performing slightly worse, based on the
370 indices. This is something that should be expected, since these areas are the furthest away and the
371 alteration in the hydrologic regime (e.g. lack of floods) and the consequent increase of the water table
372 depth, should affect them first. The riparian vegetation furthest away from the channel, may no longer
373 be able to have access to ground water year round (a characteristic required for the health of the
374 riparian vegetation), since the water table depth increases. The reduction of the groundwater level in
375 riparian areas hinders water intake by vegetation, which is especially necessary during the summer
376 season. This causes a decline in the reproduction of pioneers, followed by a successive dieback of
377 mature individuals (Stromberg et al., 1996). In addition, this vegetation is also closest to the
378 anthropogenic pressures that could also have led to the degradation of the vegetation (Naiman et al.,
379 2005; National Research Council, 2002; Zaimes and Emmanouloudis, 2012; Zaimes et al. 2011a).

380 The trend is very different for the vegetation cover of 50-75%. Specifically, it appears that the
381 vegetation trend is steady and might even be increasing. This might be due to the fact that, while the
382 water depth might have increased, this particular class of riparian vegetation is close to the river
383 channel and might, therefore, still have access to the water table year-round, i.e. it might not have

384 been negatively impacted by it. Moreover, with the stream flow being regulated by the dams, the
385 number of floods and their magnitude has decreased, thus reducing this type of disturbance which
386 can remove old vegetation and open new spaces for re-vegetation. The lack of peak floods can lead
387 to the re-vegetation of the banks, islands and even of the river channel (Hupp, 1990; Hupp and
388 Osterkamp, 1994; Friedman et al., 1998; Magilligan et al., 2003). The vegetation in this category is
389 probably also getting older and denser, due to the lack of floods, as the trend in most indices indicates
390 (i.e. increasing or steady).

391 Finally, the samples with vegetation coverage 25-49% have no clear trends. This is attributed
392 to the fact that these areas are experiencing all the impacts described previously (increased water table
393 depth, no floods) to a varying degree, leading to impacts experienced in both the 0-24% and 50-75%
394 and consequently exhibiting no clear trend.

395 Overall, our results from the trends of the vegetation indices during the 27 years of the study
396 period, support the idea that the current suggested environmental flows and water management plan
397 for the Nestos Basin and Delta, need to be revised in order to be able maintain the high ecological
398 standards of the Natura 2000 and Ramsar riparian sites, as suggested by other studies about the Delta
399 (Koutrakis et al., 2018).

400 **4.2. Understanding changes in riparian vegetation caused by dams**

401 Looking at the variables that impact riparian vegetation, based on the Mean Decrease Accuracy
402 the territorial variables seem to be more important than the climatic ones. This should be expected
403 since riparian areas are ecosystems and not biomes (that are the result of climatic conditions) and
404 called azonal because they can be found in most climatic regions. Specifically, the most important
405 ones are the distance to the dams and to the sea. The distance to the dams should be expected to be
406 an important descriptor since, as mentioned previously, dams can have detrimental effects on riparian
407 vegetation. Moving further downstream from the dams, the impacts are likely to be less significant.
408 Concerning the distance to the sea, this is related to the fact that deltas are ecotones, transition zones
409 between fluvial and maritime ecosystems. Therefore, moving away from the coastline, fluvio-
410 geomorphological processes and water composition changes are expected. In addition, the
411 construction of dams leads to less water and sediment reaching the delta and, along with climate
412 change impacts, that lead to sea water intrusion, sea level rise and the erosion and recession of deltas;
413 all major threats to these ecotones that can cause serious problems to the riparian vegetation (Bergillos
414 and Ortega-Sánchez 2017; Syvitski et al., 2009; Tessler et al., 2015; Wang et al. 2017). This is
415 especially true for Mediterranean deltas (Jeftic et al., 1996; Bergillos and Ortega-Sánchez 2017),
416 where dam construction has reduced the sediment supply by approximately 50% since the middle of

the 20th century (Poulos & Collins, 2002). This should be of concern to the authorities responsible for the management of the Nestos Delta and its riparian vegetation. The importance of the distance to the river as a descriptor is related to the increase in the water table depth (Naiman et al., 2005; National Research Council, 2002). The importance of the latter was also evident with the analysis of the vegetation indices, especially for the samples that were the furthest away from the channel with vegetation there not having access to ground water year round. For the intermediate samples (25-49% vegetation coverage), the presence of residential structures was also strongly correlated with vegetation. This land-use intensification in, and adjacent to, riparian areas with agricultural and/or urban areas in the Mediterranean region, has reduced habitat size and flora diversity (Corbacho et al., 2003; Luther et al., 2008; Magdaleno and Fernández-Yuste 2013). Finally, some of the climatic factors were also found to be important, with some related to temperature (namely, temperature of the coldest quarter, diurnal range and isothermality) and others to precipitation (precipitation seasonality and annual precipitation). These climatic factors are known to impact the growth of the riparian vegetation (Naiman et al., 2005; National Research Council, 2002).

Regarding the Mean Decrease Gini, the dominance of the territorial variables was even greater. Again, as anticipated, the distance to the sea and the distance to dams were identified as the most important parameters. The distance to the river and to residential areas were also found to be important. Finally, in agreement with other studies (Naiman et al., 2005; Schultz et al., 2009), the distance to crops was also identified as an important parameter. In Greece, especially in the lowland areas, agricultural activities are prevalent compared to other land-use practices and have led to the fragmentation of riparian forests and the degradation of deltas (Zaimis et al., 2011b). The only climatic factor that appears to be important is precipitation seasonality, which was expected to a certain extent, as it affects the vegetation growth. As previously mentioned, riparian areas can be found in all biomes, are azonal and are the result of primarily local conditions (adjacent to a water body).

5. Conclusions

Our results from the analysis of multi-temporal remotely sensed vegetation indices and a modelling exercise involving the evolution of these indices and other environmental and topographic parameters, corroborate the findings in other studies that both natural and human-induced changes influence the evolution of deltaic and riparian ecosystems (Syvitski and Saito, 2007; Simeoni and Corbau, 2009; El Banna and Frihy, 2009; Sabatier et al. 2009). With one third of the Mediterranean coastline having already been built and attracting numerous economic activities (Bergillos and Ortega-Sánchez 2017), the importance of these ecosystems in the sustainable development of the region is undeniable. These areas have been intensely exploited and settled by humans for millennia

451 (Masselink & Hughes, 2003), and therefore their protection, conservation and re-establishment
452 should be a priority for addressing environmental sustainability and land degradation neutrality.
453 Utilizing the vegetation indices and modelling exercise land and water managers can identify and
454 monitor potential changes in the riparian vegetation and what the key factors are for their recovery.
455 This can help mitigate the main anthropogenic pressures and along with the utilization of new
456 innovative practices, such as ecosystem-based approaches at the watershed scale could lead to their
457 sustainable and cost-effective management (Colls et al., 2009; Iakovoglou and Zaimis, 2017). For
458 example, following ecosystem-based approaches the current environmental flows need to be changed
459 and incorporate high flow (floods) and low flow (droughts) events every year based on the historical
460 hydrologic flows of the Delta before the dam constructions. This will allow the riparian vegetation of
461 the Delta to recover and remain healthy.

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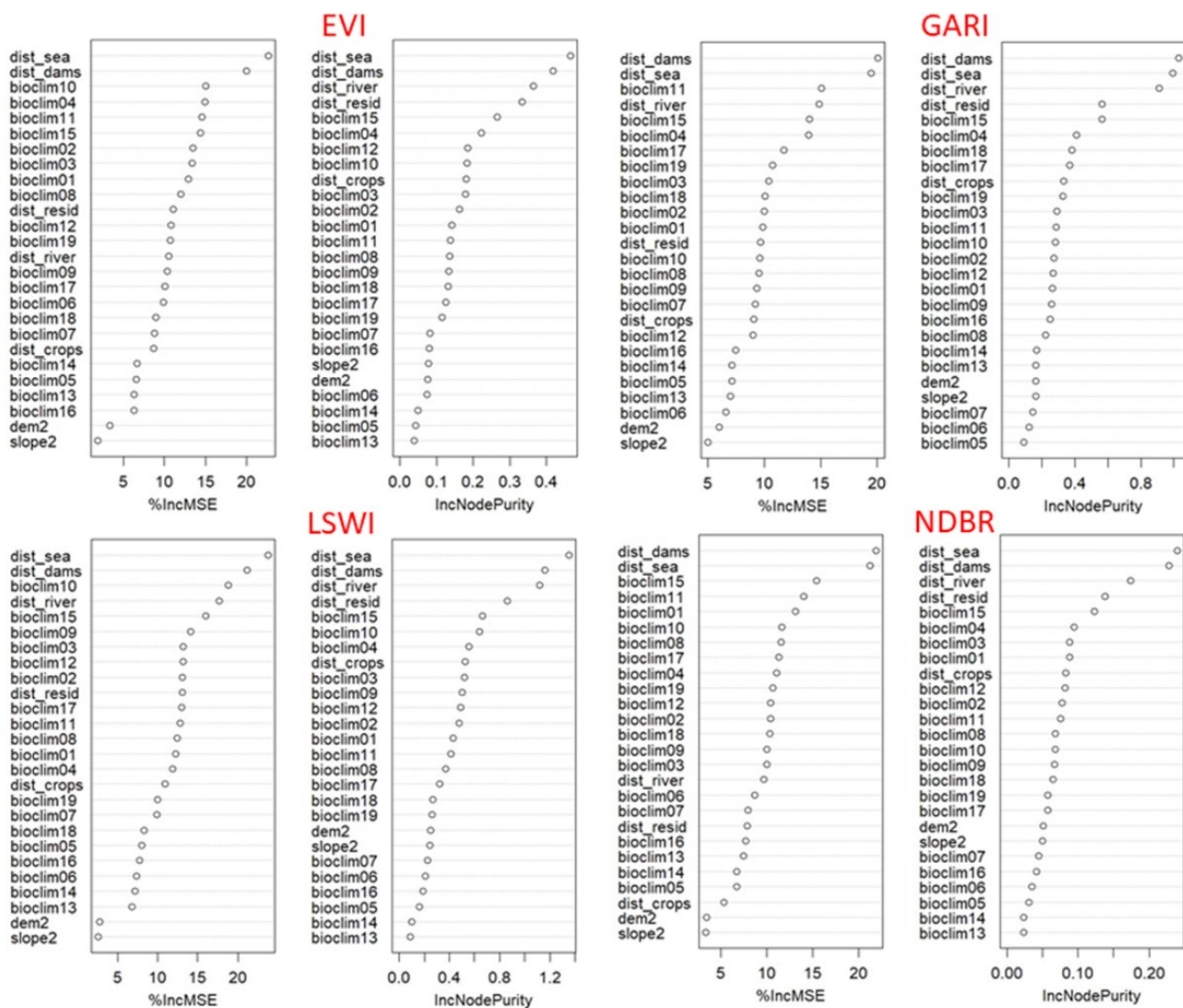
789

790 **Supplementary Material**

791 Table SM1. Characteristics of the Landsat satellite images

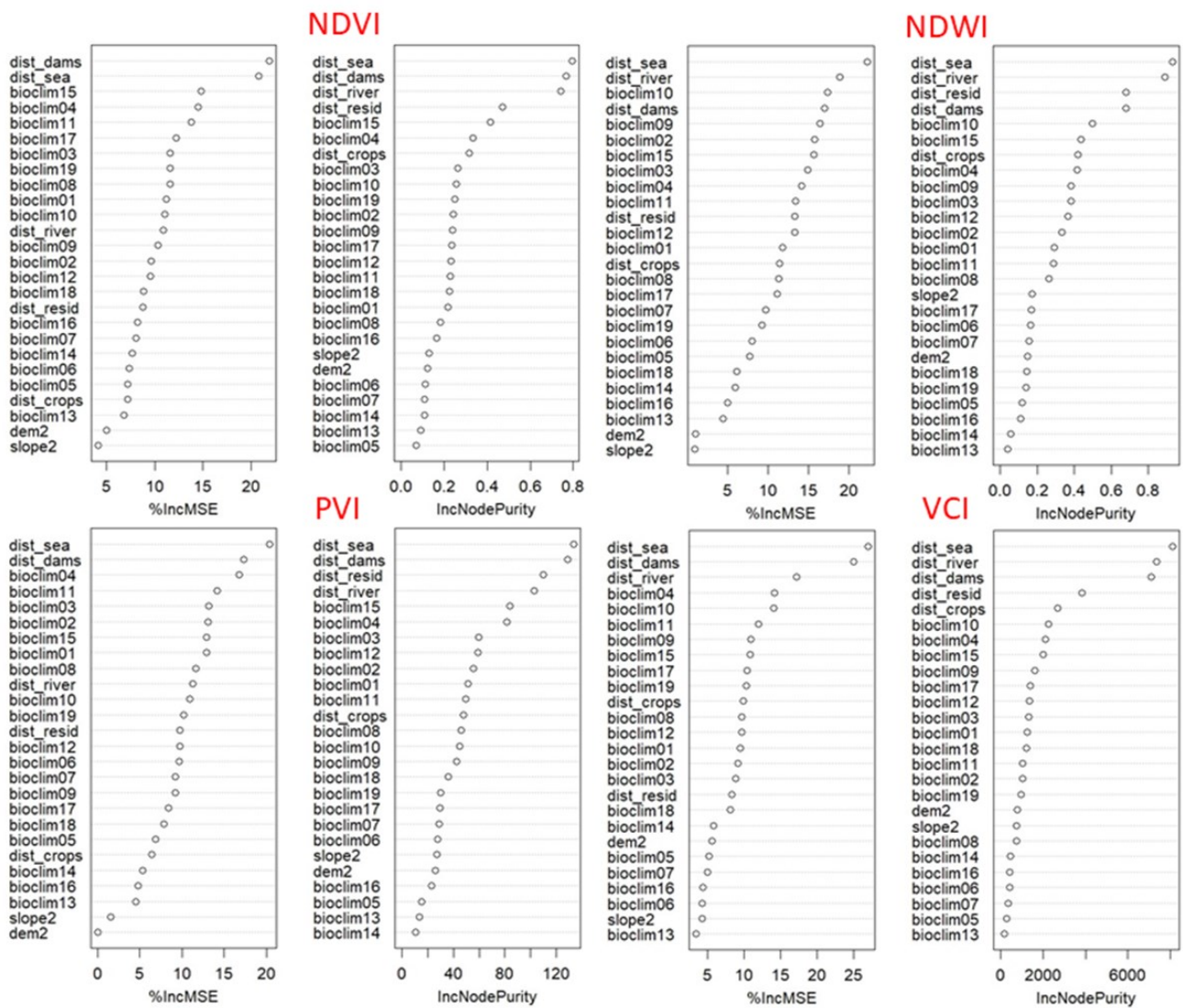
Date	Satellite	Sensor	Path	Row	Resolution
23/6/1989	Landsat 4	Thematic Mapper (TM)	182	32	30m
11/7/1995	Landsat 5	Thematic Mapper (TM)	182	32	30m
14/7/1999	Landsat 7	Enhanced Thematic Mapper + (ETM+)	182	32	30m
17/8/2000	Landsat 7	Enhanced Thematic Mapper + (ETM+)	182	32	30m
20/8/2001	Landsat 7	Enhanced Thematic Mapper + (ETM+)	182	32	30m
18/8/2003	Landsat 5	Thematic Mapper (TM)	182	32	30m
26/8/2006	Landsat 5	Thematic Mapper (TM)	182	32	30m
29/8/2007	Landsat 5	Thematic Mapper (TM)	182	32	30m
18/8/2009	Landsat 5	Thematic Mapper (TM)	182	32	30m
24/8/2011	Landsat 5	Thematic Mapper (TM)	182	32	30m
29/8/2013	Landsat 8	Operational Land Imager (OLI)	182	32	30m
16/8/2014	Landsat 8	Operational Land Imager (OLI)	182	32	30m
19/8/2015	Landsat 8	Operational Land Imager (OLI)	182	32	30m
21/8/2016	Landsat 8	Operational Land Imager (OLI)	182	32	30m

792



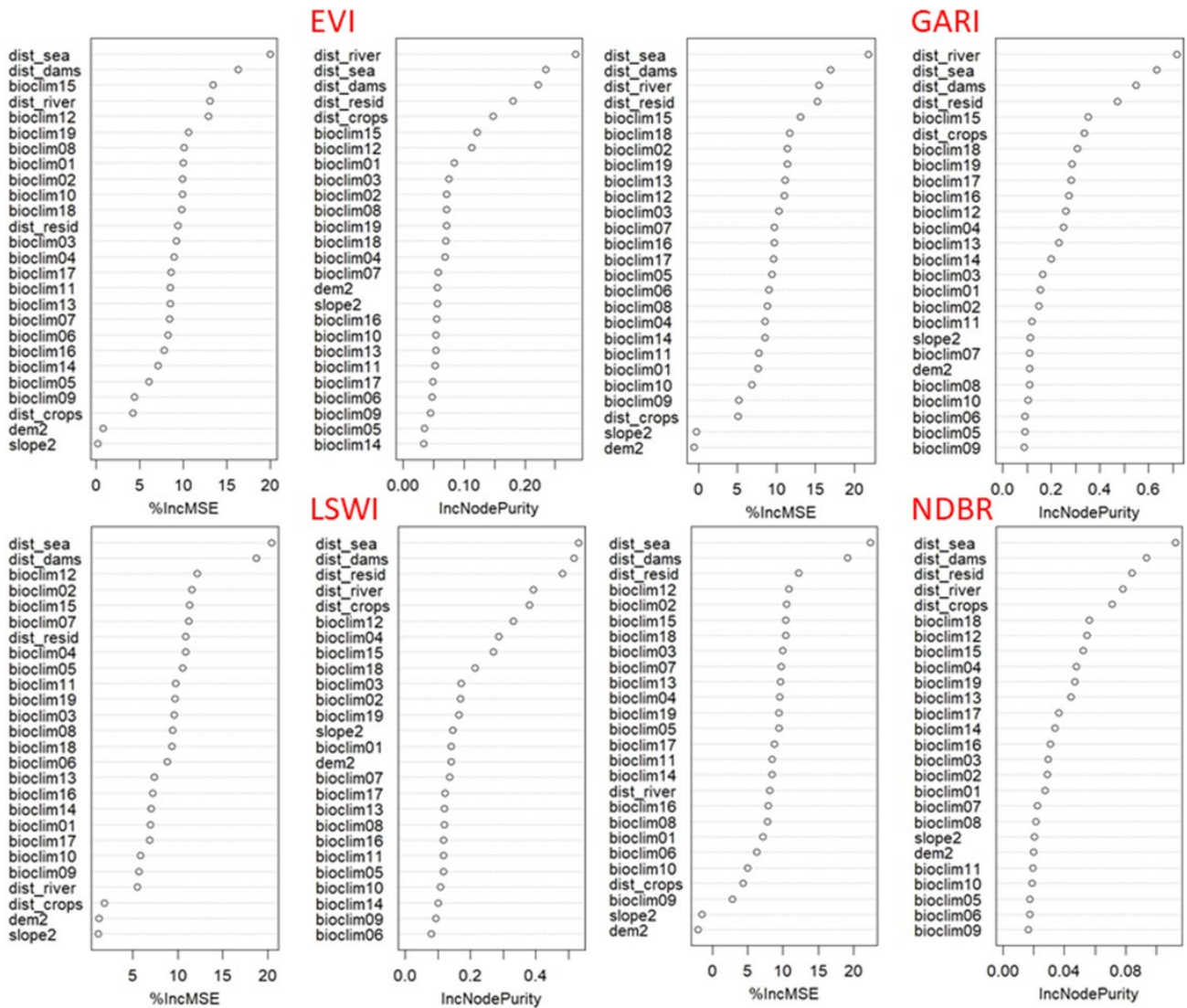
793

794 Fig. SM1: Variables importance per vegetation index graph derived from RF modelling. First interval (Percent
795 tree cover 0 – 24). %IncMSE: Mean Decrease Accuracy (%); IncNodePurity: Mean Decrease in Gini impurity
796 index.



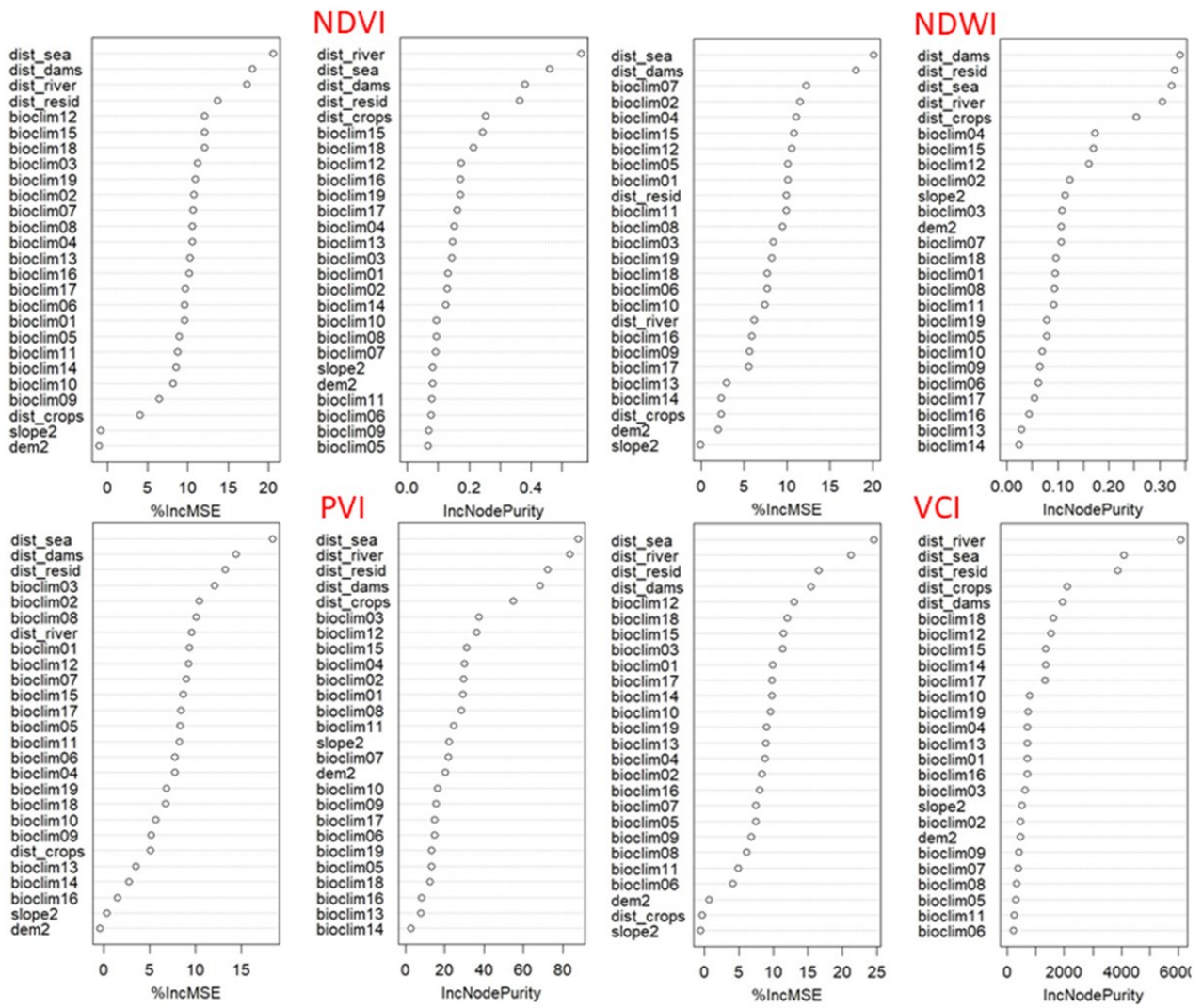
797

798 Fig. SM1: (continued) Variables importance per vegetation index graph derived from RF modelling. First
 799 interval (Percent tree cover 0 – 24). %IncMSE: Mean Decrease Accuracy (%); IncNodePurity: Mean Decrease
 800 in Gini impurity index.



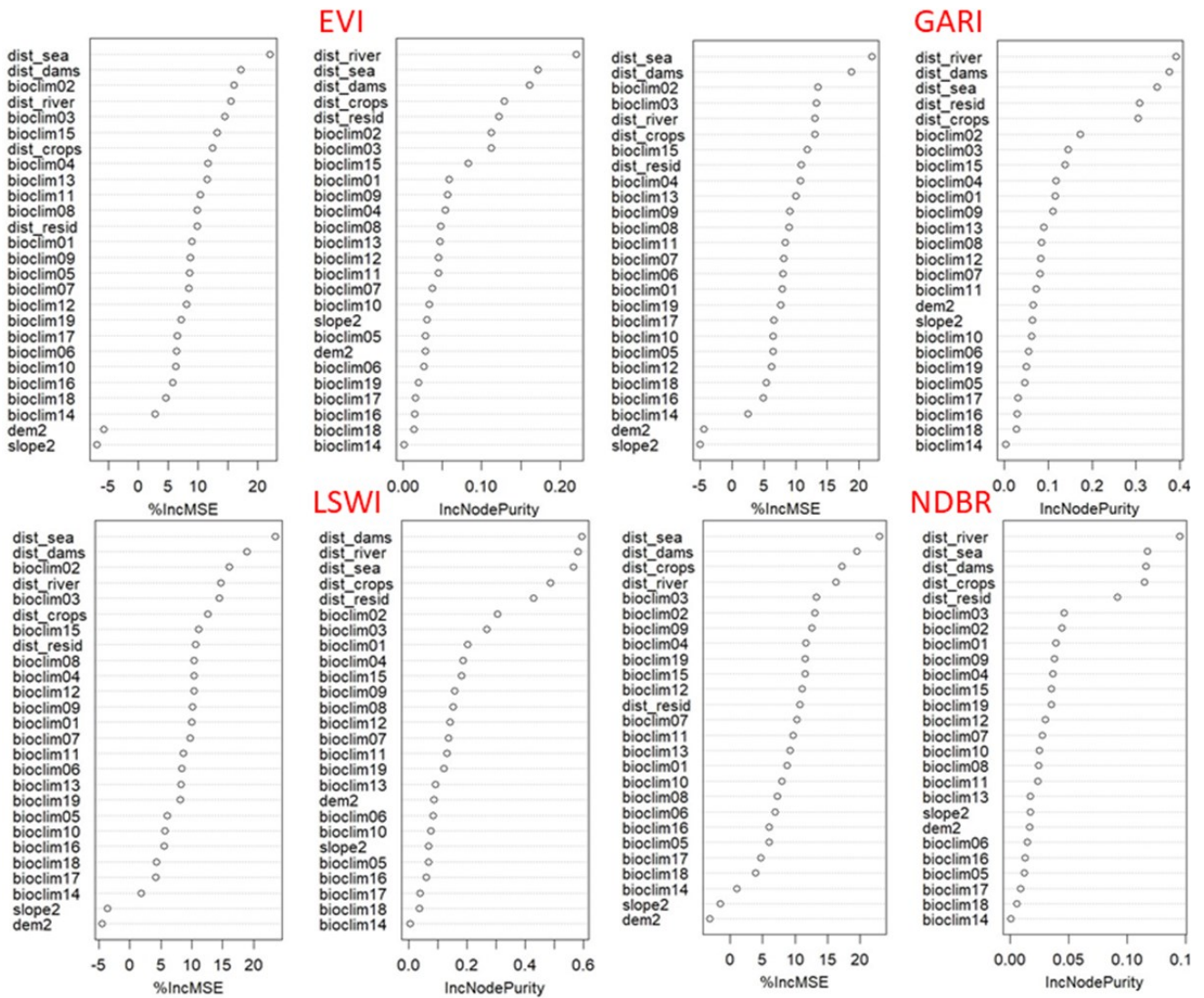
801

802 Fig. SM2: Variables importance per vegetation index graph derived from RF modelling. Second interval
 803 (Percent tree cover 25 – 49). %IncMSE: Mean Decrease Accuracy (%); IncNodePurity: Mean Decrease in Gini
 804 impurity index.



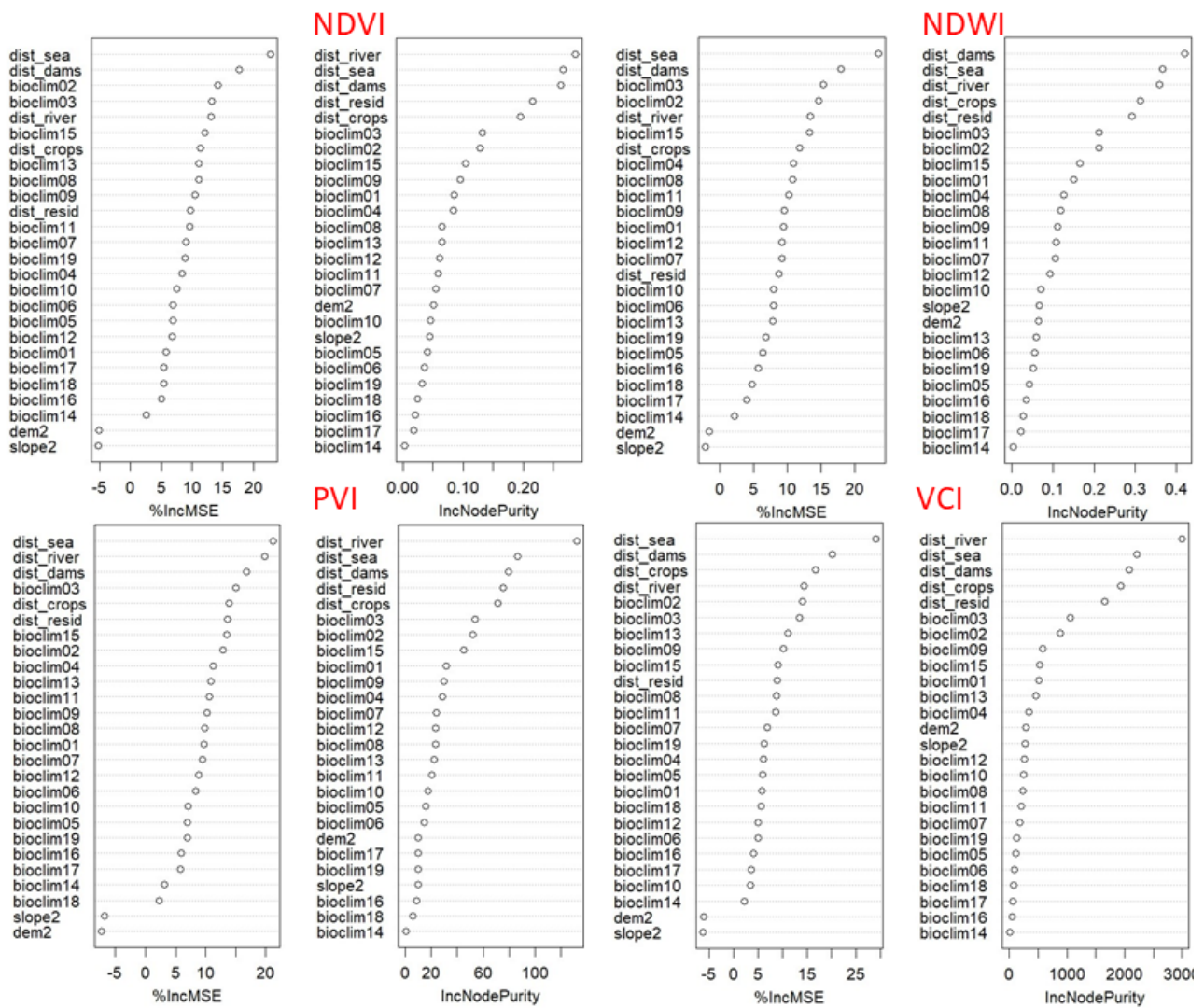
805

806 Fig. SM2: (continued) Variables importance per vegetation index graph derived from RF modelling. Second
 807 interval (Percent tree cover 25 – 49). %IncMSE: Mean Decrease Accuracy (%); IncNodePurity: Mean Decrease
 808 in Gini impurity index.



809

810 Fig. SM3: Variables importance per vegetation index graph derived from RF modelling. Third interval (Percent
811 tree cover 50 – 75). %IncMSE: Mean Decrease Accuracy (%); IncNodePurity: Mean Decrease in Gini impurity
812 index.



813
 814 Fig. 3: (continued) Variables importance per vegetation index graph derived from RF modelling. Third interval
 815 (Percent tree cover 50 – 75). %IncMSE: Mean Decrease Accuracy (%); IncNodePurity: Mean Decrease in Gini
 816 impurity index.