Modelling Water Depth, Turbidity and Chlorophyll Using Airborne Hyperspectral Remote Sensing in a Restored Pond Complex of Doñana National Park (Spain)

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Abstract: Restored wetlands should be closely monitored to fully evaluate the effectiveness of restoration efforts. However, regular post-restoration monitoring can be time-consuming and expensive, and is often absent or inadequate. Satellite and airborne remote sensing systems have proven to be cost-effective tools in many fields, but they have not been widely used to monitor ecological restoration. This study assessed the potential of airborne hyperspectral remote sensing to monitor water mass characteristics of experimental temporary ponds in the Mediterranean region. These ponds were created during marsh restoration in Doñana National Park (south-west Spain). We used hyperspectral images acquired by the CASI-1500 hyperspectral airborne sensor to estimate and map water depth, turbidity and chlorophyll a in a subset of the 96 new ponds. The high spatial and spectral resolution of the CASI sensor allowed us to detect differences between ponds in water depth, turbidity and chlorophyll a, providing accurate mapping of these three variables, and a useful method to assess restoration success. High levels of spatial variation were recorded between different ponds, which likely generates high diversity in the animal and plant species that they contain. These results highlight the great potential of hyperspectral sensors for the long-term monitoring of wetland complexes in the Mediterranean region and elsewhere.

Keywords: wetland restoration; CASI; long term monitoring; hyperspectral images; water quality; mapping

1. Introduction

Wetlands have high ecological and economic value to society. They contain high biodiversity [1–3], provide habitats where birds and other fauna can feed, drink and reproduce, and they play a significant role in global biogeochemical cycles (e.g., through carbon sequestration, [4]). However, wetlands are severely threatened by human activity and climate change [5,6]. As a result, most wetland surface area has been lost worldwide [7,8]. In response to this, ecological restoration of wetlands has increased over the years in an attempt to counteract and reverse these losses [9]. Post-restoration systematic monitoring is essential to assess the effectiveness of these restoration efforts. However, it is generally
expensive and time-consuming, and thus it is often absent or inadequate. For example, the success of restoration projects, where they exist, is typically evaluated on the basis of short-term studies or at a small spatial scale [10,11]. Nevertheless, long-term monitoring is essential to track progress, or to design correction strategies where necessary, facilitating adaptive management. To date, remote sensing data and products are widely used to map and delineate wetlands [12,13], retrieve hydroperiod [14], monitor water quality [15] or even quantify carbon stocks [16] among many other applications at local, regional and global scales.

Remote sensing is a time-saving and cost-effective method to determine long-term trends and short-term changes in restored areas [17–19]. Therefore, its application can help in the monitoring of wetland restoration success, improving the ability to conserve and manage these habitats. Traditional multispectral remotely sensed satellite images have now been used to monitor water quality for many years [20]. Major advantages of this method include the ability to study the spatial variability of water surface area and quality over large areas, analyzing temporal trends over large time periods [21,22], improving real-time water quality monitoring and detecting rapidly developing environmental threats, such as harmful algal blooms or extreme eutrophication [23].

Despite these advantages, remotely sensed images do not allow a complete assessment of wetlands worldwide. Most wetland complexes include small size waterbodies, which are too small to be monitored with the spatial resolution typical of satellite images (e.g., 30 m per pixel Landsat satellites [24]). Furthermore, the low spectral resolution of these sensors (up to 0.692 in the visible spectrum nm (8 bands total)), see [24] limits the ability to discriminate physico-chemical characteristics of water bodies. For example, chlorophyll-a concentration is not easy to discriminate in highly turbid waters due to the dominance of the spectral response of suspended sediments [23].

Airborne hyperspectral remote sensing images provide much finer spatial and spectral resolutions than satellite images [25]. For example, the Compact Airborne Spectrographic Imager (CASI) 1500 has a spectral resolution up to 2.2 nm (288 bands). This high resolution makes this type of hyperspectral sensor better suited for in-depth examination of small water bodies. Although hyperspectral airborne sensors, including the CASI, have proven useful in studies in freshwater lakes and rivers [25–29], their potential for the monitoring of small temporary ponds is not yet fully explored (but see [30,31] for some examples) and little is known about its application for monitoring restored wetlands.

In this study, we evaluated the ability of Compact Airborne Spectrographic Imager (CASI) 1500 hyperspectral images to monitor water mass characteristics in a set of new experimental ponds created during a marsh restoration project within Doñana National Park, in SW Spain. We used CASI images together with simultaneous ground truthing data to build empirical models capable of predicting spatial variation in water depth, turbidity and chlorophyll a concentration. These variables are frequently used for monitoring the dynamics and condition of shallow water ecosystems [32–36]. As has been demonstrated for medium-resolution sensors (i.e., Landsat, sensu [37]), we expected that the CASI sensor would be successful at estimating water depth and turbidity in the new ponds [38]. In addition, we expected that the CASI sensor would also efficiently estimate chlorophyll a concentration, despite potential difficulties arising from the interactive effects of turbidity and chlorophyll on spectral signals. We aimed to produce high spatial resolution maps of all three variables for the study period.

2. Materials and Methods

2.1. Study Site

This study was conducted within the Caracoles estate, which is located on the northern edge of Doñana National Park (SW Spain, Figure 1). This protected area is also a UNESCO World Heritage Site and contains a seasonally inundated marshland area of 27,000 ha situated in the Guadalquivir estuary, being one of Europe’s biggest wetlands [39,40].
In the 1960s, the Caracoles estate was hydrologically disconnected from the surrounding marshes and transformed into arable farmland [3,41]. For over 30 years, it was used for wheat and other agriculture. During 2004–2005, the area was restored and incorporated into the National Park as part of the Doñana 2005 government-sponsored restoration program [42]. This restoration aimed to re-establish the connection between the estate and the surrounding marshes [43] and to create 96 experimental temporary ponds [44]. These ponds were all of the same elliptical shape but with different diameters (60, 125 or 250 m along the longest axis) and constructed depths (30 or 60 cm). Most ponds were grouped into two main blocks (North and South) of 44 ponds each (Figure 1). These groups were located at the lowest elevation in the state leveraging original field depressions. In addition, 8 medium-sized isolated ponds were created away from the two main blocks (see Figure S1 for details).

This region has a Mediterranean climate with Atlantic influence, with hot/dry summers and moderate winters, although the timing and amount of precipitation are variable between years [45]. The new ponds generally fill with precipitation and local run-off during the wet season (from October to March) and dry out during the dry season (from May onwards). Due to their differences in depth, size, and microtopography, new ponds show different hydroperiods within a given year, but also between years [3,46,47]. Since the restoration, the colonization of the ponds by zooplankton, macroinvertebrates and waterbirds has been studied in detail for a few years each [3,46–50]. The colonization by terrestrial vegetation of surrounding areas has also been monitored during several years [51].

2.2. Imagery Acquisition and Ground Truth Data Collection

We used two hyperspectral strip images acquired over the Caracoles estate using the Compact Airborne Spectrographic Imager (CASI-1500i), flown onboard a CASA-212-200 airplane [52,53] at 6033 ft AGL (1839 m producing a GSD of 1 m), on 7 May 2013 by INTA. The CASI sensor was configured to collect 144 spectral bands in the spectral range between 380 and 1050 nm, FWHM @5.5 nm). Strip numbered 24 was acquired over the North and South blocks, in between 11:35:07 and 11:38:50 UTC time, with a solar zenith angle...
of 22.69° and an azimuth angle of 151.19°. Isolated ponds were discarded from flight
mission planning as it would have increased costs and processing time. Sensor acquisition,
georeferencing and atmospheric correction to at-sensor-radiances were processed by INTA
according to De Miguel et al. [54]. These level 1b CASI data were converted to ground
reflectance described in the following section. The geolocation of each CASI pixel is
performed from the exterior orientation information, the digital elevation model (DEM) of
the area and a detailed sensor model using the continuous acquisition data from GPS and
IMU onboard. Detailed metadata and quality parameters (Signal-to-Noise ratio) were also
provided by INTA according to EUFAR-HyQuaPro standards.

Ground truth measurements were taken close in time (i.e., between 1 and 2 days later)
to the CASI overflight.

We collected water samples and water depth measurements from a total of 18 ponds
distributed through the northern and southern blocks (see Figure S1 and Table S1 for
details) excluding isolated ponds as mentioned earlier. Water depth (cm) was measured
in situ through a measuring stick in 2 or 3 locations within each pond, depending on the
pond size. Each measurement was considered individually, and each location was recorded
with a portable Garmin GPSMAP 60Cx (Nominal Precision Error between 3 and 10 m). We
also collected 1 L water samples from each pond for laboratory analyses of chlorophyll
a and turbidity (one unique datum per pond). Chlorophyll a concentration (µg/L) was
determined using the methanol extraction method [55] and turbidity was measured with a
portable turbidity meter Hanna model HI-93703 and expressed as Nephelometric Turbidity
Units (NTU).

All measurements were taken where the water surface and pond bottom were homo-
geneous within a 3-m radius (with the naked eye).

2.3. Image Processing

The CASI image was geometrically and radiometrically corrected by the Spanish
National Institute of Aerospatiale Techniques (INTA). Geometric correction used IMU data
and the Andalusian Geodetic Positioning Network (https://www.juntadeandalucia.es/,
accessed on 27 June 2024) with a root mean square position error (RMS) below 1 pixel,
equivalent to 1 m for the study flight height [56]. Radiometric correction was applied to
convert digital numbers to at-sensor spectral radiances.

Images were atmospherically corrected using the empirical line approach [25,57]
by the GIS and remote sensing lab of the Doñana Biological Station (LAST_EBD). To do
this, reflectance data from homogeneous target reflectance areas were measured. These
include sand dunes and artificial bright targets representing high reflectance pixels, and
deep waters from the nearby Santa Olalla lagoon (Figure S2) as low reflectance values
(see [58] for method details). Reflectance measurements were collected using a field portable
spectroradiometer ASD FieldSpec Full range (400–2500 nm) and locations were recorded
with a differential GPS. Then, Regions Of Interest (ROIs, see [59] for details) were created
in the hyperspectral image over the same points where the spectral field reflectances were
recorded, and used as input for the empirical line correction using ENVI 4.6 software [60].
This method converts image radiance values from the coincident flight strips to reflectances
by linearly regressing the image radiances with the in situ collected reflectance for each
band [57]. The empirical line model assigned null reflectance values to very low reflectance
values (<0.01).

The resulting equations were subsequently applied to the rest of the flight strips. In
total, these strips covered the entire surface of 61 of the 96 ponds, plus part of the surface of
an additional 8 ponds.

3. Data Modeling

3.1. Variability of Field Data

We assessed the variability of collected field data according to the two different blocks
of ponds. Water mass condition varied between the sampled ponds in the northern and
southern blocks (Table 1). The maximum difference is observed for water turbidity which is higher for the southern block of ponds.

Table 1. Summary of the ground-truthing environmental data collected in the field from the northern (N) and southern (S) ponds.

<table>
<thead>
<tr>
<th>Code</th>
<th>Pond Location</th>
<th>Diameter (m)</th>
<th>Constructed Depth (cm)</th>
<th>Turbidity (NTU)</th>
<th>Chlorophyll a (µg/L)</th>
<th>Water Depth (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0N1GP</td>
<td>N</td>
<td>250</td>
<td>60</td>
<td>6.22</td>
<td>2.92</td>
<td>23</td>
</tr>
<tr>
<td>0N2GP</td>
<td>N</td>
<td>250</td>
<td>60</td>
<td>2.63</td>
<td>1.72</td>
<td>62.5</td>
</tr>
<tr>
<td>0N3GS</td>
<td>N</td>
<td>250</td>
<td>30</td>
<td>7.13</td>
<td>5.26</td>
<td>10</td>
</tr>
<tr>
<td>0N4GS</td>
<td>N</td>
<td>250</td>
<td>30</td>
<td>15.94</td>
<td>4.2</td>
<td>9.6</td>
</tr>
<tr>
<td>3N1PP</td>
<td>N</td>
<td>60</td>
<td>60</td>
<td>6.12</td>
<td>1.75</td>
<td>26</td>
</tr>
<tr>
<td>3N3MP</td>
<td>N</td>
<td>125</td>
<td>60</td>
<td>5.02</td>
<td>0.39</td>
<td>23</td>
</tr>
<tr>
<td>4N4PS</td>
<td>N</td>
<td>60</td>
<td>30</td>
<td>11.89</td>
<td>0.39</td>
<td>7.25</td>
</tr>
<tr>
<td>6N2MP</td>
<td>N</td>
<td>125</td>
<td>60</td>
<td>4.49</td>
<td>0.86</td>
<td>28.5</td>
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<tr>
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<td>S</td>
<td>250</td>
<td>60</td>
<td>9.26</td>
<td>2.16</td>
<td>38</td>
</tr>
<tr>
<td>0S3GS</td>
<td>S</td>
<td>250</td>
<td>30</td>
<td>54</td>
<td>1.45</td>
<td>13</td>
</tr>
<tr>
<td>1S2PS</td>
<td>S</td>
<td>60</td>
<td>30</td>
<td>31.37</td>
<td>5.08</td>
<td>12</td>
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<tr>
<td>3S1MP</td>
<td>S</td>
<td>125</td>
<td>60</td>
<td>33</td>
<td>2.63</td>
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<tr>
<td>3S2PP</td>
<td>S</td>
<td>60</td>
<td>60</td>
<td>4.41</td>
<td>0.44</td>
<td>35</td>
</tr>
<tr>
<td>3S3MP</td>
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<td>125</td>
<td>60</td>
<td>5</td>
<td>1.35</td>
<td>24.5</td>
</tr>
<tr>
<td>4S2MS</td>
<td>S</td>
<td>125</td>
<td>30</td>
<td>159</td>
<td>9.58</td>
<td>10.5</td>
</tr>
<tr>
<td>6S2MP</td>
<td>S</td>
<td>125</td>
<td>60</td>
<td>2.95</td>
<td>1.25</td>
<td>36.5</td>
</tr>
<tr>
<td>7S2PP</td>
<td>S</td>
<td>60</td>
<td>60</td>
<td>9.13</td>
<td>0.59</td>
<td>38.5</td>
</tr>
</tbody>
</table>

3.2. Model Building

3.2.1. Extraction of Reflectance Data for the Ponds

In order to avoid problems due to pond reflectance, we built a binary mask selecting pixels with a reflectance value of $\leq 0.1\%$ (i.e., to ensure spectral contrast between land and wetlands in the area). After applying the mask, we overlaid all in situ sampling points for which we had point water depth data on top of the CASI images and calculated buffer circles of different sizes: 0 (i.e., no buffer), 1, 2, 3, 4 and 5 m radius. In the case of variables for which we had a single data value per pond (i.e., turbidity and chlorophyll a) and for mean pond water depth, we either used no buffers (i.e., 0 buffer) or just 5 m distance from the edge of each pond to the inside (i.e., negative buffer) using QGIS 3.16 and Python 3.8 (with geopandas). This prevented extracting data from pixels located on the pond shoreline, which is a highly variable area [29] that may show a mixed spectral response with land. Lastly, we extracted average spectral data from the pixels within these buffers, with the exception of the data point without buffer for which spectral data correspond to the exact pixel value.

Additionally, after extracting the data, PCA transformation was performed using all available bands, preceded by a standard scaling since the data were not entirely within the range 0–1. Applying the PCA method on hyperspectral remote sensing data allows us to generate uncorrelated output bands, isolate noise components, and reduce the dimensionality of the data.
3.2.2. Models

We fitted Ordinary Least Squares Linear models for every response variable (water depth, turbidity and chlorophyll a content). We did not remove the bottom effect because our approach aims to retrieve both water depth and turbidity. To achieve this, we need the spectral contribution from the bottom of the ponds. Due to model parsimony, we used a maximum of three bands as independent variables. We built a total of 24 models combining buffer type, negative data transformation type, and using either raw explanatory bands or summarized data (PCA scores). Models were repeated after log transformation of the response variables. We fitted models with a stepwise algorithm, implemented in R [61] with backward/forward selection procedure. At each step, the model construction relied on the Akaike Information Criterion (AIC, [62]) to select the most plausible model from the analyzed set. The algorithm continued to evaluate the combinations of three independent variables (bands) until it identified the combination with the lowest AIC value (i.e., considered the best set of three variables).

For each model, we assess the degree of collinearity between each variable with Variance Inflation Factors (VIFs). This is because multicollinearity may increase the standard error of the estimates, which in turn makes it difficult to accurately assess the importance of the predictors. Only models with VIF values <5 were considered as candidates, as this indicates that there is no severe multicollinearity among the variables included in the models.

Due to the small number of samples, Bootstrap was conducted for each model (2000 samples each one) in order to reduce the uncertainty associated with the model estimator, making the model coefficients more robust and validating the model. The average Root Mean Square Error (RMSE) and the average adjusted $R^2$ obtained from the mean of all bootstrap repetitions, were used to determine model accuracy.

The RMSE (Equation (1)) indicates how far, on average, the residuals are from zero, or the average distance between observed values (O) and model predictions (P).

\[
\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (P_i - O_i)^2}
\]

The smallest RMSE indicated a more accurate prediction and the best model (out of the initial 24) was then used to predict and to map the spatial variation of each response variable using the selected bands for calculation.

A summary of the methods used is reported in Figure 2.

Finally, we used generalized linear models (GLMs) to test the effect of pond size, original pond excavation depth, and block position (north or south) on estimated values of point water depth, average pond depth and chlorophyll a. We used a Gaussian error distribution with an identity link for point water depth and average pond depth, and a Gamma distribution with a log link for chlorophyll a. We then used a Generalized Least Square (GLS) analysis for turbidity to deal with residual heterogeneity, while controlling for chlorophyll a concentration. This model included block position and the interaction between original pond excavation and pond size. We used ANOVA with type III sums of squares. Multiple comparisons with Tukey adjustment were conducted using the emmeans package [63].

Model assumptions were validated using the DHARMa package [64] or visually for GLS models.
Figure 2. Methodology Flow Diagram.

4. Results

4.1. Empirical Models

In all cases, models without log transformation superseded those with transformations of the dependent variable. For point water depth, the best model was model number 13. This was the model without any buffer that did not transform negative reflectance values. The model included the bands corresponding to 715.8, 380 and 677.4 nm. The regression empirical relationship is given by the following formula:

\[
\text{Point water depth} = 54.389 - 289.237 \times b_{715.8} - 507.019 \times b_{380} + 100.448 \times b_{677.4} \tag{2}
\]

In the case of the average pond depth, model 1 was the best model. This was the model without any buffer that replaced negative reflectance values with 0. The model included the mean value of the band corresponding to 720.6 nm, the minimum value of the band corresponding to 389.6 nm, and the standard deviation of the band corresponding to 974.4 nm.

\[
\text{Average pond depth} = 69.762 - 273.323 \times \text{mean}_{720.6} - 2370.899 \times \text{min}_{389.6} - 184.861 \times \text{std}_{974.4} \tag{3}
\]
The best model for turbidity was model 1. This was the model with a 5 m buffer inside the pond in which negative reflectance values were substituted by missing values. The model included the minimum of the bands corresponding to 384.4, 380 and 389.6 nm. The regression empirical relationship is given by the following formula:

\[
\text{Turbidity} = 9.335 - 14,606.719 \times \text{min}_b384.4 - 6919.829 \times \text{min}_b380 + 12,910.919 \times \text{min}_b389.6
\]

(4)

For chlorophyll a, model 4 was the best model. This was the model with a 5 m buffer from the inside of the pond edge that used negative reflectance values without transformation. The model included the mean value of the band corresponding to 485.5 nm and minimum values of the bands corresponding to 706.2 and 1036.5 nm.

\[
\text{Chlorophyll a} = 5.079 + 88.112 \times \text{mean}_b485.5 - 60.214 \times \text{min}_b706.2 + 71.157 \times \text{min}_b1036.5
\]

(5)

The mean RMSE and adjusted \( R^2 \) derived from the bootstrap resamples are shown in Table 2 for all models. Figure 3 shows the scatterplots illustrating the relationship between the selected bands and the response variables.

Table 2. Mean and Median RMSE and adjusted \( R^2 \) of each model.

<table>
<thead>
<tr>
<th>Model</th>
<th>RMSE Mean</th>
<th>RMSE Median</th>
<th>Adjusted ( R^2 ) Mean</th>
<th>Adjusted ( R^2 ) Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>Point water depth</td>
<td>7.429</td>
<td>7.348</td>
<td>0.797</td>
<td>0.801</td>
</tr>
<tr>
<td>Average pond depth</td>
<td>7.745</td>
<td>4.004</td>
<td>0.931</td>
<td>0.941</td>
</tr>
<tr>
<td>Turbidity</td>
<td>13.073</td>
<td>7.770</td>
<td>0.639</td>
<td>0.707</td>
</tr>
<tr>
<td>Chlorophyll a</td>
<td>1.145</td>
<td>1.088</td>
<td>0.772</td>
<td>0.835</td>
</tr>
</tbody>
</table>

Figure 3. Scatterplots illustrating the relationship between the selected bands and the response variables.

4.2. Mapping of Water Depth, Turbidity and Chlorophyll Content

Maps generated by applying the best empirical models for point water depth, average pond depth, chlorophyll a concentration and turbidity for ponds in the northern block,
the southern block and isolated ponds are displayed in Figures 4–7, respectively. For point water depth and average pond depth, the estimated values varied between 0 and 50.6/60 cm, respectively (Figures 4 and 5). The estimated values for average pond depth and point water depth were significantly related to the original excavated depth ($p < 0.001$). The estimated values for chlorophyll a concentration varied between 0 and 9.7 $\mu$g/L (Figure 6). The GLM model showed that when controlling for turbidity, chlorophyll a was lower in deeper ponds (emmeans = z-ratio = −2.52; $p = 0.01$). The estimated turbidity values ranged between 0 and 65.1 NTU (Figure 7). The GLS model reveals that, for turbidity (while controlling for chlorophyll a with a covariable), the interaction original excavated size $\times$ depth is close to significance (chisq = 5.95; $p = 0.051$). Specifically, turbidity was higher in original smaller, shallower excavated ponds respect to original bigger, shallower excavated ponds (post hoc: t ratio = −3.2; $p = 0.028$). Turbidity was also lower in the northern block with respect to the southern block (emmeans: t ratio = −2.18; $p = 0.035$).

Figure 4. Maps derived from individual measurement of water depth (cm) of the ponds located in the Northern and Southern blocks within the Caracoles estate, and of two isolated ponds between them (center). Ponds in white were not covered by the flight.

Figure 5. Map derived from pooled measurement of mean water depth (cm) of the ponds located in the Northern and Southern blocks within the Caracoles estate, and of two isolated ponds between them (center). Ponds in white were not covered by the flight.

Figure 6. Map derived from pooled data of chlorophyll a concentration ($\mu$g/L) of the ponds located in the Northern and Southern blocks within the Caracoles estate, and of two isolated ponds between them (center). Ponds in white were not covered by the flight.
Figure 7. Map derived from pooled measurement of turbidity (NTU) of the ponds located in the Northern and Southern blocks within the Caracoles estate, and of two isolated ponds between them (center). Ponds in white were not covered by the flight.

5. Discussion

To our knowledge, this is the first study that examines the potential of the CASI sensor to predict water mass characteristics in shallow-restored ponds, validated with ground truth data. We showed that data from the CASI imagery accurately estimated water depth, turbidity and chlorophyll concentration in these experimental ponds. These results highlight the ability of the CASI sensor to monitor spatial-dynamics in small ponds, and its utility to evaluate the effectiveness of restoration projects.

Turbidity emerged as the best-modeled variable, followed by average water depth and chlorophyll a concentration. These findings are not surprising, as a good estimation of water turbidity in shallow ponds, similar to those in this study, has already been proven by Bustamante et al. [38]. Unlike the Landsat sensors used by Bustamante et al. [38], our results indicate that the CASI sensor might differentiate between classes of low, medium, and high turbidity in shallow waters with submerged aquatic vegetation.

Water turbidity is caused by a mix of suspended solids, colored dissolved organic matter (CDOM) and plankton. When turbidity is composed mostly by suspended sediments, reflectance increased in the red region, i.e., 630–660 nm [38,65].

However, we found that the minimum of three bands: those located at 380, 384.4, and 389.6 nm were the best bands to model water turbidity. These bands correspond to UV-B wavelengths, suggesting that turbidity in the restored ponds should consist mostly of colored dissolved organic matter (CDOM), which dominates the absorption in many inland waters [60], and affects the reflectance value at wavelengths <500 nm [66,67]. Nonetheless, the proportion of total suspended solids can vary seasonally, consequently model parameters should be modified for different seasons so as to achieve the best accuracy for turbidity models [27,68].

Our GLS model based on estimated values also showed that water turbidity was affected by the original pond size and constructed depth. Specifically, in the case of shallower constructed ponds, smaller ponds were more turbid than larger ones. Several factors can influence turbidity in such small-sized ponds. For example, smaller ponds can experience faster drying than larger ponds of similar excavation depth, resulting in particle accumulation and higher turbidity. Some smaller ponds showing higher turbidity also appear to be closer to desiccation (Figures 2–5). In addition, ponds in the northern block were also less turbid than those in the southern block. The high values in the southern block may be attributed to several factors, including differences in the coverage of submerged vegetation, which can reduce sediment resuspension [69]. Also, wind can have a greater re-suspension effect on shallower ponds [43].

Considering the significance of turbidity in wetland ecosystems, further studies should explore this topic in greater detail.

Maps of water depth also showed that, generally, water level within ponds reflected their maximum excavation, as also confirmed by GLM models. Nonetheless, different water depth values were also observed for ponds of similar depth (e.g., ON1GP and 0N2GP...
both of 60 cm, see Figure S1), partly as a consequence of variable microtopography and its influence on the catchment area of each pond. A previous study conducted in the same pond complex [49] showed that, during months of high rainfall, connectivity between new ponds and other water bodies in surrounding areas increased. Thus, differences in real water depth among ponds with equal excavation depth probably also reflect larger water connections between these ponds and those in the surroundings, including seasonal streams, temporary ponds and adjacent natural marshes in rainy months. Since temporary ponds started drying up in May onwards, it seems plausible that at the time of image acquisition many of these connections had already evaporated, while some others remained visible (Figure S3). Nonetheless, it should be noted that reflectance of sediments at the bottom of the ponds could significantly affect the accuracy of water depth estimation [38]; however, we were not able to include this variable in this study. Spectral contribution from the bottom of shallow ponds can be mixed together with a high turbidity water column, which can also result in weak modeling under these circumstances.

The model for chlorophyll a concentration combined bands located in the blue, red and near-infrared regions. Specifically, it showed a positive relationship with the mean reflectance value at the 485.5 nm band, which indicates that increases in chlorophyll a concentration increase reflectance in this band. Nonetheless, chlorophyll should absorb in the blue portion of the spectrum, where reflectance should be low. Chlorophyll is found in various phytoplankton types (e.g., diatoms, cyanophytes, etc.) each possessing distinct pigments with specific reflectance values. For example, chromophyte algae, such as diatoms contain chlorophyll c, which has peaks at around 485 nm [70]. The positive correlation between chlorophyll and the band at 485 suggests the potential presence of elements whose pigments exhibit high reflectance in this spectral range.

Nevertheless, the model also incorporated bands in the near-infrared (NIR) regions at minimum wavelengths of 706.2 nm and 1036.5 nm. This suggests potential influences from water absorption or vegetation. The latter may include macrophytes either at the bottom of ponds or floating on the surface, as these can exhibit NIR values exceeding 700 nm [66,71]. Other studies should examine the accuracy of this model in the studied area and in other locations for estimating chlorophyll a concentration.

The GLM model for chlorophyll a revealed an inverse relationship between original pond excavation depth and chlorophyll concentration, i.e., shallower ponds contain more chlorophyll. This is not surprising, since shallower ponds contain less water, allowing for increased light penetration and, consequently, enhanced photosynthetic activity among aquatic organisms. This can also include chlorophyll content in submerged vegetation such as Chara spp., Ruppia spp. and Danisionium spp. abundant in the restored ponds.

Overall, the results revealed that water quality and depth are similar between the northern and southern blocks. However, within the same block, ponds with similar excavation depths can maintain water for different periods during the drying phase [47]. This variation may reflect differences in topography due to their position. We also found that when close to desiccation, water quality in smaller and shallower ponds was worse (i.e., more turbid and productive) than those in larger and deeper ones. High turbidity and chlorophyll concentration can affect biodiversity and can also have consequences on pond functions and the services they provide [72]. However, even the highest concentrations of chlorophyll we recorded are well below those recorded in other parts of Doñana more affected by anthropogenic nutrient inputs [73].

6. Conclusions

Although wetland restoration activities are increasing, post-restoration monitoring is often inadequate. From a conservation point of view, a continuous and consistent monitoring program of a restored area is vital to fully understand the long-term effectiveness of ecological restorations and the need for readjustments. This is especially relevant in a period when ecosystem restoration has been declared a priority [74].

Our study demonstrated the following:
• Suitability of CASI 1500: The resolution of the CASI 1500 is suitable to monitor water depth, turbidity and chlorophyll concentration in shallow ponds. This allows mapping of variations among ponds through the development of empirical models for the studied location and year.

• Application in wetland restoration monitoring: This promises to be a valuable method to monitor the outcomes of restoration projects across years and the response of temporary wetlands to changing climatic variation and human impacts such as water extraction and eutrophication [45,73,75].

• Model optimization: The performance of the models should be optimized in future studies, mainly by improving the homogeneity and quantity of the data used to build and validate them.

• Heterogeneity of Caracoles pond complex: Remote sensing with the CASI 1500 reveals how the Caracoles pond complex is a very heterogeneous and variable system, with limited explanation of the extensive differences recorded between ponds. These differences highlight the need for further research to understand the dominant ecological and hydrogeological processes involved, and to assess how the system is evolving since restoration.

• Need for ongoing monitoring: Remote sensing provides an excellent tool for monitoring long-term trends in pond characteristics in Doñana and elsewhere, e.g., due to eutrophication, ecological succession, and ongoing climate change (i.e., changing precipitation and temperature patterns, and extreme weather events such as major floods).

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/rs16162996/s1, Figure S1: Map of the Caracoles estate showing the location of the northern and southern blocks; Figure S2: Location of Santa Olalla lagoon; Figure S3: False color composites of the Caracoles estate CASI images; Table S1: Sampled ponds.

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