Deep-Learning Based Super-Resolution of Sentinel-2 Images for Monitoring Supercentenarian Olive Trees

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ABSTRACT

In the present work deep-learning based super-resolution (SR) is applied on Sentinel-2 images of the Zakynthos island, Greece, with the intention of detecting stress levels in supercentenarian olive trees due to water deficiency. The aim of this study is monitoring the stress in supercentenarian olive trees over time and over season. Specifically, the Carotenoid Reflectance Index 2 (CRI2) is calculated utilizing the Sentinel-2 bands B2 and B5. CRI2 maps at 10m and at 2.5mspatial resolutions are generated. In fact, the images of band B2 with original spatial resolution 10m are super-resolved to 2.5m. Regarding the images of band B5, these are SR resolved from 20m firstly to 10m and secondly to 2.5m. Deep-learning based SR techniques, namely DSen2 and RakSRGAN, are utilized for enhancing the spatial resolution to 10m and 2.5m. The following five seasons are considered autumn 2019, spring 2019, spring 2020, summer 2019 and summer 2020. In the future, comparisons with field measurements could better assess for the proposed methodology effectiveness regarding the recognition of stress levels in very old olive trees.

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CCS CONCEPTS

• **Machine learning**; • **Earth and atmospheric sciences**; • **Environmental sciences**;

KEYWORDS

Image super-resolution, Deep-Learning,Sentinel-2, Supercentenarian olive tree

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1 INTRODUCTION

Agriculture constitutes an important industrial sector that offers support and employment to millions of professionals and scientists globally. Additionally, it is a decisive factor for health, nourishment, economic and political stability, employment, business as well as biological ecosystems. Thereafter, in agriculture apart from productivity maximization, an all-inclusive view for addressing environmental sustainability issues is needed. Regarding olive trees, the supercentenarian ones (i.e. trees older than 110 years) are a significant part of cultural heritage. Thus, these trees have to be mapped and their time changes need to be examined [1]. Remote sensing technologies and particularly satellite images can serve for olive trees monitoring. Due to the launch of the Sentinel-2 satellite constellation of the European Space Agency (ESA) in 2015, multispectral images of up to 10 meter (m) ground sampling distance (GSD) are freely available. In fact, Sentinel-2 delivers an image of the same earth spot roughly every five days thanks to the high revisit frequency. Nevertheless, for certain application tasks, like detecting and counting objects [2], which need more high-resolution (HR) evidence, the spatial resolution of 10m GSD is insufficient. Super-resolution (SR) techniques, and in specific deep-learning based ones [3], can be utilized for increasing the satellite sensor inherent spatial resolution.

The study which is presented in [4] super-resolves the low-resolution (LR) Sentinel-2 bands at 20m and 60m to 10m by means of convolutional neural network (CNN). SR per factors 2 and 6 is separately performed via two deep network models. Net training considers that transferring high-frequency information across spectral bands is changeless over a range of scales. Sentinel-2 images from various geographical locations globally are selected as training data. The proposed SR networks demonstrate generalization ability over various climate zones and land covers whilst they are fast and preserve spectral characteristics. The 10m RGB bands of Sentinel-2 are super-resolved to spatial resolution equal to 5m in [5]. RapidEye satellite images of 5m, of nearly the same spectral band that were acquired the same date, are used to train the network. Dissimilar zones have not been included in the training image pairs. A modified version of the enhanced deep residual network has been utilized. Various learning plans which are based on progressive data resizing are considered. Three different types of deep CNNs are developed and applied for SR in [6]. The first basic network, named SRDCN[1], relies on hierarchical architecture for learning the mapping from the LR image to the HR image. Also, there are presented two other SRDCN extension networks, named DSRDCN and ESRDCN[2], that are based on residual learning and multiscale, respectively. The proposed SR networks outperform custom sparse representation techniques regarding both multispectral and hyperspectral images. The study in [7] proposes an improved SR generative adversarial network (GAN) called ISRGAN. This network presents greater training stability and better generalization ability through locations and sensors than SRGAN. Data from the Landsat 8 OLI and the Chinese GF1 sensors are utilized for land use classification and ground-object extraction.

In this work deep-learning based SR techniques are applied on Sentinel-2 images of the Zakynthos island, Greece, for recognizing stress levels in supercentenarian olive trees owing to water deficiency. In particular, the Sentinel-2 bands B2 and B5 are used for calculating the Carotenoid Reflectance Index 2 (CRI2). Actually, CRI2 maps at 10m and at 2.5m spatial resolutions are produced. The SR techniques DSen2 and RakSRGAN are utilized for achieving the final spatial resolutions of 10m and 2.5m.The current work aims at monitoring the stress in supercentenarian olive trees over time as well as over season**.** Five seasons get under consideration namely autumn 2019, spring 2019, spring 2020, summer 2019 and summer 2020. The proposed monitoring of supercentenarian olive trees in the future could be supplemented with comparisons with field measurements.

[1]. super-resolution with deep convolution network

[2] extensive super-resolution with deep convolution network

The current work is organized into three sections. Section 2 presents the methodology where Sentinel-2 images SR and CRI2 index calculation are described. Results are also given in this section. The conclusions are drawn in Section 3.

2 METHODOLOGY

2.1 Satellite Image Super-Resolution Based on Deep-Learning

Initially, the Sentinel-2 band B5 is SR resolved from the original spatial resolution 20m to the resolution 10m by means of the SR technique which is described in [4]. The employed network called DSen2 is a deep configuration of ResNet architecture. The number of convolutional layers equals 14 and there arise 1.8 million tunable weights. DSen2 is a light network, quick in training and prediction, achieving satisfactory accuracy. It should be noticed that DSen2 presents a long, additive skip connectionstraightforwardly from the resized input to the output. So, the entire network actually learns the additive correction from the bilinearly upsampled image to the target output. In this way, the radiometry of the input image can be preserved. Regarding the B2 band, it inherently presents the spatial resolution of 10m as captured by the satellite sensor. Afterwards, the 10m images of bands B2 and B5 are further spatially SR resolved per the factor of 4 and reach the spatial resolution 2.5m. The SR method which is presented in [8], called RankSRGAN, has been employed for achieving the latter resolution. The RankSRGAN framework demonstrates 3 stages. In stage 1, super-resolved images of public SR datasets are created by means of different SR techniques. Then, pair-wise images get ranked according to the quality score being calculated by a chosen perceptual metric and the respective ranking labels are kept. Stage 2 regards Ranker training. The learned Ranker, that presents a Siamese architecture, is expected to be able to rank images in accordance to their perceptual scores. As far as stage 3 is concerned, the trained Ranker is used to define a rank-content loss for a standard SRGAN to produce visually pleasing images.Figures 1–5demonstrate the band B2 at spatial resolutions 10m and 2.5m as well as the band B5 at resolutions 20m, 10m and 2.5m. All five seasons under consideration are depicted.

2.2 The Carotenoid Reflectance Index

The CRI2 index can be used for detecting and assessing the stress levels in supercentenarian olive trees due to water deprivation [1]. In the present work this index has been calculated by means of the Sentinel-2 B2 and B5 bands at 10m as well as at 2.5m. The CRI2 index is given by equation 1):

$$\mathrm{CRI2} = \left(\frac{1}{\mathrm{B}_2} - \frac{1}{\mathrm{B}_5}\right) \tag{1}$$

where B_2 and B_5 stand for the homonymous Sentinel-2 bands. Figure 6 depicts the CRI2 maps of the different spatial resolutions for the various seasons. Water deprivation condition may be much more intense and thus, more traceable, the autumn season in comparison with the spring and summer seasons. This is true since in

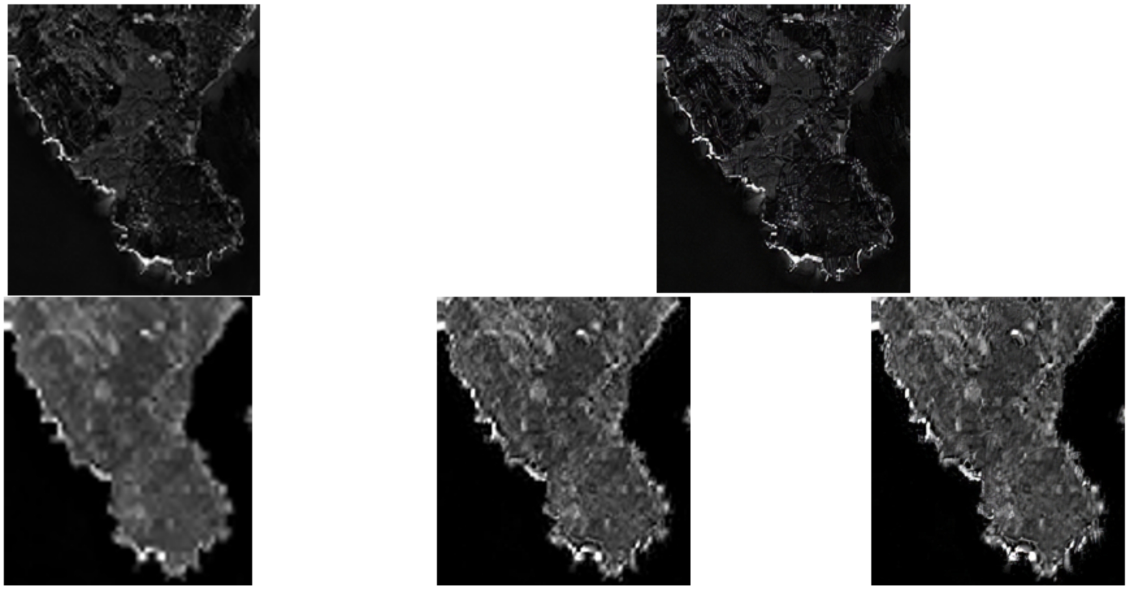

Figure 1: The Zakynthos island in the season autumn 2019 is depicted. The first row shows Sentinel-2 B2 band at spatial resolutions 10m and 2.5m in the first and second column, respectively. The second row demonstrates Sentinel-2 B5 band at spatial resolutions 20m, 10m and 2.5m in the first, second and third column, correspondingly.

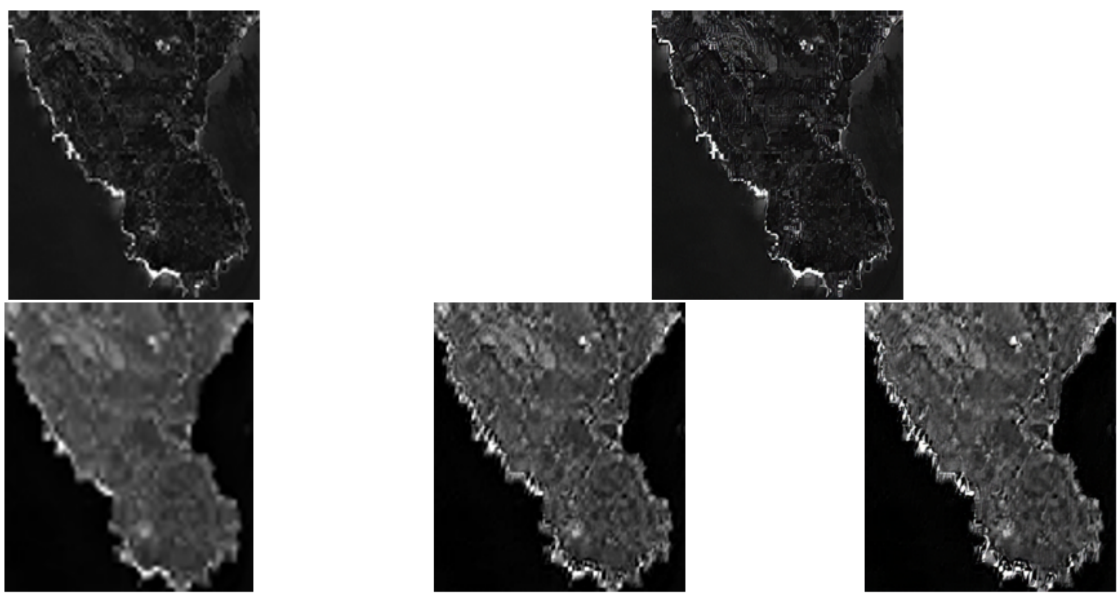

Figure 2: The Zakynthos island in the season spring 2019 is depicted. The first row shows Sentinel-2 B2 band at spatial resolutions 10m and 2.5m in the first and second column, respectively. The second row demonstrates Sentinel-2 B5 band at spatial resolutions 20m, 10m and 2.5m in the first, second and third column, correspondingly.

the intervention time before autumn high temperatures and lack of raining predominate as weather conditions. The depiction of CRI2 index in autumn 2019 presents certain lightcolor points which possibly denote the existence of supercentenarian olive trees. The finer spatial resolution of 2.5m has the potential of indicating with greater precision the points of supercentenarian olive trees, when compared with the resolution of 10m.

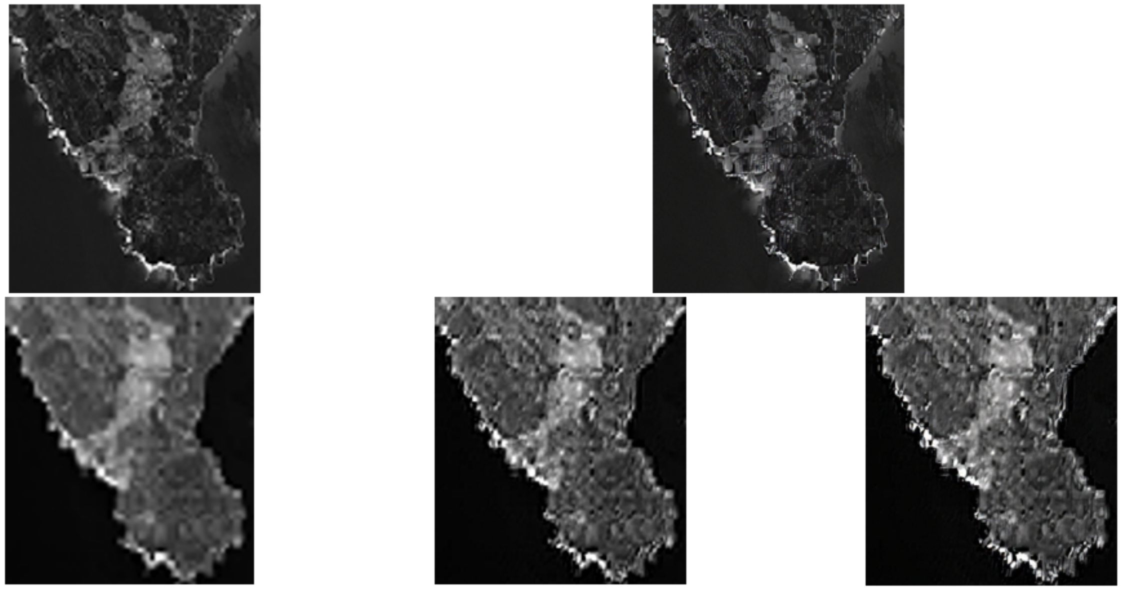

Figure 3: The Zakynthos island in the season spring 2020 is depicted. The first row shows Sentinel-2 B2 band at spatial resolutions 10m and 2.5m in the first and second column, respectively. The second row demonstrates Sentinel-2 B5 band at spatial resolutions 20m, 10m and 2.5m in the first, second and third column, correspondingly.

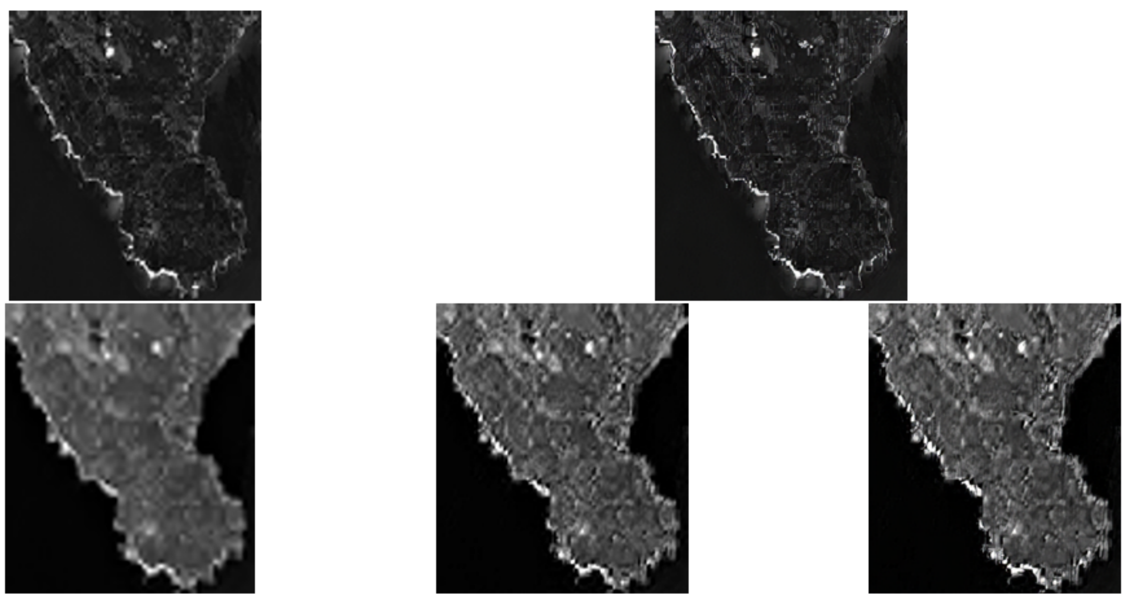

Figure 4: The Zakynthos island in the season summer 2019 is depicted. The first row shows Sentinel-2 B2 band at spatial resolutions 10m and 2.5m in the first and second column, respectively. The second row demonstrates Sentinel-2 B5 band at spatial resolutions 20m, 10m and 2.5m in the first, second and third column, correspondingly.

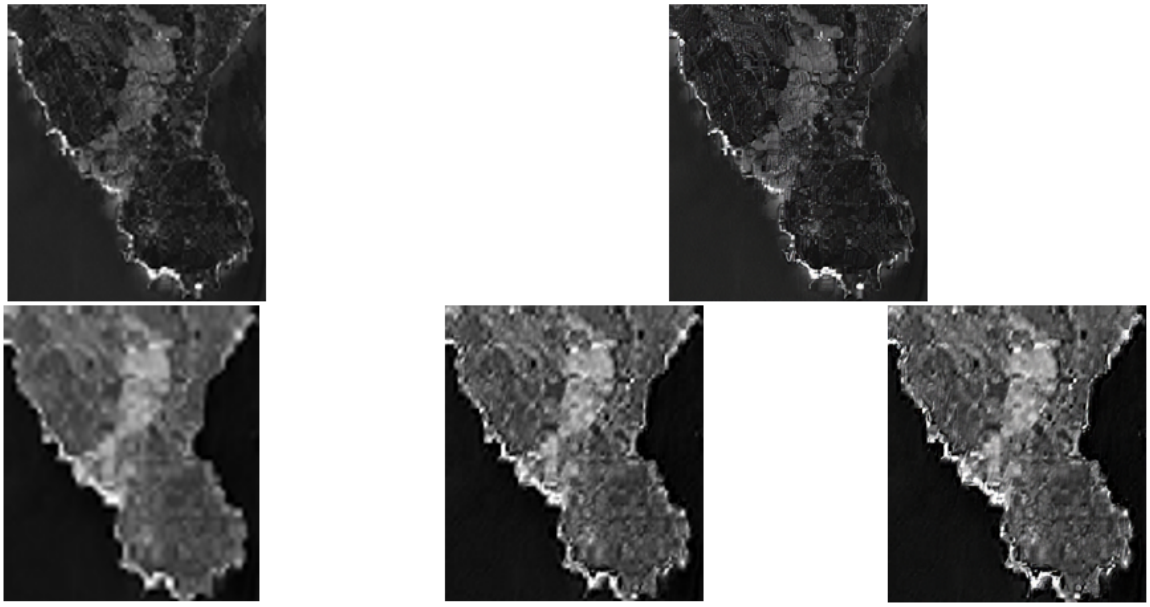

Figure 5: The Zakynthos island in the season summer 2020 is depicted. The first row shows Sentinel-2 B2 band at spatial resolutions 10m and 2.5m in the first and second column, respectively. The second row demonstrates Sentinel-2 B5 band at spatial resolutions 20m, 10m and 2.5m in the first, second and third column, correspondingly.

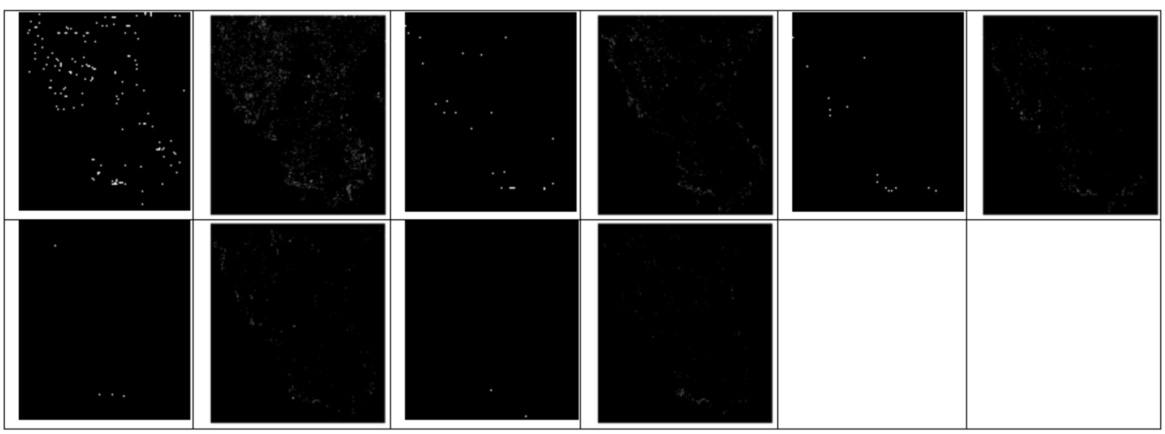

Figure 6: Illustration of the CRI2 index for the Zakynthos island. In the first row, the season autumn 2019, the season spring 2019 and the season spring 2020 is shown in the first, second and third cell, respectively. In the second row, the seasons summer 2019 and summer 2020 are depicted in the first and second cell, correspondingly. In each cell, the image in the first column presents spatial resolution 10m while the one in the second column has resolution 2.5m.

3 CONCLUSIONS

In the present work deep-learning based super-resolution is applied on Sentinel-2 images of the Zakynthos island, Greece, aiming at the detection of stress levels in supercentenarian olive trees that is caused by water deprivation. Actually, the stress in supercentenarian olive trees is observed over time as well as over season**.** To be more specific, the Carotenoid Reflectance Index 2 is calculated utilizing the Sentinel-2 bands B2, B5 where maps at 10m and at 2.5m spatial resolutions are produced. Five seasons are considered namely autumn 2019, spring 2019, spring 2020, summer 2019 and summer 2020. The condition of water deficiency may be much more intense and hence, more detectable, the autumn season in comparison with the spring and summer seasons. Indeed, there appear lightcolor points which possibly denote the existence of supercentenarian olive trees in the CRI2 map of autumn 2019. In fact, the finer spatial resolution of 2.5m can give with greater precision the indication of the points with supercentenarian olive trees, in comparison with the resolution of 10m. In future work, olive tree field measurements could serve for comparisons and assessment of the proposed methodology efficacity in concern with the detection of stress levels in supercentenarian olive trees.

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