Advancing Coral Structural Connectivity Analysis through Deep Learning and Remote Sensing: A Case Study of South Pacific Tetiaroa Island

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Abstract

Structural connectivity is an important factor in preserving coral diversity. It maintains the stability and adaptability of coral reef ecosystems by facilitating ecological flow, species migration, and gene exchange between coral communities. However, there has always been a lack of consistent solutions for accurate structural connectivity describing and quantifying, which has hindered the understanding of the complex ecological processes in coral reefs. Based on this, this paper proposes a framework that uses advanced remote sensing and deep learning technologies to assess coral structural connectivity. Specifically, accurate coral patches are firstly identified through image segmentation techniques. And the structural connectivity is quantified by assessing the connectivity patterns between and within these coral patches. Furthermore, Tetiaroa Island in the South Pacific is used as a case study to validate the effectiveness and accuracy of the framework in assessing coral structural connectivity. The experimental results demonstrate that the framework proposed in this paper provides a powerful tool for understanding the internal ecological processes and external spatial patterns of coral reef ecosystems, thereby promoting scientific understanding and effective management of coral reef conservation.

1. Introduction

Coral reef ecosystems are among the most biodiverse ecosystems on Earth. They provide habitat, shelter, nursery areas, and food for over nine million species of flora and fauna (Frys et al., 2020). However, the combination of large-scale stressors (such as El Niño-Southern Oscillation, global warming, and the Indian Ocean Dipole) and local stressors (such as overfishing, pollution, and disease) has led to the loss and degradation of coral habitats (Gamoyo et al., 2019, Klein et al., 2024, Lachs et al., 2023, van Woesik and Kratochwill, 2024). Habitat loss and fragmentation further lead to the loss of structural connectivity, constituting a major reason of global coral ecosystem collapse and biodiversity decline (Faryuni et al., 2023, Saint-Amand et al., 2023, Figueiredo et al., 2022). Structural connectivity describes the spatial distribution and ecological patterns of habitats, considering how different landscape attributes facilitate or impede species movement or flow, which is crucial for coral reefs to maintain gene flow, biodiversity, and ecosystem resilience (Baguette et al., 2013, Jiang et al., 2024, Spanowicz and Jaeger, 2019, Hilty et al., 2020). However, due to the complex interplay of topography and biological communities, coral reefs exhibit characteristics such as wide distribution, large size disparities, and susceptibility to marine environmental factors. Consequently, it is empirically challenging to measure coral structural connectivity, especially when dealing with large-scale coral reefs spanning hundreds of kilometers or even the globe. Therefore, the effective description and quantification of structural connectivity have become pivotal issues in the conservation of coral reef ecosystems.

To measure structural connectivity, habitats are typically depicted as discrete habitat patches, and these patches represent individual coral colonies or coral communities. Structural connectivity is often based on the migration or dispersal between (inter-patch connectivity) or within (intra-patch connectivity) these patches (Spanowicz and Jaeger, 2019, Galpern et al., 2011, Erős et al., 2012). From a functional perspective, structural connectivity can also be summarized as the connectivity within individual patches, the connectivity of connections between different patches, and the connectivity that serves as a stepping stone to maintain connections between other patches (Crouzeilles et al., 2013, Tambosi et al., 2014). However, in the routine observation and survey of coral habitats, identifying these patches is not always easy to achieve, as traditional methods for identifying coral habitat patches often rely on manual visual interpretation or the use of remote sensing supervised classification tools, which require expert-supported empirical models and significant human resource costs (Han et al., 2022, Kussul et al., 2017). In recent years, the widespread application of the cutting-edge image understanding technology in remote sensing has provided better promising solutions for analyzing coral structural connectivity. These deep learning-based remote sensing monitoring methods can acquire high-level, abstract and implicit feature representations of coral reefs in an end-to-end manner without the intervention of human expertise (Mo et al., 2022, Yuan et al., 2021, Yuan et al., 2020). They have the potential to offer cost-effective patch identification and quantify coral habitat structural connectivity by evaluating the distance, structure, and connectedness among different coral patches. However, there is still a lack of a consistent framework for utilizing remote sensing monitoring methods to support coral structural connectivity research, which leaves a gap between theory and practice of remote sensing-based coral structural connectivity analysis.

Based on this, this paper provides a consistent framework for using advanced remote sensing observation technology to study coral structural connectivity. It uses the South Pacfic Tetiaroa Island as a case study to explore how remote sensing monitoring can effectively help quantify and analyze the impact of coral connectivity on coral ecological patterns and health status. By integrating remote sensing technologies with deep learning technologies, the framework enables standardized and accurate assessments of connectivity patterns across diverse reef ecosystems. This contributes to the understanding of coral reef growth status and resilience, thereby providing a scientific basis for formulating effective conservation measures to protect fragile coral reef ecosystems.

2. Coral Structural Connectivity Measurement

Inter-patch connectivity is a crucial factor influencing species movement between landscape habitat patches, and numerous metrics have been proposed to study it. This includes metrics such as inter-patch distance index, area index, and graph theory connectivity indices (Justeau-Allaire et al., 2024, Saura and Rubio, 2010, Uroy et al., 2021). However, only considering inter-patch connectivity can lead to a problem that the connectivity value is zero for a landscape comprising a single habitat patch, even if that patch covers the entire landscape. This indirectly advocates habitat fragmentation to enhance connectivity, resulting in negative impacts on ecological conservation (Laita et al., 2011, Tischendorf and Fahrig, 2000). The phenomenon underscores the importance of intra-patch connectivity, which characterizes the ecological processes and interactions between different parts within coral patches. Nevertheless, the exploration of intra-patch connectivity is still in its preliminary stages (Zhao et al., 2022, Watts and Handley, 2010). The most robust connectivity indices currently available are those that consider both inter-patch connectivity and intra-patch connectivity. They comprehensively consider the complex ecological processes within coral communities and the material and genetic exchange between coral communities, thereby providing a more comprehensive assessment of the ecological status of corals (Saura and Pascual-Hortal, 2007, Bodin and Saura, 2010).

This study selected the Integral Index of Connectivity (IIC) (Pascual-Hortal and Saura, 2006, Baranyi et al., 2011) to quantify connectivity both inter- and intra-patch within the study area. It is based on a binary connectivity model to uncover the topological structure and connectivity patterns of habitat networks, integrating ecological pattern information such as patch size, landscape size, and edge configuration. The definition of IIC is as shown in Equation 1.

$$IIC = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} (\frac{a_i \cdot a_j}{1+nl_{ij}})}{A^2} \tag{1}$$

where n is the total number of patches, a_i is the area of patch i, nl_{ij} is the number of connections between patches i and j, and A is the area of the total landscape. The value range of IIC is from 0 to 1, where 0 indicates no connections between patches, and 1 indicates that the entire landscape consists of habitat patches. However, excessively small values of IIC may weaken the differentiation between connectivity levels in different regions. To better quantify and interpret changes in connectivity, this paper used Equivalent Connectivity (EC) corresponding to the IIC metric (EC(IIC)) as the final measure of connectivity (Saura et al., 2011). It is defined as the area of a single habitat patch that provides the same connectivity as the IIC value, as shown in Equation 2. The EC (IIC) possesses all the desirable properties and prioritization capabilities of IIC, while also being able to quantify connectivity in a more intuitive manner by reflecting the same units as habitat attributes.

$$EC(IIC) = \sqrt{\sum_{i=1}^{n} \sum_{j=1}^{n} (\frac{a_i \cdot a_j}{1+nl_{ij}})} \tag{2}$$

To further determine the connectivity contributions of each patch to the overall landscape connectivity, this paper introduce the deltas IIC (dIIC), which indicates the IIC importance values of different patches. The definition of dIIC of patch i is shown in Equation 3.

$$dIIC_i = \frac{IIC - IIC_{remove}}{IIC} \tag{3}$$

where IIC represents the landscape connectivity, and IIC_{remove} represents the landscape connectivity after removing patch i. Considering the different functions in which each patch contributes to landscape connectivity, dIIC can also be expressed as Equation 4.

$$dIIC_i = dIICintra_i + dIICflux_i + dIICconnector_i \tag{4}$$

Among them, $dIIC_i$ denotes the contribution of patch's area (or other attributes) to its own connectivity. $dIICflux_i$ corresponds to the area-weighted (or other attributes-weighted) dispersal flux through the connections of patch i to or from all of the other patches in the landscape when i is either the starting or ending patch of that connection or flux. This primarily evaluates the strength of patch's own connectivity. $dIICconnector_i$ represents the role of patch i as a stepping stone in maintaining the connectivity of other patches in the landscape. $dIICconne-ctor_i$ depends on the position of the patch in the landscape pattern, with higher values indicating that the loss of patch would weaken the connectivity between other patches (Saura and Rubio, 2010).

3. Experimental Results and Analysis

3.1 Automatic identification of coral habitat patches

The accurate identification of coral habitat patches is the basis for coral structural connectivity analysis. This paper utilized the classical U-Net (Ronneberger et al., 2015) neural network for the automatic coral patches identification. As one of the most popular semantic image segmentation networks, it achieves pixel-level accurate identification of coral patches by employing a symmetric U-shaped network comprising a contracting path and an expansive path. Specifically, the U-Net network architecture consists of an encoder and a decoder. The encoder gradually extracts feature information from the input image through convolution and pooling operations, while the decoder maps these features back to the spatial resolution of the input image. Skip connections directly link corresponding layers of the encoder and decoder, aiding in learning high-level abstract

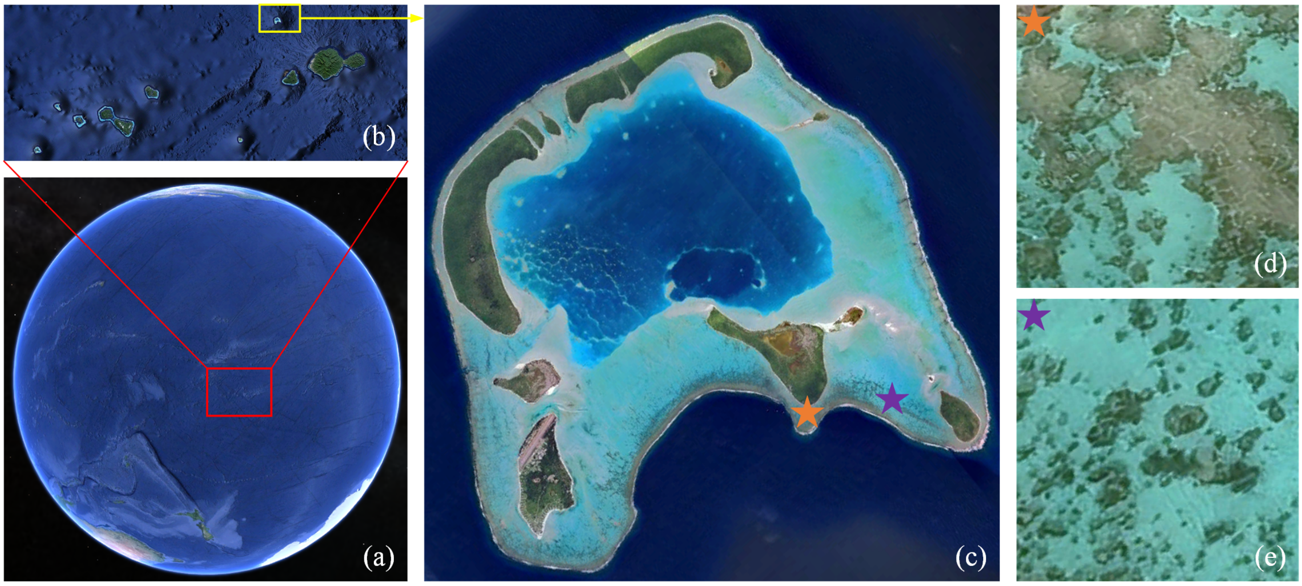

Figure 1. Locations of the experimental data. (a) South Pacific, (b) Society Islands, French Polynesia, (c) Tetiaroa Island, (d) Test Area 1, (e) Test Area 2.

features while preserving and propagating low-level feature information, thus achieving accurate image understanding and segmentation results.

As for training dataset, this paper utilized Google Earth Imagery of the Tetiaroa region (17.0°S, 149.5°W) in May 2022 as research data, as shown in Figure 1. To achieve fine-grained coral connectivity monitoring, we utilized Google imagery with the perspective altitude of 400 meters, which offers sub-meter-level benthic coral satellite remote sensing images. Two test areas were selected to more clearly characterize connectivity details and spatial distribution. We randomly cropped and manually annotated 956 training sub-images of size 256 pixels × 256 pixels in Tetiaroa Google Earth Imagery. To enhance network's generalization capacity and prevent overfitting, a range of data augmentation techniques were utilized, including random hue transformation, random contrast transformation, random translation, random rotation, random flip, and random multi-scale transformation. These augmented datasets were then used for U-Net training, enabling it to possess robust and precise characterization of coral reef features. Subsequently, the trained network was utilized for coral patch segmentation in non-overlapping test areas. The segmentation results are shown in Figure 2.

The experimental results indicate that although there are cases of misclassification in some regions due to the similarity between coral and background textures (as indicated by the red boxes), overall, semantic segmentation network accurately distinguishes the vast majority of coral and background classes. It's worth noting that even very small coral patches can be correctly identified. From a quantitative perspective, semantic segmentation network yielded accurate coral identification results, with a mean Intersection over Union (mIoU) (Hao et al., 2020) of 83%. This demonstrates the potential of using deep learning semantic segmentation networks to identify habitat patches, thus assisting in the measurement and analysis of coral structural connectivity.

3.2 Coral Structural Connectivity Analysis

This paper calculated the overall landscape connectivity of the two test areas and the results are shown in Table 1. Exper-

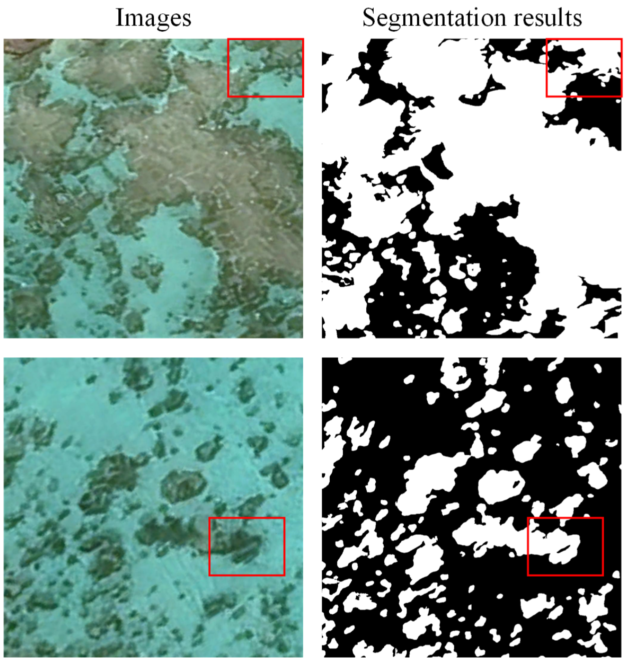

Figure 2. The coral segmentation results of the test areas, where white represents the coral class and black represents the background class. The first row shows the results of test area 1 while the second row shows the results of test area 2.

imental results demonstrate the potential of using connectivity to indicate coral ecological patterns. From an overall connectivity perspective, densely distributed multiple patches tend to achieve higher regional overall connectivity compared to a single large coral patch. This indicates that connectivity between habitat patches promotes growth and reproduction, thereby enhancing biodiversity.

To further identify the contributions of individual patches to regional overall connectivity, this paper calculated the dIIC of every coral patches and visualize them in the coral satellite im-

	EC(IIC)
Area 1	894.72
Area 2	3204.54

Table 1. Overall landscape connectivity of the test areas.

agery. The connectivity map is shown in Figure 3. It can be seen that the connectivity of a single patch may be related to its size and spatial connectivity pattern with neighboring patches. Larger habitat patches are more likely to exhibit higher connectivity. This is not only reflected in its own high connectivity, but also in connecting surrounding patches to form a core highly-connected area. Even smaller patches near highly-connected areas may demonstrate higher connectivity due to their proximity to core coral areas, as shown in the second column of Figure 3.

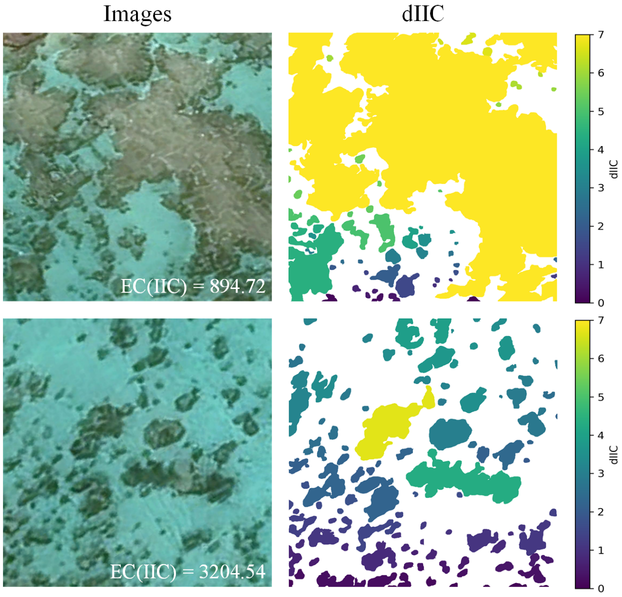

Figure 3. Connectivity map of the test areas. The first column shows the remote sensing images of the test areas, with the overall connectivity index EC(IIC) value displayed in the bottom right corner. The second column shows the dIIC values for each patch, with different colors indicating the magnitude of the dIIC value. The first row represents the results of test area 1 while the second row represents the results of test area 2.

To understand the functional roles of different patches in promoting connectivity between landscapes, this paper calculated the average values of dIICintra, dIICflux, and dIICconnector for all patches in each test area. Considering that the absolute values of the averages are not comparable between different test areas, we computed the ratios of the three types of functional connectivity to the overall connectivity, the results are shown in Table 2.

	IICintra(%)	IICflux(%)	IICconnector(%)
Area 1	2.76	80.93	16.31
Area 2	1.93	94.64	3.43

Table 2. Connectivity functional contributions of the test areas.

Overall, the connectivity of a specific area largely depends on the mutual connections between patches, that is, IICflux. Furthermore, large core patches are meaningful for regional connectivity, not only because of their large size thus resulting in higher IICintra, but also because they can serve as stepping stones to connect surrounding patches. For instance, in area 1, the coral colony spanning the entire area contributes to a relatively higher proportion of IICintra and IICconnector to the overall connectivity. For area 2, composed of many adjacent small patches, its connectivity is more reflected in the interconnection between these small patches, i.e. IICflux. This insight inspires us to take measures to protect large core habitat communities while simultaneously establishing ecological corridors to facilitate connectivity between small communities, thus enhancing the stability and sustainability of the overall ecosystem. The selection of coral refuges can also be inspired by this, prioritizing areas with high connectivity that harbor core coral communities.

4. Conclusions

In this paper, we use Tetiaria Island in the South Pacific as a case study to propose and validate an advanced framework for analyzing coral structural connectivity through deep learning and remote sensing. It determines the key factors influencing structural connectivity and coral ecological health by analyzing the overall connectivity of different areas and the contribution of each community to the overall connectivity. Furthermore, this paper distinguishes different functional modes in which coral communities promote landscape connectivity, including the connectivity within different parts of a single community, connectivity between different communities, and connectivity where communities serve as stepping stones to promote connections between other communities. This provides insights into improving coral ecological diversity by adjusting the spatial arrangement. Our experimental results demonstrate that protecting large core coral habitat communities and facilitating connectivity between small coral communities through the establishment of ecological corridors can significantly improve the ecological stability of coral ecosystems.

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