Wetland Condition Change Index using remote sensing images and Google Earth Engine

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Keywords: Floodplain, tropical savanna, Landsat, Google Earth Engine, spectral indices, habitat integrity.

Abstract

Wetlands and floodplains areas are crucial for biodiversity and ecosystem services, such as regulating hydrological regimes and controlling flood risks. Despite their importance, these environments have been significantly degraded by human activities. Brazil, Australia, and other tropical areas are key regions for global wetland conservation, yet they face severe threats. Australia’s wetlands, covering 4.4% of the country, face degradation, particularly in the Northern Territory. Considering this background, the present study introduces the Wetland Condition Change Index (WCCI) to assess wetland condition changes, focusing on the Adelaide River floodplain in Northern Australia. The WCCI, using Landsat images processed in Google Earth Engine, integrates indicators for soil, water, vegetation, and impervious surfaces. Trends were determined using Sen’s slope, and the results were validated with field observations and accuracy metrics. The Adelaide River Catchment was adopted as a study case, motivated by the lack of updated information. Results indicate that urban and agricultural developments contribute to negative trends, while natural areas show stable or positive trends. The WCCI reveals minimal changes in the Adelaide River floodplain’s wetlands, with some regions impacted by intensive livestock activity and new agricultural developments. However, anomalies in certain areas suggest natural environmental changes needing further investigation. The WCCI proved effective in assessing wetland conditions and can be applied to other tropical regions, including Brazil, enhancing understanding of wetland dynamics and aiding in conservation and management efforts.

1. Introduction

Wetlands and floodplains areas are vital for supporting biodiversity and the provision of essential ecosystem services. They are very diverse in their typologies, complexities, and dimensions which enable them to regulate hydrological regimes and perform multiple environmental functions, degrade pollutants and control flood risks, and other benefits even when they have small areas or are already pressured by human activities. Global wetland conservation priorities are concentrated in a few countries, including Brazil, Australia and other tropical regions (Yi et al., 2024). These areas can contribute significantly to global wetland biodiversity conservation.

Despite international recognition of their importance, these environments have been continuously degraded due to human activities. Since 1700, the cumulative loss of wetlands has reached 3.4 million km² at alarming rates, particularly in inland areas (Fluet-Chouinard et al., 2023). Most of this loss occurred during the twentieth century, with an increasing rate, especially in developing countries (Davidson, 2014). This decline highlights the urgent need for updated and comprehensive knowledge about the state of remaining wetlands, particularly in regions with development projects that could affect their quality.

In Brazil, as an example, 20% of the territory is classified as wetlands [1]. Recent data from the MapBiomas project indicate that natural covers strongly related to wetlands — such as mangroves, floodable forests, flooded grasslands, and swamps — have been reduced by 4.9 million hectares from 1985 to 2023 [2]. In Australia, wetlands covering 4.4% of the country, with 66 designated as internationally important under the Ramsar Convention, also face threats (Bino et al., 2016). The Northern Territory, in particular, hosts 33 nationally significant wetlands, lacking updated information since 2005.

Wetland conditions are significantly influenced by disturbances both within the wetlands and in the surrounding landscape. These conditions are closely tied to conservation efforts, management practices, and mitigation strategies implemented at site-specific and landscape scales (Yang et al., 2021). A precise understanding of the current status and evolving trends of wetland conditions in northern Australia is crucial for enhancing environmental management and promoting sustainable development (Zhang et al., 2023).

Beyond land use/land cover change, contemporary processes contributing to this scenario include the implementation of infrastructure that drains wetlands, the introduction of materials such as nutrients and sediments into water bodies, and other actions that impact wetland hydrological regimes.

To assess the impacts of these threats and ongoing losses, this study proposes the Wetland Condition Change Index (WCCI).

[1] there are different estimates, such as in the work from JUNK, W. J. et al. Parte I: Definição e Classificação das Áreas Úmidas (AUs) Brasileiras: Base Científica para uma Nova Política de Proteção e Manejo Sustentável. Em: Classificação e Delineamento das Áreas Úmidas Brasileiras e de seus Macrohabitats. Cuiabá: EdUFMT, 2015.

[2] Data from MapBiomas.org, Collection 8

https://doi.org/10.5194/isprs-archives-XLVIII-3-2024-135-2024

The index is a simple measure designed to highlight areas that have undergone changes over time, potentially aiding in the identification of actions impacting wetlands.

The WCCI was specifically developed for the Adelaide River Catchment in the Northern Territory, Australia. This whole region accounts for 70% of the continent’s freshwater runoff and has significant information gaps in wetland management. However, the WCCI can be applied to other areas, enabling comparisons and enhancing our understanding of wetland dynamics on multiple scales. The WCCI is a composition made using Landsat images operated using Google Earth Engine platform, samples of the territory and basic statistical analysis. The methods of its application and validation are described in the following sections.

2. Study area

Situated in the Northern Territory, our study area spans 200 km of coastal wetland between Darwin and Kakadu National Park. With high annual rainfall (approximately 1600 mm - http://www.bom.gov.au/climate/data/), the region experiences distinct wet and dry seasons. Our focus is on the Adelaide River floodplain, where flooding, influenced by groundwater storage, transitions from freshwater dominance in the wet season to saline intrusion with tidal effects in the late dry season. This area combines conservation, agricultural, and pastoral tenures. The floodplain’s low-lying topography, shaped by seasonal monsoonal rains, creates diverse wetland habitats crucial for breeding and feeding, contributing significantly to the ecological health of the area.

3. Material and Methods

To evaluate trends in wetland condition changes, we used remote sensing indicators based on previous studies developed to assess wetlands condition. From literature review and consultation with experts, four components of remote sensing-based indicators were selected. They refers to soil, water, vegetation, and impervious surfaces. These indicators reflect the main biophysical components of wetlands and their interactions with human activities. These selected components are closely related to landscape patterns and are affected by human activities, which can be directly perceived by people and are used to infer ecological conditions and vulnerabilities.

Remote sensing indices were selected for each component (Table 1). Using Landsat images from 1986 to 2022, we computed the selected remote sensing indices to form annual mosaics. Pre-processing procedures of each image were applied to avoid clouds and shades. Also, each index were added as a band. The final mosaics were then reduced by the median value by pixel and year. Trends for each pixel were determined using Sen’s slope, a robust non-parametric estimator of trends over time less subject to outliers in a data set - usually applied to access environmental qualities. We then calculated the average Sen’s slope for each component (soil, water, vegetation, and impervious surfaces).

Indices	PV	NV
Vegetation: Greeness (from Tasseled Cap Transformation), with equations that varies according to Landsat missions. NDVI (Normalized Difference Vegetation Index): $\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red}}, \quad (1)$ EVI (Enhanced Vegetation Index): $\mathrm{EVI} = \frac{(2.5 \times \mathrm{NIR} - \mathrm{Red})}{(\mathrm{NIR} + 6 \times \mathrm{Red} - 7.5 \times \mathrm{Blue} + 1)}, \quad (2)$ SAVI (Soil Adjusted Vegetation Index): $\mathrm{SAVI} = \frac{(\mathrm{NIR} - \mathrm{Red})(1 + L)}{(\mathrm{NIR} + \mathrm{Red} + L)}, \quad (3)$	+	-
Soil: BSI (Bare Soil Index): $\mathrm{BSI} = \frac{(\mathrm{SWIR1} + \mathrm{Red}) - (\mathrm{NIR} + \mathrm{Blue})}{(\mathrm{SWIR1} + \mathrm{Red}) + (\mathrm{NIR} + \mathrm{Blue})}, \quad (4)$ NDBSI (Normalized Difference Bare Soil Index): $\mathrm{NDBSI} = \begin{cases} -\left\| \frac{\mathrm{SWIR1} - \mathrm{Blue}}{\mathrm{SWIR1} + \mathrm{Blue}} \right\|, & \text{if } k < 0 \\ \frac{\mathrm{SWIR1} - \mathrm{Blue}}{\mathrm{SWIR1} + \mathrm{Blue}}, & \text{if } k > 0 \end{cases} \quad (5)$ where $k = r \times v$ $r = 1 - \frac{SWIR1 - NIR}{3 \times \|NIR - Red\|}$ $v = Red - Green$	-	+
Imperviousness: NDBI (Normalized Difference Built-up Index): $\mathrm{NDBI} = \frac{\mathrm{SWIR1} - \mathrm{NIR}}{\mathrm{SWIR1} + \mathrm{NIR}}, \quad (6)$ IBI (Index-Based Built-up Index): $\mathrm{IBI} = \frac{\|NDBI - (SAVI + MNDWI)/2\|}{\|NDBI + (SAVI + MNDWI)/2\|}, \quad (7)$	-	+
Water: Wetness (from Tasseled Cap Transformation), with equations that varies according to Landsat missions. MNDWI (Modified Normalized Difference Water Index): $\mathrm{MNDWI} = \frac{\mathrm{Green} - \mathrm{SWIR1}}{\mathrm{Green} + \mathrm{SWIR1}}, \quad (8)$	+	-

Table 1. Components and respected remote sensing indices used to compose the Wetland Condition Change Index. PV = positive values; NV = Negative values.

To integrate these components into an overall wetland condition

This contribution has been peer-reviewed.
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metric, we utilized the median value on a normalized scale. This composition was derived from interpreting wetland quality for each component, taking into account both positive and negative slope values (PV and NV, respectively). The final image was normalized using values obtained from field observations and reference sites, based on preliminary fieldwork that identified maximum negative changes (wetland loss due to land use) and established the maximum negative variation in wetland condition (wetland loss).

Using these reference sites, values from Sen’s slope were normalized to a range of -1 to 1. A value of 1 indicates an increase in the index, which may signify a decrease in disturbance or another cause of index increase. Values close to -1 represent maximum negative changes in the pixel, serving as a proxy for maximum disturbance occurring during the period. These procedures resulted in the Wetlands Condition Change Index (WCCI), where values close to zero indicate stable areas (i.e., areas where no significant changes were detected by Sen’s slope regression).

The entire process was developed using Google Earth Engine to ensure replicability in other regions. Field observations of the Adelaide River catchment were supported by data collected through helicopter surveys, complemented by a land use map of the Northern Territory [3].

The validation of results were done considering random samples distributed along the catchment. They were visually classified as areas that shows evidence of human activities (generally with negative tendencies or degraded), and areas with no evidence of human degradation (more conserved and thus, without perceivable negative pressures). Were generated 459 random samples. From a visual appraisal, 110 of them were evaluated as degraded, that is, associated with roads, housing, infrastructure, bare soil, paths generated by cattle, etc.; and 155 points, as conserved areas, related to wetlands with conserved vegetation or water (except from man-made ponds for mining). The remaining samples were not possible to classify using high resolution imagery and ancillary datasets, thus they were eliminated from the analysis.

A confusion matrix were calculated using the samples, envisioning to obtain metrics of accuracy to the final map. The overall, user and producer’s accuracy were calculated according to the equations below. The accuracy analysis was done by using variable proportions of all available samples, allowing to indicate the stability of results.

$$\text{Overall Accuracy (OA)} = \frac{\sum_{i=1}^{n} C_{ii}}{N} \tag{9}$$

where (n) is the number of classes,
(C_{ii}) is the number of correctly classified samples for class (i),
(N) is the total number of samples.

$$\text{User's Accuracy (UA)}_i = \frac{C_{ii}}{\sum_{j=1}^{n} C_{ij}} \tag{10}$$

where C_{ii} is the number of correctly classified samples for class i,
$\sum_{j=1}^{n} C_{ij}$ is the total number of samples classified as class i.

$$\text{Producer's Accuracy (PA)}_i = \frac{C_{ii}}{\sum_{j=1}^{n} C_{ji}} \tag{11}$$

where C_{ii} is the number of correctly classified samples for class i,
$\sum_{j=1}^{n} C_{ji}$ is the total number of actual samples in class i.

These metrics were employed to assess both the uncertainty of the results and the trend values indicative of potential degradation process. Specifically, we evaluated the significance of slope values in the context of wetland condition to identify regions of uncertainty within the index considering the knowledge about Adelaide River Catchment. This assessment was based on the average WCCI values for both negative and positive slopes from random samples. The accuracy analysis was conducted over a range of $|WCCI| \geq a$, where $0 \leq a \leq 1$.

4. Results and discussion

4.1 Accuracy assessment

The accuracy analysis reveals that the results are promising. The Figure 1 shows that for values of $|WCCI| \leq 0.2$, the overall accuracy increases to less than 0.85. Above this value there is a region with more stable results, until about 0.42, from which the accuracy metrics varies without getting stable again and finally decrease in accordance with the proportion of samples available. The quantity of sample decreases because they are filtered by $|WCCI|$ values. That is, for more restrictive conditions for the index, less samples are available to test the results, since they carry the WCCI as its property. That’s why we are also showing the stability of results according to ranges of the index, as will be discussed further.

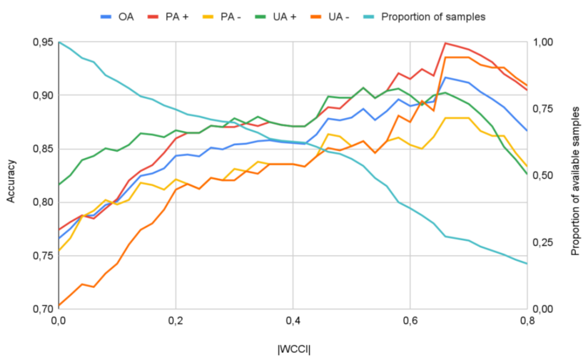

Figure 1. Accuracy metrics variations according to $|WCCI|$ values. OA is overall accuracy; PA+ is the producer’s accuracy for positive values of WCCI; PA- is the producer’s accuracy for negative values of WCCI; UA+ is the user’s accuracy for positive values of WCCI; UA- is the user’s accuracy for negative values of WCCI. For $|WCCI| \geq 0.8$ the results were critically low and then not considered in this analysis.

[3] https://www.agriculture.gov.au/abares/aclump/land-use/alum-classification

Considering all the available samples, the average value for points of positive trends of WCCI was 0.33. Also, for negative values, the average was -0.33. This was a key value to analyze how the accuracy varies if different proportions of samples are tested and check if alternative thresholds works well. We selected this WCCI threshold and a couple of others to discuss the use of the index and its interpretation (Figure 2).

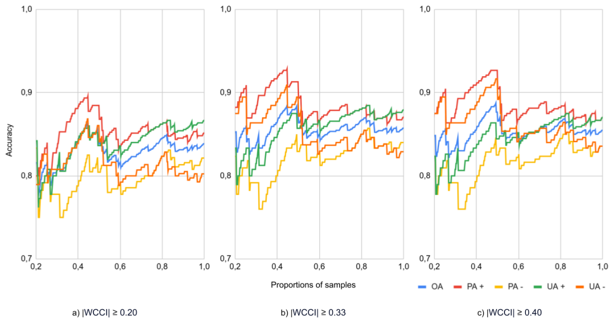

Figure 2. Accuracy metrics variations according to proportion of samples for specific |WCCI| values.

4.2 Quantitative analysis

Beyond the accuracy metrics, we also calculate how much area of each condition category must be related to the main tested values of |WCCI|. These categories are summarized as (1) areas with negative trends, (2) areas without significant trends, and (3) areas with positive trends. By doing this, we show the range of areas eligible to be classified in each category (as in Figure 3).

The areas change substantially for each case. For example, when adopting |WCCI| $\geq$ 0.3, the area under this category is estimated to be 98.76 thousand hectares, but it can be larger if we include all values with a negative tendency. As mentioned before, each category is associated with an uncertainty. The same applies to the other categories. However, it is worth noting that for ’not significant trends’, the quantities are computed inversely (i.e., for high levels of |WCCI|, the area under uncertainty is larger).

Considering the properties of the samples, we also present how each of the components (selected to form the WCCI) behaves individually over the time series (as in Figure 4). This result confirms the differences between each category, clearly indicating that areas with positive and negative trends are accurately represented by the WCCI according to the previously established interpretation of the index (see Table 1). In other words, the empirical data align with the expected outcomes of the WCCI.

Figure 5 illustrates another potential use for the index, customized to each type of wetland in the catchment under analysis. In this case, the land use/land cover were also used as a samples property observing available maps for the year of 2022. This example draws attention to the fact that the range of ’significant trend’ can vary across the landscape. Another call, even considering that the samples were not distributed evenly (that is, the random distribution didn’t consider classes of wetlands), is the absence of samples classified with negative trends for water, mangrove and short mangrove, and samphire/salt-flat. Considering areas that effectively change from a natural land cover to an anthropic one

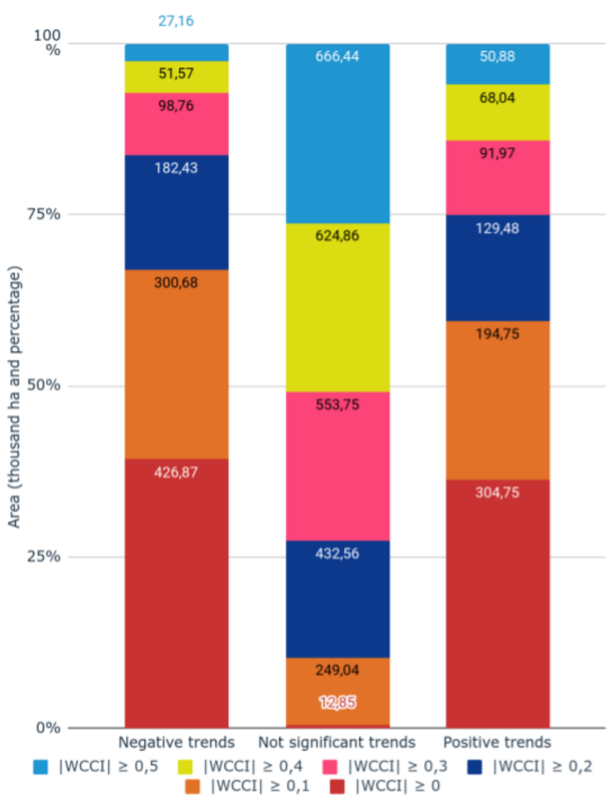

Figure 3. Area (thousand hectares and percentage) by $|WCCI|$. Each column shows a comparison between the thresholds tested. The same color in different bars refers to the same threshold.

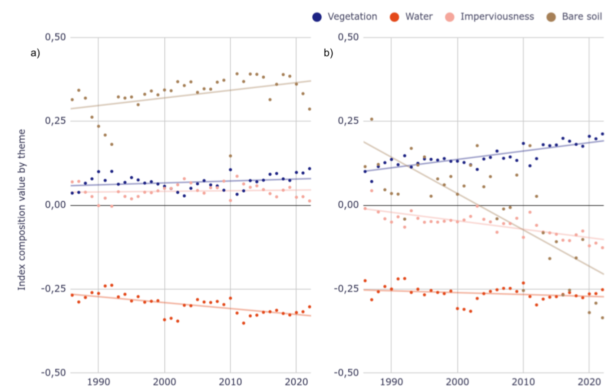

Figure 4. Index composition variation along the time series for $|WCCI| \geq 0.33$ by component. a) Negative trends. b) positive trends.

can help in future applications of the index to perceive negative trends.

This graph and maps derived can be a practical tool for decision-making processes, particularly when the analysis needs to consider actual land use and land cover. The WCCI demonstrates that anthropogenic pressures are not evident for certain types of wetlands, where even negative values are not interpreted as significant, as in the case of water. However, to be more confident in this assumption, the samples must be adequately distributed for each class, which is not currently the case. Another useful application would be to conduct the same analysis based on older maps, enabling the verification of trends related to each land use/land cover class or wetland type. In this sense, an alternative possibility is to use the WCCI combined with automatic image classification, improving its replicability.

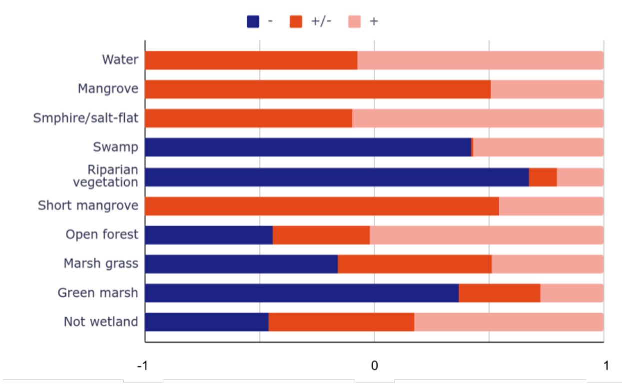

Figure 5. Thresholds of WCCI by wetland considering the available samples. Each series refers to the components adopted to represent

4.3 Qualitative analysis

The Wetland Condition Change Index (WCCI) analysis revealed minimal alterations in the wetlands of the Adelaide River floodplain (Figure 6). Urban and agricultural development, especially along highways, were linked to negative trends, while natural areas like inundated savannas, marshes, and riparian vegetation showed neutral to positive trends.

Field observations and land use data supported these findings, highlighting negative impacts in regions with intensive cattle and buffalo activity - such as soil degradation in high livestock density areas, correlating with high bare soil values and low vegetation indices. Conversely, the eastern floodplain areas displayed stable or improving conditions.

Anomalies in Djukbinj National Park, showing negative trends, suggest natural environmental changes that need further investigation. New agricultural developments, such as mango crops, were associated with positive ecological trends, though further examination is needed to distinguish between true ecological improvement and land use changes reflected in increased NDVI and wetness values. The WCCI's performance in water surface analysis was limited, consistent with previous studies that masked water surfaces (Williams et al., 2021). For these cases, the interpretation of WCCI values must consider different ranges of $|WCCI|$, as discussed earlier. This reinforces the need to improve the samples distribution considering areas that effectively changed from different land use/ land cover.

5. Final considerations

The Wetland Condition Change Index (WCCI) has proven to be an effective tool for assessing wetland conditions, even in comprehensive and complex areas. Its ability to integrate flexible data sources and the growing availability of remote sensing imagery greatly enhance its utility and robustness in monitoring wetland ecosystems. However, the limited field measurements in Northern Australia underscore the necessity

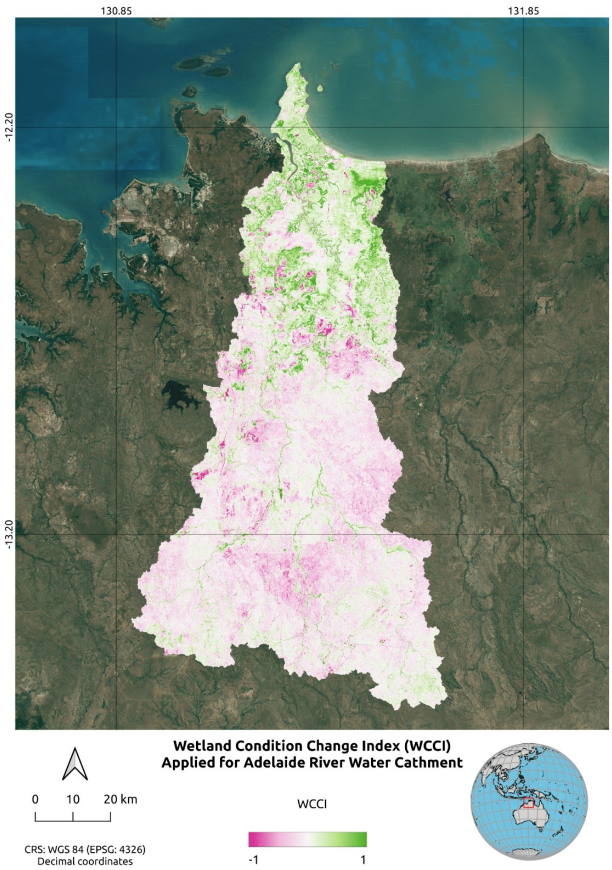

Figure 6. Wetland Condition Change Index (WCCI) for the Adelaide River Catchment showing positive and negative trends.

for developing more refined indicators and methodologies tailored to this region's unique ecological characteristics.

Future improvements should focus on engaging a broader range of experts to refine ecological indicators, thereby enhancing the index's applicability and accuracy across diverse wetland environments. This collaborative approach will ensure that the WCCI can more accurately reflect the intricate dynamics of wetland ecosystems, providing more reliable data for conservation and management efforts.

The analysis indicated that urban development and livestock activities have had adverse effects on wetland conditions, whereas natural and agricultural areas showed signs of stability or improvement. This dichotomy highlights the critical need for targeted conservation strategies that mitigate the negative impacts of urbanization and livestock while promoting sustainable agricultural practices.

Refining the WCCI with more comprehensive field data and continued expert input will significantly enhance its effectiveness in monitoring wetland conditions. Such enhancements will provide policymakers, conservationists, and land managers with a more powerful tool to guide conservation efforts, ensuring the protection and sustainable management of wetlands in Northern Australia and beyond. Additionally, the ongoing integration of advanced remote sensing technologies and ecological research will further bolster the WCCI's capability to serve as a reliable indicator of wetland health in the face of environmental changes.

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