Development of an Assessment Model for Reservoir Dam Turf Health Based on UAV and AI Technologies

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Abstract [**Objectives**] To develop an assessment model for reservoir dam turf health based on UAV and AI technologies, to achieve automated and precise assessment of slope protection turf health, and to enhance the refined level of dam safety management. [**Methods**] An assessment indicator system covering four dimensions (coverage rate, weed index, degradation rate, and uniformity) was established. High-resolution images were captured by UAV, and pixel-level land cover classification and recognition were performed using the U-Net semantic segmentation model. The Gray-Level Co-occurrence Matrix (GLCM) was introduced to quantify turf uniformity. The Analytic Hierarchy Process (AHP) was employed to determine indictor weights, and a comprehensive assessment model of the Dam Turf Health Index (DTHI) along with five-level health grading criteria was constructed. [**Results**] On the test set, the U-Net model achieved a mean pixel accuracy of 97.55%, a Mean Intersection Over Union (*MIOU*) of 91.13%, and an F_1-*score* of 0.954 5, enabling accurate identification of target turf, weeds, bare soil, and degraded areas. The DTHI model converted multi-dimensional indicators into intuitive health grades (Excellent, Good, Medium, Poor, and Inferior), providing decision support for graded maintenance management. [**Conclusions**] This assessment model can effectively improve the efficiency and objectivity of turf health monitoring, reduce the safety risks associated with manual inspection, and provide a feasible technical solution for intelligent management and maintenance of dam turf.

Key words Unmanned Aerial Vehicle (UAV), Artificial intelligence (AI), Dam turf health index (DTHI), U-Net model

0 Introduction

Reservoir dams are critical water infrastructure, and their slope protection serves as the first line of defense against water flow erosion and soil erosion. At present, vegetated slope protection is one of the most widely applied, cost-effective, and environmentally friendly engineering measures. A healthy turf on the dam slope can stabilize soil through its well-developed root system, effectively reduce slope runoff, and prevent soil erosion, thereby maintaining the integrity and stability of the dam body[1]. Therefore, regular, accurate monitoring and scientific health assessment of dam turf growth conditions are indispensable tasks for ensuring the long-term safe operation of the dam. However, current turf management and assessment for dam slopes mostly still rely on traditional manual inspection, which suffers from the following drawbacks: strong subjectivity and lack of uniform standards; low efficiency and insufficient coverage; safety risks for inspection personnel; and assessment results are mostly qualitative descriptions that are difficult to convert into structured data, thus hindering trend analysis and predictive early warning.

In recent years, the advancement of Unmanned Aerial Vehicle (UAV) remote sensing technology and artificial intelligence (AI) technology has provided a brand-new technical pathway to address the aforementioned challenges. UAVs equipped with high-resolution or multispectral cameras can rapidly acquire high-resolution image data of dam slopes, while AI, particularly computer vision technology based on deep learning, can perform automated and in-depth analysis and information extraction from massive image data. Its performance in tasks such as image recognition, classification, and segmentation has already far surpassed traditional methods[2]. The combination of both technologies offers a new approach for achieving comprehensive, objective, efficient, and safe intelligent assessment of dam turf health.

1 Overall framework

The overall framework consists of three major steps. First, informed by knowledge from hydraulic engineering and vegetation ecology, we define and quantify four core dimensions for turf health assessment (namely, coverage rate, weed index, degradation rate, and uniformity), to establish clear targets for the subsequent intelligent analysis. Second, we develop accurate AI-driven analytical algorithms, in which deep learning-based semantic segmentation models are employed to perform automated, pixel-level interpretation of UAV-captured turf images; these are supplemented by image texture analysis to precisely derive the four health indicators. Third, we construct a comprehensive health assessment model for dam turf, in which the Analytic Hierarchy Process (AHP) and other decision-science methodologies are adopted to build an integrated Dam Turf Health Index (DTHI) assessment model that synthesizes multi-dimensional indicators, alongside a set of corresponding health grading standards. The model is an end-to-end system that integrates data acquisition, processing, analysis, and decision support. Finally, the health index and grade of each grid are calculated based on the model.

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The DTHI comprehensive assessment model mainly comprises four architectural layers, as shown in Fig. 1. The data acquisition layer consists of UAVs, multispectral cameras, and other equipment, responsible for executing flight missions according to standard procedures and collecting raw image data. The data processing layer includes a suite of software tools responsible for preprocessing, feature extraction, and analysis of the image data, extracting color, texture, spectral features, and other data, and performing grid-based processing, which serves as the foundation for AI model computation. The intelligent analysis layer, acting as the brain of the system, is deployed on cloud-based AI servers, invoking the trained deep learning model U-Net for semantic segmentation and computing the indicator data. The decision support and visualization layer hosts more flexible applications. In addition to routine data querying, statistics, and turf health report generation, it can be presented to reservoir managers through web applications or GIS platforms, for example, displaying health grade distributions as heatmaps on 3D dam models, with different colors representing different health grades. Meanwhile, through the analysis of historical data, it can illustrate the evolution trend of turf health conditions and enable predictive maintenance, among other functions.

2 Establishment of the turf assessment indicator system

Establishing a scientific, comprehensive, and quantifiable assessment indicator system is the foundation for achieving turf health assessment. Based on the core functional requirements of reservoir dam slope turf (soil and water conservation, structural stability, and ecological aesthetics) and is primary degradation manifestations, this study selects coverage rate, weed index, degradation rate, and uniformity as the four primary assessment indicators. Their calculation formulas and physical meanings are presented in Table 1.

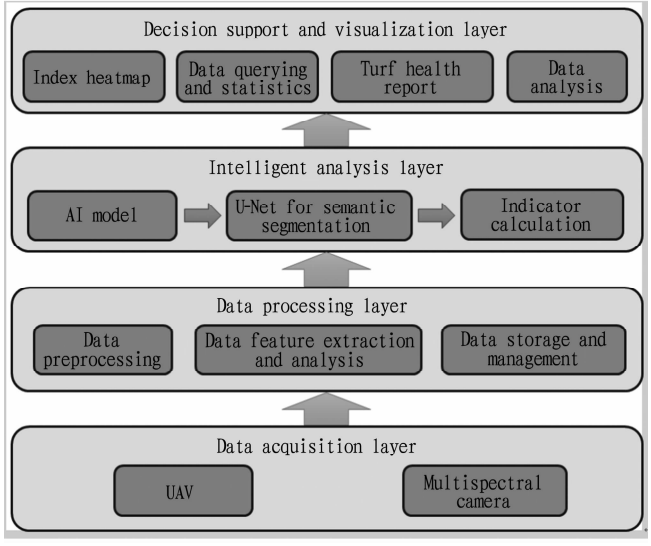


Fig. 1 Architecture of the dam turf assessment system

Table 1 Quantitative calculation of turf features

Indicator	Calculation formula	Physical meaning	Indicator positive
Coverage rate (I_C)	$I_c = \frac{P_{\text{turf}}}{P_{\text{total}}} \times 100\%$	Healthy turf pixel proportion	Positive
Weed index (I_W)	$I_W = \frac{P_{\text{weed}}}{P_{\text{total}}} \times 100\%$	Weed pixel proportion	Negative
Degradatuib rate (I_D)	$I_D = \frac{P_{\text{yellow}}}{P_{\text{green}} + P_{\text{yellow}}} \times 100\%$	Brown/yellow area proportion	Negative
Uniformity (I_U)	$I_U = \sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1 + (i-j)^2}$	Homogeneity/uniformity	Positive

2.1 Coverage rate Coverage rate is defined as the percentage of the vertical projection area of the above-ground parts of the target slope protection turf species relative to the total area of the entire assessment region. It is the most fundamental and important indicator for measuring turf growth density and surface protection capacity. A high coverage rate implies more comprehensive protection of the slope soil by the turf, enabling more effective prevention of rainfall erosion and runoff erosion[3]. In this study, orthophotos are acquired via UAV cameras, and the trained semantic segmentation model is employed to classify the images of the assessment region into three main categories: target turf (including healthy and mildly degraded turf), weeds, and bare soil/rock, *etc*. The number of pixels occupied by each of the above three land cover types is then counted, with the total number of pixels denoted as P_{total}.

$$P_{\text{total}} = P_{\text{turf}} + P_{\text{weed}} + P_{\text{bare}} \quad (1)$$

where P_{turf}, P_{weed}, and P_{bare} are the pixel counts of healthy target turf, weeds, and bare soil/rock areas, respectively. This method is based on pixel-level precise calculation of actual land cover types and achieves high accuracy.

2.2 Weed index The weed index quantifies the extent of weed encroachment within the assessment region. Weeds compete with the slope protection turf for water, nutrients, and light, impairing turf vigor, and in some cases, the overgrowth of aggressive weed species may undermine the structural integrity of the slope protection. Traditional weed survey methods rely on intricate calculations involving abundance, frequency, dominance, and other measures, which are challenging to fully replicate in an automated assessment framework. To address this, the present study adopts a simplified yet effective approach, using the "weed coverage rate" (a more intuitive and readily extractable metric from image analysis) as the core weed index. Leveraging the outputs of the seman-

tic segmentation model, the pixel count of weeds (P_{weed}) is directly obtained, and its proportion of the total pixel count provides a straightforward indication of the spatial extent of weed encroachment.

2.3 Degradation rate Degradation rate refers to the proportion of the turf area that exhibits poor growth (*e.g.*, yellowing or wilting) caused by factors such as pests, diseases, drought, and nutrient deficiency, relative to the total turf coverage area. The turf in degraded areas has reduced physiological activity and weakened soil-binding and slope-protection capacity, making it a priority zone requiring focused attention and maintenance[3]. In this study, health analysis of the target turf region (P_{turf}) is performed through color space segmentation. By setting thresholds or training a dedicated classifier, turf pixels are further subdivided into P_{green} (healthy green turf) and P_{yellow} (degraded yellow turf), and the proportion of degraded yellow turf is calculated, thereby enabling precise quantitative assessment of turf degradation.

2.4 Uniformity Uniformity is an indicator that measures the spatial distribution consistency of turf in terms of color, density, and texture. Turf with high uniformity generally implies consistent growth conditions and proper maintenance management, resulting in uniform and stable overall slope protection performance. Conversely, turf exhibiting patchiness or uneven density may indicate localized water/nutrient issues, soil problems, or punctate disease outbreaks, representing potential weak points. Uniformity is a typical texture feature that is difficult to quantify through simple pixel counting. To address this, the present study adopts the Gray-Level Co-occurrence Matrix (GLCM), a classic texture analysis technique in image processing, for quantification[4]. The specific procedure is as follows: the color turf images of the assessment region are first converted to grayscale, and then an GLCM square matrix is constructed. From the GLCM, multiple statistical measures describing texture can be computed. This study selects *Homogeneity* as the direct quantitative value of the uniformity indicator[5].

$$Homogeneity = \sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1 + (i-j)^2} \quad (2)$$

The dimension of the GLCM is determined by the number of gray levels in the image, denoted as N, where i and j represent the gray values of two pixels[6]. $P_{i,j}$ is the element value in the normalized GLCM matrix. This value ranges between [0, 1] and represents the probability that two pixels in the image have gray values i and j, respectively. When the gray value variation within the image region is small (*i.e.*, uniform texture), the matrix elements near the diagonal of the GLCM are large, and the *Homogeneity* value approaches 1. In contrast, when the gray values vary drastically (*i.e.*, coarse and non-uniform texture), the *Homogeneity* value is relatively small.

3 Turf image analysis based on AI

This study employs artificial intelligence technologies, particularly deep learning-based computer vision models, to perform automated analysis on preprocessed UAV imagery, enabling precise quantification of the four major indicators. The research adopts the convolutional neural network-based image segmentation algorithm (U-Net). Originally designed specifically for biomedical image segmentation, U-Net features a unique "encoder-decoder" architecture and "skip connections", which enable it to effectively integrate high-level semantic information with low-level fine-grained edge and texture details. This capability is particularly effective for precisely segmenting grass leaf edges and distinguishing morphologically similar turf species and weeds[7], overcoming the poor robustness of traditional image processing methods in complex scenarios. As a result, it achieves pixel-level precise classification of elements such as "target turf", "weeds", "bare soil", and "degraded yellow turf" within the imagery. The specific implementation process is as follows:

3.1 UAV image acquisition A UAV equipped with a multispectral camera was employed to perform low-altitude flights over the dam turf, with data coverage encompassing the entire reservoir dam turf area, including the crest, upstream and downstream slopes, and surrounding green belts. The number of raw images captured depends on the dam area, generally amounting to approximately 2 000 images per square kilometer. The typical UAV flight parameters are presented in Table 2.

Table 2 UAV flight parameters

Parameter	Recommended value (Approximate)	Goal
Flight altitude	30 m	Corresponding ground sampling distance (GSD) is approximately 0.8 cm/pixel, ensuring clear identification of turf species, weeds, bare soil, and other details.
Forward overlap	80%	Ensures continuity and accuracy of image mosaicking, avoiding gaps and ghosting effects, particularly on undulating dam slopes.
Side overlap	70%	Works together with forward overlap to guarantee that each ground point is covered by at least 3 – 4 images, improving the accuracy of 3D reconstruction and orthophoto generation.
Flight speed	6 m/sec	Balances flight efficiency with image quality, ensuring clear and continuous image acquisition under the predefined overlap rates and shutter speed.
Flight mode	Nadir flight mode	Camera points vertically downward, maintaining consistent geometric relationships across images and facilitating subsequent orthorectification and mosaicking.

3.2 Image preprocessing The image sequences acquired by the UAV, which carry high-precision POS (Position and Orientation System) data, are imported into professional photogrammetric software. Through Structure from Motion (SfM) and Multi-View Stereo (MVS) algorithms, a series of processes including aerial triangulation, point cloud generation, and model construction are performed, ultimately generating an orthophoto covering the entire dam turf area with uniform scale and geographic coordinates, along with a high-accuracy Digital Surface Model (DSM) and Digital Elevation Model (DEM). Finally, the orthophoto is divided into a series of fixed-size grid cells, and the subsequent AI analysis and indicator calculations will be carried out on the basis of these grid cells as the fundamental units.

3.3 Data annotation Representative image patches were selected from the collected UAV imagery, and professional annotation tools were employed to assign class labels to each pixel within the images, creating training, validation, and test sets. The annotated classes mainly include target turf (healthy), target turf (degraded), weeds, bare soil, shadows, and others (Table 3).

3.4 Model training The annotated data are fed into the U-Net network for training. The network weights are iteratively adjusted through the backpropagation algorithm and an optimizer, with the objective of minimizing the loss function between the model predictions and the manually annotated ground truth. In general, the original image data are split as follows: 70% as the training set for model training, 20% as the validation set for model validation and hyperparameter tuning during the training process, and 10% as the test set for final model performance assessment.

Table 3 Data annotation set

Category No.	Category name	Color	Description
0	Background	Black	Non-turf: roads, buildings, water, *etc.*
1	Target turf	Green	Main planted grass species on dam.
2	Weed	Yellow	Non-target species.
3	Bare soil	Brown	Soil without vegetation.
4	Degraded areas	Red	Poor growth, yellowing, or sparse turf.

3.5 Model assessment Upon completion of training, the final performance of the model is evaluated on an independent test set. The assessment metrics include the following[8]: (i) Pixel Accuracy (*PA*): the proportion of correctly classified pixels to the total number of pixels. (ii) Mean Intersection over Union (*MIOU*): the most fundamental and widely used metric for evaluating semantic segmentation model performance. It is calculated by first computing the Intersection over Union (*IOU*)—the ratio of the intersection to the union of the predicted region and the ground-truth region—for each class, and then averaging the IoU values across all classes (*MIOU*). (iii) F_1-*Score*: a comprehensive metric commonly used in deep learning for evaluating classification model performance, defined as the harmonic mean of *Precision* and *Recall*, which collectively reflects the model's ability in both precision and recall.

Table 4 Example of performance assessment results for the semantic segmentation model

Assessment indicator	Target turf	Weed	Bare soil and rock	Degraded turf	Mean
PA//%	98.9	95.4	99.1	96.8	97.55
IOU//%	94.2	85.7	96.5	88.1	91.13
F_1-*Score*	0.976	0.923	0.982	0.937	0.954 5

4 Construction of the turf grading index model

To transform the multi-dimensional assessment results into a single, intuitive, and readily interpretable conclusion for managers, a comprehensive assessment model needs to be constructed.

4.1 Standardization of indicator data The four indicators differ in their dimensions and value ranges, and are further categorized into positive indicators (larger values indicate better conditions) and negative indicators (larger values indicate worse conditions). Prior to weighted summation, these indicators must be standardized to a unified scoring interval of [0, 100]. Coverage rate (I_C) and uniformity (I_U) are positive indicators, and the linear mapping formula is applied as follows:

$$S_i = \frac{I_i - I_{\min}}{I_{\max} - I_{\min}} \times 100 \tag{3}$$

Both weed index (I_W) and degradation rate (I_D) are negative indicators, and the reverse linear mapping formula is applied as follows:

$$S_i = \left(1 - \frac{I_i - I_{\min}}{I_{\max} - I_{\min}}\right) \times 100 \tag{4}$$

where S_i denotes the standardized score, I_i represents the raw indicator value, and $I_{\max}$ and $I_{\min}$ correspond to the theoretical upper and lower bounds of the indicator, which may also be replaced by empirically established thresholds.

4.2 Determination of indicator weight The Analytic Hierarchy Process (AHP), a well-established multi-criteria decision-making method, is employed to determine the weights of each indicator. This method can transform qualitative expert judgments into quantitative weights, offering both scientific rigor and domain expertise. In accordance with the primary functions of dam slope protection, namely "stability" and "protection", a judgment matrix is constructed by simulating expert scoring, and the resulting weight allocation is presented as follows.

Table 5 Example of indicator weight allocation results

Indicator (criterion layer)	Weight	Importance ranking and justification
Coverage rate (W_C)	0.45	Most important. It is fundamental to slope protection function, directly affecting surface soil protection and erosion control.
Degradation rate (W_W)	0.25	Relatively important. It reflects the physiological vitality of turf. Large-scale degradation is a precursor to functional loss.
Weed index (W_D)	0.25	Moderately important. Aggressive weeds can undermine slope stability, but their early-stage impact is less severe than the first two indicators.
Uniformity (W_U)	0.10	Less important. It primarily reflects maintenance quality and aesthetic appeal, with a more indirect influence on structural safety.

4.3 Turf index model and grading criteria The final Dam Turf Health Index (*DTHI*) model is constructed using the linear weighted summation method as follows:

$$DTHI = \sum_{i=1}^{4} W_i S_i \quad (5)$$

To make the assessment results more instructive, and with reference to relevant grassland degradation grading standards and turf quality classification specifications, the *DTHI* score is divided into five grades: "Excellent, Good, Fair, Poor, and Bad".

Table 6 Dam turf grading criteria and recommendations

Grade	Score interval	Status description	Maintenance recommendations
Excellent	[90, 100]	Lush growth, very high coverage, negligible weeds/degradation, uniform color.	Continue routine care to maintain good condition.
Good	[75, 90)	Good growth, high coverage, occasional weeds or slight degraded spots, generally uniform.	Increase inspections; apply targeted local measures (*e. g.*, manual weeding, light fertilizing).
Fair	[60, 75)	Moderate growth, localized coverage deficiency, weed invasion, or evident yellowing.	Develop a special plan: chemical/physical weed control, pest/disease diagnosis, and nutrient supplement for degraded areas.
Poor	[40, 60)	Severe degradation, contiguous bare soil, rampant weeds, extensive wilting, poor uniformity.	Take emergency actions: large-scale weeding, soil improvement, re-seeding/replanting.
Bad	≤40	Slope protection largely lost, extensive bare soil, fragile ecosystem, high erosion risk.	Engineering restoration required (*e. g.*, turf replacement or other slope protection); conduct root-cause analysis.

5 Conclusions and prospects

This study explores and constructs a theoretical framework and technical scheme for health assessment of reservoir dam turf based on artificial intelligence technologies. It integrates turf coverage rate, weed index, degradation rate, and GLCM-quantified uniformity into a comprehensive, objective, and quantifiable assessment system. Meanwhile, the study applies the deep learning-based semantic segmentation model represented by U-Net, which enables pixel-level precise identification of multiple land cover types on turf, thereby enabling automated and high-accuracy computation of various health indicators, demonstrating the great potential of artificial intelligence in refined vegetation monitoring. In addition, the study constructs the *DTHI* comprehensive health index model and a five-level grading standard, successfully translating complex multi-dimensional analysis results into a single, intuitive health grade, significantly enhancing the practical utility and decision-making value of the assessment outcomes. This approach improves assessment efficiency and accuracy while substantially reducing the safety risks and costs associated with manual operations, offering broad application prospects.

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