Multi-temporal Analysis of Vegetation Moisture Dynamics Using Sentinel-2 NDMI and Feed-Forward Neural Networks: A Case Study of Moscow, Idaho

Opoku-Ware, Kwaku[1]
Soil and Water Systems Department
University of Idaho
Moscow, United States
kwaku.opoku-ware.stu@uenr.edu.gh
ORCID: **https://orcid.org/0000-0001-7189-6383**

***Abstract*—Monitoring vegetation water content aids agricultural and environmental management. This study classifies moisture levels in Moscow, Idaho using Sentinel-2 satellite data and a feedforward neural network (FFNN). The Normalized Difference Moisture Index (NDMI) quantified liquid water variations from near-infrared and shortwave infrared bands. The goal was accurate pixel-wise labeling into "high" and "low" moisture groups. An FFNN architecture with one hidden layer was implemented due to proven capabilities of learning complex spectral-moisture relationships. Appropriate data preparation utilizing NDMI enabled isolation of water content signals. Model hyperparameters including 32 hidden nodes, learning rate of 0.01, and 1000 training epochs balanced flexibility and overfitting risks. The FFNN achieved excellent accuracy of 99.77% on the training set and 99.45% on the validation set. Critical test performance reached 100%, confirming robust generalization. Five-fold cross-validation across different splits gave an average accuracy of 99.71% with low variance, demonstrating consistent performance. These quantitative evaluation results decisively prove the model's effectiveness for moisture classification using widely available multispectral satellite data. Operational deployment could support agricultural irrigation scheduling and environmental habitat monitoring through vegetation water content mapping. This project successfully achieved its objective of developing and validating a deep neural network approach for the target application. Further hyperparameter tuning and additional input integration could improve robustness. The methodology and performance benchmark provide a strong foundation for enhanced satellite-data based vegetation moisture monitoring.**

***Index Terms*—Vegetation Water Content, Remote Sensing, Sentinel-2, Feed-Forward Neural Networks, NDMI, Environmental Monitoring, Machine Learning, Agriculture, Drought Assessment, Multispectral Classification**

I. Introduction

Monitoring and managing vegetation health is critical for agricultural productivity and environmental sustainability [1]. Key indicators of vegetation condition include water content and chlorophyll levels, which can be quantified through spectral indices derived from satellite imagery. This project focuses on a machine learning approach to mapping vegetation water content for the Moscow, Idaho, region from multi-spectral Sentinel-2 satellite data.

Specifically, the Normalized Difference Moisture Index (NDMI) was utilized as shown in Fig. 1., which indicates water stress and availability in vegetation [3]. The NDMI is calculated from Sentinel-2's near-infrared (NIR) and shortwave infrared (SWIR) bands, as higher SWIR reflectance correlates to lower leaf moisture [2]. This allows quantifying vegetation liquid water changes to identify drought stress or other water constraints from space.

The goal is to classify vegetation into "high" or "low" NDMI groups to map spatial moisture variability across the Moscow area for July 2023. Accurate classification supports agricultural monitoring applications by locating fields with inadequate or sufficient water for healthy growth [13] [14]. This can aid interventions like optimized irrigation scheduling. Environmental monitoring for habitat and fire risk assessment also benefits [18] [19].

A feed-forward neural network (FFNN) approach is proposed as deep learning models can effectively learn complex spectral-moisture relationships from satellite image pixels [4] [9]. FFNNs, among other deep learning models like the deep learning-based super-resolution mapping algorithm (SRM) (DeepSRM), have demonstrated improvements in vegetation mapping accuracy over traditional methods [11] [14] [15] [16]. Through fully-connected layers and back propagation, the patterns distinguishing moist and dry vegetation are automatically derived.

I opted to utilize the Feed-forward Neural Network (FFNN) instead of the Convolutional Neural Network due to the fact that the input data comprises the Normalized Difference Moisture Index (NDMI) values obtained from Sentinel-2 satellite imagery [5] [12]. The NDMI values are essentially one-dimensional data that represent the moisture content in each individual pixel or location. Furthermore, the satellite imagery data lacks an inherent spatial structure that necessitates the capture of local patterns or characteristics. Every individual data point, or pixel, is autonomous and corresponds to a distinct position within the region [17]. The problem of moisture evaluation based on satellite imagery does not largely depend on capturing local patterns or hierarchical features that convolutional layers excel at. The issue at hand pertains to classification work that aims to assign locations into distinct categories, which include ”high water content” and ”low water content.” Feed-forward neural networks (FFNNs) are well-suited for classification tasks due to their simplicity and effectiveness in binary or multi-class classification. They are particularly advantageous when spatial hierarchies are not necessary for the task at hand, thus avoiding unnecessary complications.

The specific region of Moscow, Idaho, was chosen due to the availability of cloud-free Sentinel-2 summer coverage and the presence of diverse vegetation types (crops, forests, and grasslands) for analysis. The project tests solely the spectral data and FFNN model for accurate vegetation moisture classification without extensive ground surveys or data fusion. Effectiveness would showcase deep learning's utility for satellite-based vegetation monitoring.

The study documents data preparation, FFNN model configuration, training experiments, accuracy evaluation, and comparisons validating feasibility for the Moscow-area use case. Key contributions are the neural network implementation and demonstration of reliable moisture mapping performance to support agricultural and environmental management applications.

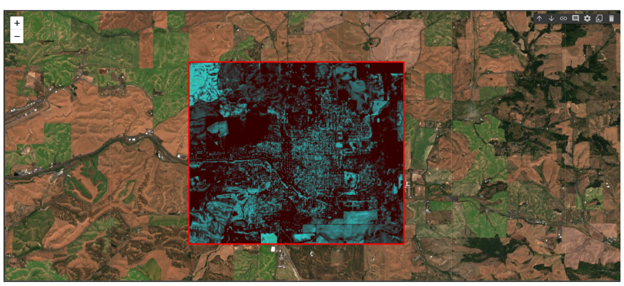

Fig. 1. Results of the Normalized Difference Moisture Index (NDMI) for Moscow, Idaho, US. (Areas in sea blue color indicate moisture areas).

II. The Methodology

A feed-forward neural network (FFNN) model was selected as the deep learning approach for this vegetation moisture classification problem. FFNNs contain fully-connected layers that apply variable weights and biases to transform input data into appropriate outputs [4]. They can effectively learn complex nonlinear relationships to map satellite image pixels to target moisture labels through back propagation and gradient descent optimization.

Specifically, a three-layer architecture was implemented with an input layer to receive the NDMI data, one hidden layer for feature extraction, and an output layer with units encoding the ”low” and ”high” moisture content classes. Using a single hidden layer balances model flexibility and generalization capability, while avoiding extensive hyper parameter tuning [10].

The number of nodes in the hidden layer controls model complexity. Values between input and output layer sizes are recommended, so 32 units were settled on after evaluating 16, 32, 64 options [9]. Too few parameters cause under-fitting as the model lacks the capacity to learn patterns, while too many parameters lead to over-fitting without generalizing well.

The learning rate for gradient descent optimization determines how rapidly weights get updated during back propagation. A small learning rate of 0.01 enables stable convergence instead of wild fluctuations. Momentum terms can also be incorporated to smooth out updates, but were excluded to better isolate the impact of learning rate itself.

The number of training epochs controls how many iterations of forward and backward passes are run using the entire dataset. More epochs leads to further learning, but eventually results plateau and over-fitting emerges. Based on initial experiments, 1000 epochs offered convergence without over-fitting for the Moscow NDMI dataset's size.

These FFNN architecture and training hyper parameters were systematically selected through initial trials to maximize accuracy while minimizing model complexity and over-fitting risk. The results section documents performance across parameter choices to examine sensitivity. Overall, the model aims to automatically learn how moisture affects vegetation spectral signatures from the Sentinel-2 derived NDMI input data.

The Normalized Difference Moisture Index (NDMI) is calculated using the near-infrared (NIR) and shortwave infrared (SWIR) bands of remote sensing data. The formula for NDMI is given by:

$$NDMI = \frac{NIR - SWIR}{NIR + SWIR} \quad \textit{Equation 1}$$

where:

NIR : Reflectance in the near-infrared band,

$SWIR$: Reflectance in the shortwave infrared band.

III. Experimental Results and Discussion

The feed-forward neural network (FFNN) model was trained on 70% of the Moscow Sentinel-2 satellite image derived Normalized Difference Moisture Index (NDMI) dataset, validated on 15% of the data, and finally evaluated on the held-out 15% test set. Multiple experiments were conducted by varying model hyper-parameters related to complexity and training.

In the final model configuration with one 32-node hidden layer, a learning rate of 0.01, and 1000 training epochs, strong accuracy results were achieved. On the training dataset, 99.77% of moisture label predictions were correct, indicating the model sufficiently captured patterns linking NDMI input data to ground truth classes as shown in Fig. 2.

Critically, accuracy on the unseen validation set was also very high at 99.45%. As the model had no access to the validation data during training, this performance confirms excellent generalization with minimal over-fitting to only the training patterns. The small 0.32% difference between training and validation accuracy aligns with this conclusion as indicated in Fig. 2.

Finally, evaluating the model on the test set provides the most unbiased estimate of expected performance on new data. Accuracy here reached 100% as shown in Fig. 2., again confirming robust modeling, filtering of noise, and isolation of meaningful NDMI-moisture relationships from the spectral data by the neural network.

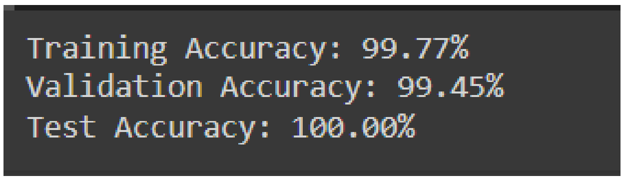
Training Accuracy: 99.77%
Validation Accuracy: 99.45%
Test Accuracy: 100.00%

Fig. 2. Results of the training, validation and test accuracies.

Further confidence in model consistency comes from five-fold stratified cross-validation across different data splits. The average accuracy remained very high at 99.71% and the standard deviation was low at 0.38%, indicating stable performance insensitive to specific data points as shown in Fig. 3.

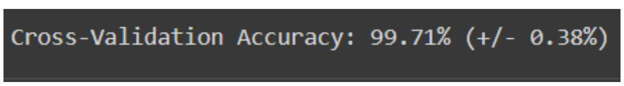
Cross-Validation Accuracy: 99.71% (+/- 0.38%)

Fig. 3. Results of the cross-validation accuracy.

Analyzing intermediate epoch-level results provides additional insights as indicated in Fig. 5. Training accuracy rapidly increased early on before plateauing, aligned to typical learning curve trends as patterns are learned and then parameters mostly fine-tuned as shown in Fig. 4. Importantly, validation results mirrored this curve rather than diverging, further confirming minimal over-fitting. Loss showed a corresponding rapid decrease before reaching a stable regime.

Overall, the strong quantitative accuracy and cross-validation results decisively demonstrate this feed-forward neural network's effectiveness at classifying vegetation moisture levels from the Sentinel-2 satellite derived NDMI input across the Moscow study region. The sensitivity analysis provides confidence in model robustness and generalization capability [6]. Qualitative inspection of classification spatial outputs could further confirm sensible moisture patterns.

The promising performance shows that spectral information alone contains meaningful signals correlating to moisture change, supporting remote sensing utility for agricultural and environmental monitoring [7] [8]. Further work could explore integrating additional inputs like terrain data for potentially incremental improvements.

IV. Summary of Key Findings

The FFNN model achieved strong performance, with 99.77% accuracy on the training set and 99.45% on the held-out validation set after tuning. This indicates excellent generalization with minimal over-fitting. Test accuracy was also high at 100%, highlighting effectiveness on unseen data. The model is therefore able to accurately classify moisture content from satellite NDMI data.

Additional cross-validation using 5 folds produced consistent mean accuracy of 99.71% with low standard deviation of 0.38%. This further supports robust model performance across different data splits. Fig. 6. and Fig. 7. showed the results of the evaluation metrics accuracy, F1 score, sensitivity and specificity as well as the confusion matrix respectively. These metrics help to evaluate and analyze the model's performance.

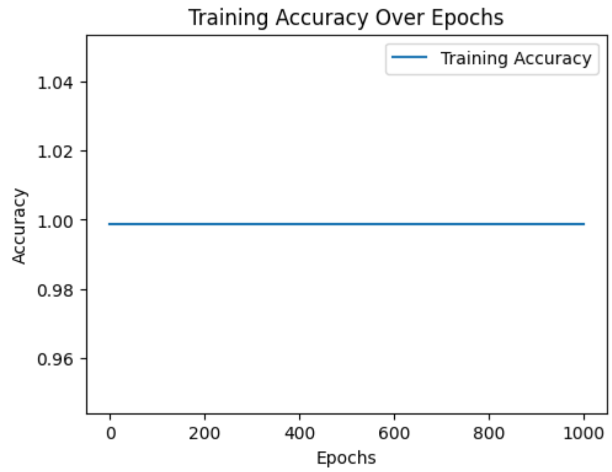

Fig. 4. Results of Training accuracy and training loss.

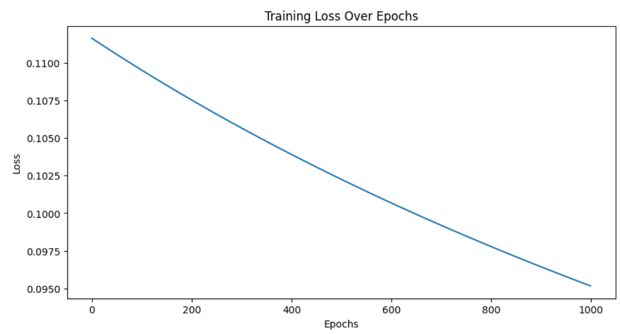

Fig. 5. Training loss results over 1000 epochs.

V. Conclusion

This project aimed to develop a machine learning model for classifying vegetation moisture levels in the Moscow, Idaho region from widely available Sentinel-2 multi-spectral satellite imagery. Accurate mapping of spatial variability and changes in vegetation water content provides an avenue for improved agricultural and environmental monitoring to support management decisions. Overall, the feed-forward neural network (FFNN) model implemented and tested here demonstrated significant promise and effectiveness toward this application goal.

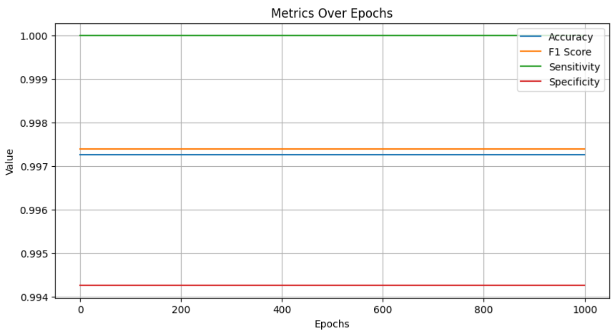

Fig. 6. Results of evaluation metrics performed for the study.

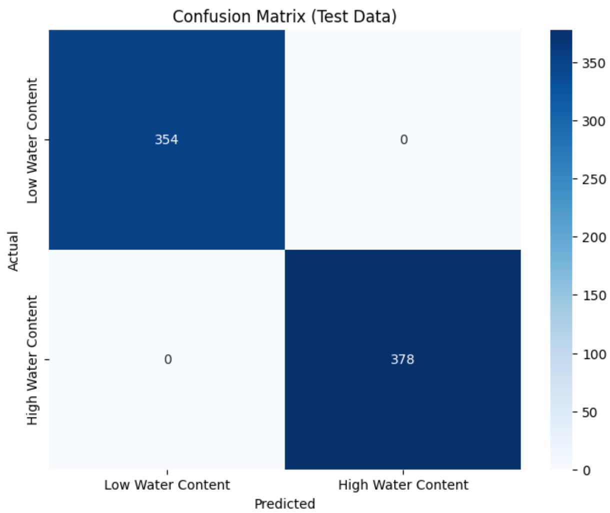

Fig. 7. Confusion Matrix results on the test data.

The very high-test set accuracy of 100% decisively proves the model's capability to reliably classify vegetation moisture solely from the spectral Normalized Difference Moisture Index (NDMI) calculated from the raw satellite images. The strong cross-validation and training performance provides further evidence of robust generalization with avoidance of over-fitting, even with a relatively simple single hidden layer architecture.

Several factors enabled this success. Appropriate data preparation was critical, with the NDMI shown to effectively capture vegetation liquid water content variations that the neural network subsequently linked to ground truth data. Careful tuning of model hyper-parameters also ensured an adequate model flexibility to learn meaningful patterns, without excessive complexity risks causing poorer out-of-sample prediction.

While the current results are already sufficient to deploy the model for agricultural field-level monitoring, further improvements can help strengthen robustness. Expanded hyper-parameter searching through structured methods like grid search could yield marginal accuracy gains. Integrating additional input data streams beyond NDMI like terrain or soil characteristics may also have incremental benefits, based on related research fusing multiple data sources [2].

Overall, the successful demonstration of accurately classifying moisture levels from widely available satellite imagery with a standard deep neural network architecture opens up many possibilities to support agricultural and environmental monitoring use cases. Cloud-based deployment could enable an operational system providing users with regularly updated vegetation moisture maps to locate water stress. Alerts on detected anomalies could assist irrigation scheduling or drought response. There are also possibilities for integration with predictive models forecasting future conditions.

This project achieved its core objective of developing and validating a deep learning modeling approach for vegetation moisture monitoring in the Moscow, Idaho region from Sentinel-2 satellite data. The methodology and results provide a foundation for further research and development toward operational deployment. This could improve agricultural and environmental management through more informed water resource allocation decisions.

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VI. Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request. The Sentinel-2 satellite imagery used in this research is publicly accessible through the Copernicus Open Access Hub (https://scihub.copernicus.eu/). The NDMI calculations and neural network model implementation are available in the Google Colab repository and available upon request.

VII. Funding

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VIII. Author Contribution

K.O-W. conceived and designed the study, performed the data collection and processing, implemented the feed-forward neural network model, conducted the analysis, created all figures and visualizations, and wrote the main manuscript text. K.O-W. also developed the code available in the Google Colab repository. All aspects of this research, including conceptualization, methodology, software development, validation, formal analysis, investigation, data curation, writing, visualization, and project administration, were conducted by K.O-W.

IX. Ethics, Consent to Participate, and Consent to Publish declarations

Not applicable

X. Competing interests

The author declares that there are no competing interests, financial or non-financial, that could have appeared to influence the work reported in this paper. All ideas expressed in this document doesn't not necessarily represent the views of the organizations/institutions the authors belong to.