Slovak University of Technology in Bratislava
Faculty of Civil Engineering

Ing. Aneta A. Óžvat

Dissertation Thesis Abstract

Natural Numerical Networks for supervised deep learning classification of protected habitats

to obtain the Academic Title of *Philosophiae Doctor (PhD.)*
in the doctorate degree study programme
9.1.9 Applied Mathematics
full-time study

Bratislava 2024

The dissertation thesis has been prepared at the Department of Mathematics and Descriptive Geometry, Faculty of Civil Engineering, Slovak University of Technology in Bratislava

Submitter: Ing. Aneta A. Ožvat
Department of Mathematics and
Descriptive Geometry
Faculty of Civil Engineering, STU, Bratislava

Supervisor: prof. RNDr. Karol Mikula, DrSc.
Department of Mathematics and
Descriptive Geometry
Faculty of Civil Engineering, STU, Bratislava

Dissertation Thesis Abstract was sent: ....

Dissertation Thesis Defence will be held on .... at .... am/pm at the Department of Mathematics and Descriptive Geometry, Faculty of Civil Engineering, Slovak University of Technology in Bratislava, Radlinského 11, 810 05 Bratislava.

prof. Ing. Stanislav Unčík, PhD.
Dean of Faculty of Civil Engineering

Abstract

This dissertation explores the development of Natural Numerical Networks (NatNet) for the classification of protected habitats using supervised deep learning. A significant innovation is the introduction of a forward-backward diffusion model on the graphs, which enhances data clustering and habitat identification by improving classification accuracy and efficiency. The research also involves the implementation of NatNet in the NaturaSat software, creating a user-friendly tool that allows researchers to classify habitats using satellite data seamlessly. Furthermore, numerical experiments validate the model's robustness and accuracy across various regions, demonstrating its power over traditional classification methods and highlighting its potential for environmental monitoring and conservation efforts.

Abstrakt

Dizertačná práca sa zaoberá konštrukciou prirodzených numerických sietí (NatNet) s cieľom vytvorenia nástroja na klasifikáciu chránených biotopov pomocou kontrolovaného hlbokého učenia. Významnou inováciou je zavedenie dopredno-spätného modelu difúzie na grafoch, ktorý zlepšuje zhlukovanie údajov a identifikáciu biotopov zlepšením presnosti a efektívnosti klasifikácie. Výskum tiež zahŕňa implementáciu NatNet v softvéri NaturaSat, čím sa vytvára užívateľsky prívetivý nástroj, ktorý umožňuje výskumníkom klasifikovať biotopy pomocou satelitných údajov. Okrem toho, numerické experimenty potvrdzujú robustnosť a presnosť modelu a zdôrazňujú jeho potenciál pre monitorovanie životného prostredia s cieľom jeho ochrany.

Contents

1 Introduction

The increasing deterioration of natural habitats calls for improved methods of environmental monitoring and conservation. Effective classification of these habitats is essential for managing and protecting the Natura 2000 network. Conventional classification methods such as Support Vector Machines, Random Forests, and k-Nearest Neighbors, while useful, often fall short of addressing the complexities and variations found in natural environments. This dissertation presents a new approach using Natural Numerical Networks (NatNets) for supervised deep learning classification of protected habitats through multispectral satellite imagery. The primary objective is to enhance the precision and efficiency of habitat classification by integrating graph-based diffusion models with deep learning techniques.

Inspired by the research of Eldad Haber and Lars Ruthotto, which links successful deep learning models like Residual Neural Networks (ResNet) to the numerical solutions of differential equations [5, 6, 3], this work employs nonlinear forward-backward diffusion equations in a graph structure. In this model, graph vertices represent segmented habitat areas, and edges depict the relationships between these types. Forward diffusion is applied to edges connecting vertices with similar characteristics, promoting clustering, while backward diffusion is applied to edges connecting dissimilar vertices, promoting separation. This dual diffusion process results in a robust classification structure.

The numerical discretisation of these equations transforms them into a numerically solvable system, representing the behaviour of the NatNet, where vertices from the same habitat cluster together while those from different habitats repel each other. This method also generates relevancy maps by calculating relevancy coefficients for each pixel in the satellite imagery, allowing for visual differentiation of habitat types.

NatNet is implemented in the NaturaSat software, which provides a user-friendly interface for habitat classification. The software facilitates data input, preprocessing, and application of the NatNet model, making advanced classification accessible to researchers and practitioners. Numerical experiments validate the model's robustness using datasets from various regions, demonstrating superior accuracy compared to traditional methods. This research offers a significant advancement in habitat classification, supporting effective environmental monitoring and biodiversity conservation.

2 Methods used in the construction of NatNet

The graph $G = (V(G), E(G))$ is defined where $V(G)$ represents a set of vertices and $E(G)$ represents the edges between them [2]. Let G be a complete and undirected graph, meaning each vertex is connected to every other vertex by an edge.

The spatial coordinates of vertex $v \in V(G)$ at time t by $X(v,t) = (x_1(v,t), \dots, x_k(v,t))$ is described, where k is the dimension of the feature space $\mathbb{R}^k$. The diffusion of $X(v,t)$ on the graph G is given by the partial differential equation (PDE):

$$\partial_t X(v,t) = \nabla \cdot (g \nabla X(v,t)), \qquad v \in V(G), \qquad t \in [0,T], \quad (1)$$

where g is the diffusion coefficient [4]. This equation is considered by the initial condition $X(v,0) = X_0(v)$. The boundary conditions are not necessary to prescribe because diffusion occurs between all vertices of the complete undirected graph G.

The distance between vertices v and u is defined as the Euclidean distance between points $X(v,\cdot)$ and $X(u,\cdot)$ in $\mathbb{R}^k$, denoted $L(v,u)$. For each edge $e = \{v,u\}$, the diffusion coefficient g depends on the edge length $L(e)$:

$$g(e) = \varepsilon(e) \frac{1}{1 + KL^2(e)}, \qquad K \geq 0. \quad (2)$$

The $\varepsilon(e)$ value in the diffusion coefficient controls which type of diffusion will be applied on every single edge of the graph G.

If the $\varepsilon(e)$ has a positive value, the forward diffusion is applied on the edges. If the $\varepsilon(e)$ is a negative constant, the backward diffusion is applied on the edges of the graph G.

During the evaluation of the model, it was observed that a possible improvement in the duration of the classification could be made. The graph G is rewritten as a directed graph with directed edges [1]. The new observation is connected to the other points in the graph only with one-way edges, and the diffusion coefficient is defined as

$$g(e_{vw}) = \max(\varepsilon(e_{vw})\frac{1}{1+\sum_{i=1}^{k}(K_i\ l_i^2(e_{vw}))} - \delta,\ 0), \quad \varepsilon(e_{vw}) > 0 \tag{3}$$

at all directed edges entering the new observation $w \in V(G)$, where δ is a parameter of the size of the "diffusion neighbourhood". The aforementioned modification causes only the points for which the diffusion coefficient is larger than δ to attract new observation point w in the classification process.

To discretise the right-hand side of the equation (1), we use the balance of diffusion fluxes (inflows and outflows) in each vertex $v \in V(G)$ and the approximation of the diffusion flux to the vertex v along its directed edges. For numerical discretisation of the equation (1), the time interval $[0, T]$ is divided into M steps with t_n, $n = 1, \ldots, M$, and the time step size τ [7]. The time derivative is approximated using the finite difference method:

$$\partial_t X(v,t) = \frac{X^n(v) - X^{n-1}(v)}{\tau}, \tag{4}$$

where $X^n(v) = X(v, t_n)$.

The semi-implicit scheme for the discretised version of the diffusion equation (1) is:

$$\frac{X^n(v) - X^{n-1}(v)}{\tau} = \sum_{\substack{u \in V(G)\ : \\ e_{uv} \in A(G)}} g_{e_{uv}}(X(u,t) - X(v,t)). \tag{5}$$

which can be rewritten as a system of linear equations for each time step $n = 1, \ldots, M$:

$$(1 + \tau \sum_{\substack{u \in V(G)\ : \\ e_{uv} \in A(G)}} g_{e_{uv}}^{n-1}) X^n(v) - \tau \sum_{\substack{u \in V(G)\ : \\ e_{uv} \in a(G)}} g_{e_{uv}}^{n-1} X^n(u) = X^{n-1}(v). \tag{6}$$

A relevancy coefficient is defined to quantify the relevancy of the classification of new observations. The value of the relevancy coefficient is calculated based on the distance of the classified observation to the centroid of the cluster to which it is assigned by the dynamics of the trained NatNet and the distances of the classified observation to the centroids of the other clusters. The defined coefficient is used both in the evaluation of the success of the network and in the creation of relevance maps. A relevance map is a visual representation of relevancy coefficients in a desired geographic area. The map is created by classifying the given area, then calculating the relevancy coefficient of the classification and writing the value into the relevancy map. The result is a grayscale map on which it is possible to identify areas with a high level of explored habitat as a pixel with a high value of relevancy coefficient.

To extend the possibilities of the described approach, the graph-Laplacian is defined based on the physical Laplacian. Instead of finite volume V, we consider vertex v of the graph G and its neighbouring vertices u connected with v by an edge e_{vu}. If we denote image intensity as f at the vertices $v, u \in V(G)$, the graph-Laplacian has the form

$$\begin{aligned} \Delta f(v) &= \sum_{\substack{u \in V(G) \\ e_{vu} \in E(G)}} a_{vu}(f(u) - f(v)) \qquad (7) \\ &= \sum_{\substack{u \in V(G) \\ e_{vu} \in E(G)}} a_{vu}\ f(u) - \sum_{\substack{u \in V(G) \\ e_{vu} \in E(G)}} a_{vu}\ f(v), \end{aligned}$$

where $a_{vu} = \frac{1}{d_{vu}}$ is a weight by which the values of $f(u)$ in neighbouring vertices are multiplied while the value $f(v)$ is multiplied by the sum of all the weights with the minus sign and d_{vu} is the distance between vertices v and u.

3 Software Implementation of NatNets

The NaturaSat software is designed to facilitate the identification, monitoring, and evaluation of habitats using remote sensing techniques [10]. Implemented in C++ and targeting the Windows operating system, NaturaSat employs the Qt widget toolkit for its graphical user interface (GUI). NaturaSat consists of multiple components that offer various services, such as data management and user interaction tools. The backend includes tools for filtering, segmentation, monitoring, classification, basic hydrological modelling, and map transformation:

- **Filtering Tool** - Provides various filtering methods for preprocessing data.
- **Semi-automatic Segmentation Tool** - Facilitates semi-automatic segmentation of areas of interest.
- **Automatic Segmentation Tool** - Fully automates the segmentation process.
- **Monitoring Tool** - Enables quality and area monitoring.
- **Classification Tool** - Uses Natural Numerical Networks for classification and relevancy map creation.
- **Basic Hydrological Modeling Tool** - Performs hydrological modelling.

- **Historical Maps Transformation Tool** - Identifies corresponding areas on historical and current maps.

The primary focus of this study is on the Classification Tool in the NaturaSat software, which utilises the NatNet framework for classification purposes. The Classification Tool offers two functionalities: one for area classification and another for generating relevancy maps.

The workflow for area classification, as illustrated in Figure 1 (left), shows that the user initiates the classification process by clicking on the "Classification of area" button in the Classification Tool. This action triggers the classification of the area enclosed by the selected polygon. Subsequently, the user selects polygons for classification from the "Polygons" menu in the "Classification Of Area" dialogue box. The envelope of each polygon is computed, and the features for classification points in these envelopes are determined. These features include mean value, standard deviation, minimum and maximum values, and Graph-Laplacian with 5×5 mask of all channels of Sentinel-2 satellite in the pixel's neighbourhood in the polygon envelope.

The user then selects a trained network from the "Network Explorer". This network has been trained on specific habitats corresponding to the date and Sentinel-2 tile, with this information provided to the user during network selection. The points in the polygon envelopes are classified using this trained network in

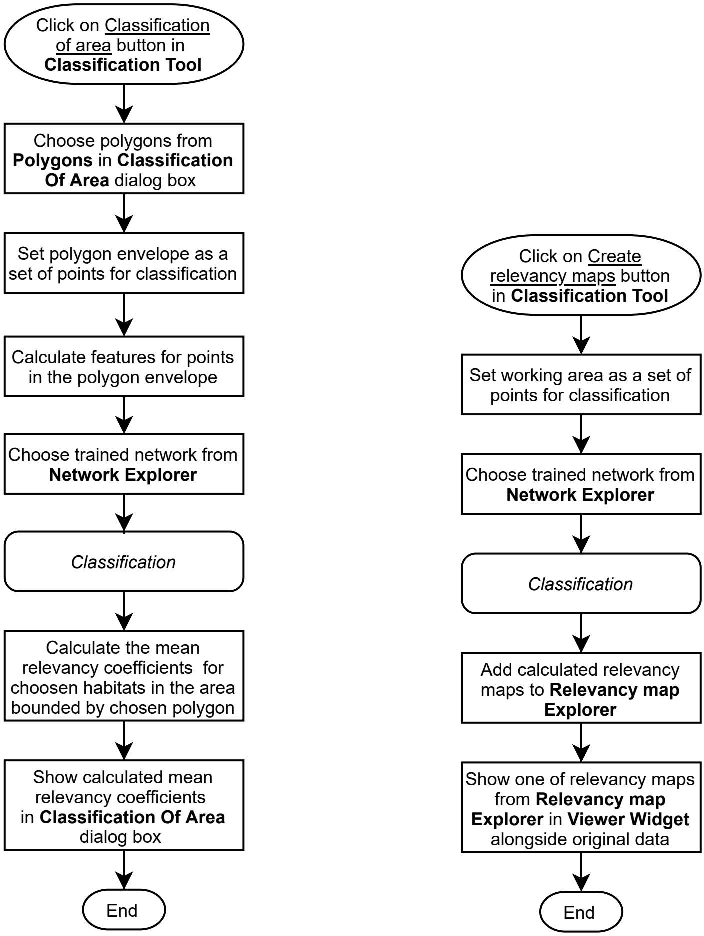

Figure 1: Workflow for classification of polygon envelope (left) and creating relevancy maps (right).

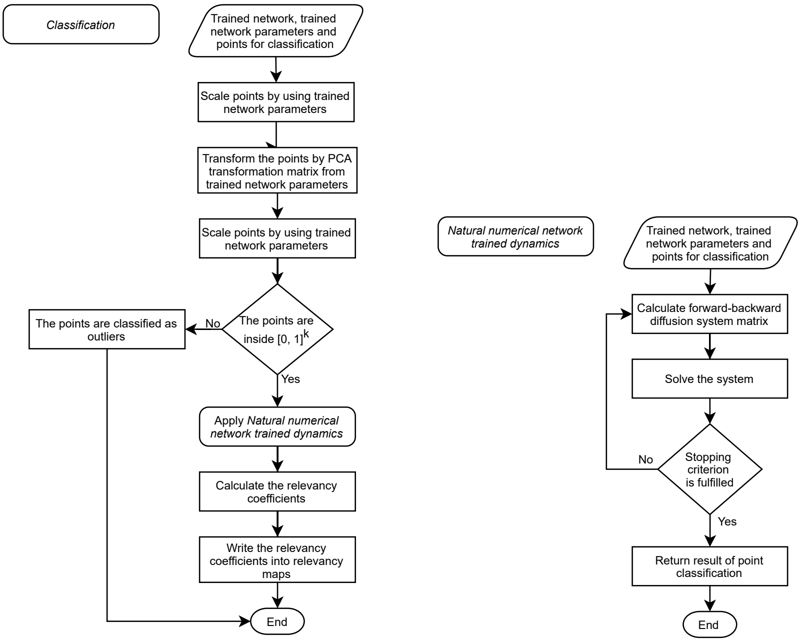

Figure 2: Workflow for *Classification* process (left) and *Natural numerical network dynamics* (right).

the classification process.

The workflow for the classification algorithm is depicted in Figure 2 (left). Unclassified points are prepared for classification by scaling, transforming using the PCA and again rescailing. Then the points are classified using the Natural Numerical Network. Relevancy coefficients for each habitat are computed, and these values are written into the habitat relevancy maps.

The workflow for the "Natural numerical network dynamics" process is depicted in Figure 2 (right), illustrating the forward-backward diffusion process solved by the system until the stopping criterion is fulfilled.

Mean relevancy coefficients for all habitats from the chosen trained network are calculated from all points inside the polygon for area classification, presented in the table in the "Classification Of Area" dialogue box.

Alternatively, the user can create relevancy maps by clicking on the "Create relevancy maps" button in the Classification Tool. This process is described in the workflow in Figure 1 (right). The working area is defined as a set of points for classification, and the user selects the desired size of the resulting relevancy maps and the trained network from the "Network Explorer". The relevancy maps for habitats are then calculated using the classification process, as depicted in the workflow in Figure 2 (left). The calculated relevancy maps are added to the "Relevancy map Explorer," and one of them is displayed in the "Viewer Widget" alongside the original data.

The NaturaSat GUI has centrally displayed satellite data in the "Viewer Widget". On the left side is shown "Data Explorer" together with "Curves Explorer", while below it are the "Properties" menu and the "Preview Map". The right side of the window

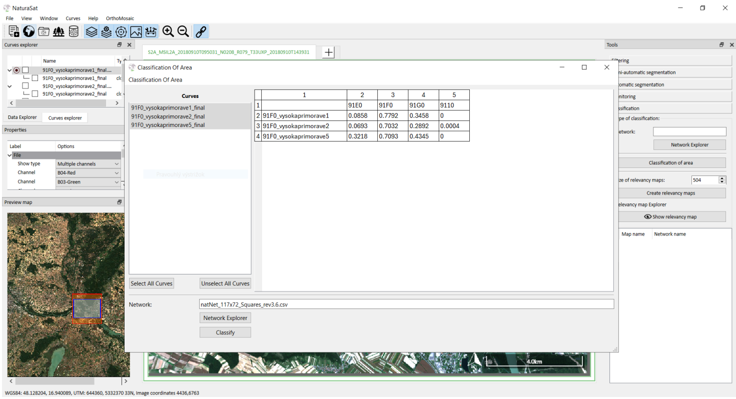

Figure 3: The NaturaSat GUI with the shows "Classification of area" dialogue box, where the relevancy coefficient for three curves in four clusters has already been calculated.

occupies the "Tools" menu, with the "Classification" tab open.

Figure 3 presents the interface following the selection of the "Classification of the area" option. The "Classification of Area" dialogue box is displayed when this option is activated from the Classification Tool. All three curves from the "Curves" menu have been selected, and their relevancy is listed in the accompanying table. The number and type of clusters from the first row of the table are determined by the selected Natural Numerical Network from the "Network Explorer".

After selecting the "Creating the relevancy maps" option from

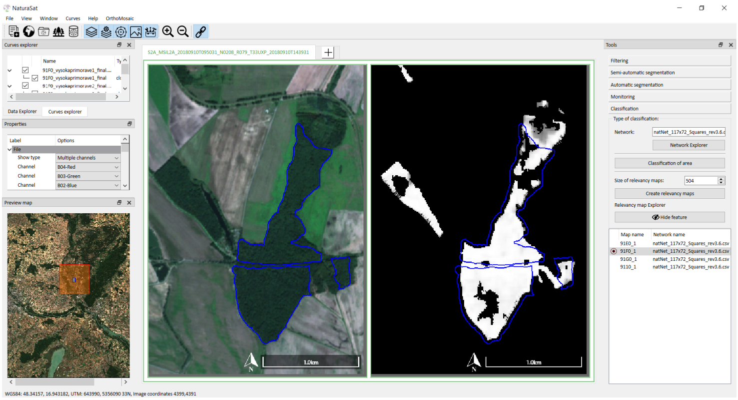

Figure 4: The NaturaSat GUI, where the calculated relevancy maps were added in the "Relevancy map explorer", and one of the maps is chosen and shown alongside the Sentinel-2 data.

the Classification Tool, the interface state is shown in Figure 4. The calculated relevancy maps appear in the "Relevancy Map Explorer", with the second relevancy map selected and displayed alongside the original data. The relevancy maps are sized at 504×504 pixels, as indicated by the settings in the "Classification" tab.

4 Numerical Experiments

The primary objective is to validate the accuracy of NatNet in identifying and exploring protected habitats based on multispectral satellite imagery. For that purpose, ground-based vegetation data were collected through field surveys, which involved sampling plots in targeted habitats and segmenting areas of target habitats by semi-automatic and automatic segmentation through NaturaSat [9, 8, 10]. Each plot's species composition was recorded, and this data was used to train the NatNets. Subsequently, multispectral data from the Sentinel-2 satellite was obtained, providing high-resolution images across various spectral bands. These images were processed to extract spectral characteristics specific to different habitat types. The spectral characteristics from the satellite are used as input features for the NatNet, facilitating the classification of habitats. The learning phase involved optimising the network graph topology to maximise classification accuracy. By adjusting the parameters of the forward-backward diffusion model, the NatNet was fine-tuned to achieve high classification success rates for the learning dataset.

The qualitative (visual) comparisons of the Natura 2000 habitat segmented areas with the final relevancy maps for target habitats 91E0 softwood floodplain forests and 91F0 hardwood floodplain forests are plotted in Figure 5. As the figure shows, the inte-

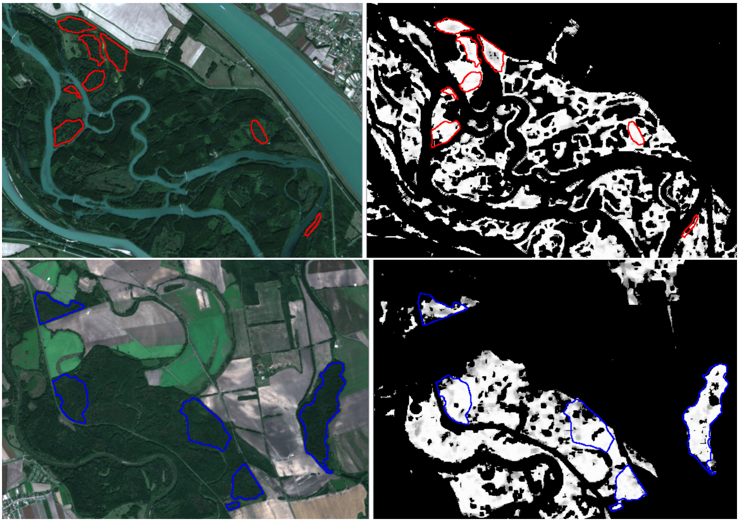

Figure 5: The segmented areas of 91E0 habitat (top) and 91F0 habitat (bottom) plotted on the Sentinel-2 image (left) and on the final relevancy map (right).

rior of the segmented areas on each relevancy map contains bright colours. This reflects the correct high relevancy of classification inside the segmented areas and, thus, the correct assignment of the image pixels to the Natura 2000 habitat. For the quantitative evaluation of the classification accuracy, we calculate the mean relevancy inside each segmented area.

The exploration of other regions in Slovakia extended the application of NatNet. During the exploration of the relevancy maps

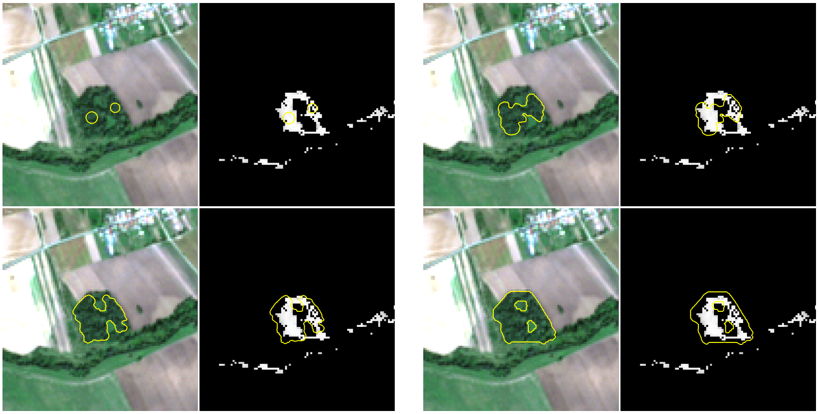

Figure 6: The area around the Rimava river in the south of Central Slovakia, the Sentinel-2 image (left) and relevancy map (right) with subsequent automatic segmentation of newly found 91E0 habitat area.

created for the southern area of the Central Slovakia region, we found that the Natural Numerical Network assigns a high 91E0 relevancy to the area around the Rimava River close to the village of Dubovec (Figure 6 right). The discovered area has never been identified as a target habitat, and no databases contain such information (the Slovak vegetation database or the database of the State Nature Conservancy of the Slovak Republic, where all currently known areas of Natura 2000 habitats are collected). We segmented the area by applying the automatic segmentation method [8], as shown at the bottom right in Figure 6, to obtain the final segmentation result. The computed mean relevancy inside the segmented area is equal to 0.6079, and it again indicates a possible new appearance of the 91E0 habitat. This demonstrated the model's potential for large-scale ecological monitoring and conservation efforts.

The efficiency of NatNet is further explored in specific forest types, particularly oak forests. Two forest habitats were analysed: those dominated by QC Quercus cerris and those with QP Quercus petraea. These habitats, part of the Natura 2000 network, were segmented using the NaturaSat software [10]. Statistical characteristics of these segments were computed to construct the initial NatNet graph. The classification process showed high accuracy, in distinguishing between the different oak forest habitats, underscoring the model's effectiveness in fine-scale habitat classification. Figure 7 depicts the area of Martinsky les special protected area with the segmented areas of QC forests (red curves). On the left part in Figure 7, there is the image from the Sentinel-2 satellite, and on the right part, there is the relevancy map for the QC forests. The relevancy map shows bright colours in the interior of the segmented areas, which means a high relevancy coefficient in the pixels and reflects the correct classification of the segmented area.

The relevancy maps created using the graph-Laplacian high-

Figure 7: The segmented areas of QC forests (red curve) plotted on the Sentinel-2 image (left) and on the relevancy map for QC forests (right).

lighting biodiversity hotspots with greater precision. By combining the relevancy map calculated for the target habitat with the graph-Laplacian, areas with significant species diversity were effectively identified. As depicted in the first row of Fig. 8, the alluvial areas of the Danube River are shown on the Sentinel-2 image on the left, while on the right is displayed the relevancy map for the willow-poplar floodplain forest from the Danube River alluvial areas. Additionally, segmented regions denoting natural forests (yellow curves) and planted forests (red curves), provided by botany experts from the Plant Science and Biodiversity Centre SAS using semi-automatic and automatic segmentation methods

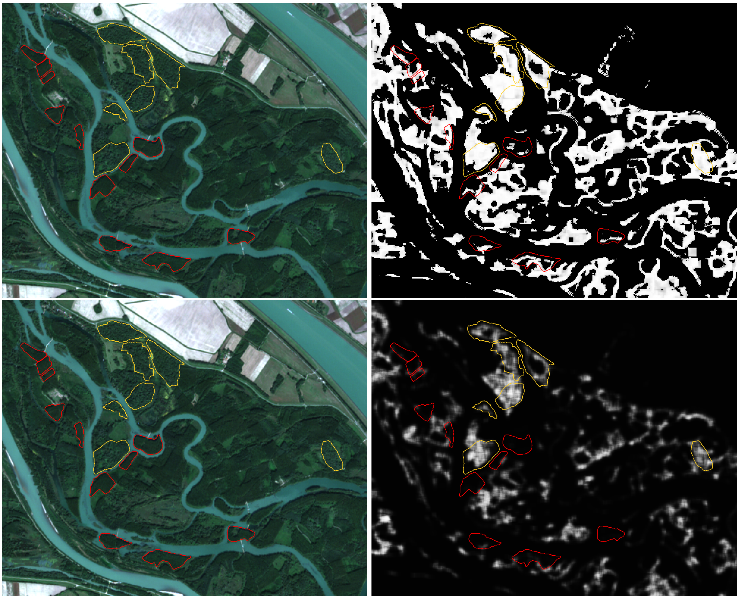

Figure 8: The comparison of the relevancy map created by the Natural Numerical Network (upper row) and the Mean graph-Laplacian map (bottom row). The upper left and bottom left images depict the Sentinel-2 image. The images also depict segmented areas of natural forests (yellow segmented areas) and planted forests (red segmented areas).

[9, 8], are illustrated in all subfigures of Fig. 8. It is evident that the interior of the yellow segmented areas exhibits white colours, indicating high relevancy for the softwood floodplain for-

est habitat. However, we also observe white colours in the interior of the red segmented areas, suggesting that these areas are potential candidates for the softwood floodplain forest due to similar species composition. Since these areas are not natural, they must be excluded from the Natura 2000 habitat identification.

This methodology proved particularly useful in excluding planted forests and transitional zones, focusing on areas with true ecological significance. The mean graph-Laplacian map further refined the relevancy map, reducing false positives and enhancing the identification of natural habitats with high biodiversity.

5 Conclusion

This research introduces Natural Numerical Networks for supervised deep-learning classification of protected habitats, specifically focusing on satellite imagery for ecological monitoring. Using Sentinel-2 optical data, NatNets shows high classification accuracy for complex Natura 2000 habitats across Europe, employing a forward-backward diffusion process as a core innovation. NatNets significantly outperforms traditional methods, achieving high accuracy in identifying intricate habitat structures from multispectral data. The spectrum of fundamental statistical features like mean, standard deviation, and minimal and maximal values are enlarged, and the graph-Laplacian is added as a new feature to pinpoint areas of high biodiversity. Relevance maps, together with optimisation of network graph topology, refine the classification process. Implemented in the NaturaSat software, NatNets provide a user-friendly interface for researchers and conservationists, automating habitat classification and enhancing accessibility.

This research highlights NatNets as a pivotal tool in ecological monitoring and conservation, promising improved biodiversity management in the Natura 2000 network. Future research could expand NatNets to new regions and enhance algorithms with additional environmental variables, advancing global conservation efforts.

References

[1] J. Bang-Jensen and G. R. Gutin, *Digraphs: Theory, Algorithms and Applications*, Springer-Verlag London, 2st ed., 2010.

[2] A. Bondy and U. S. R. Murty, *Graph Theory*, Springer-Verlag London, 1st ed., 2008.

[3] B. Chang, L. Meng, E. Haber, L. Ruthotto, D. Begert, and E. Holtham, *Reversible architectures for arbitrarily deep residual neural networks*, in 32nd AAAI Conference on Artificial Intelligence, AAAI 2018, vol. 32, 04 2018, pp. 2811–2818.

[4] J. Friedman and J.-P. Tillich, *Calculus on graphs*, CoRR, cs.DM/0408028 (2004).

[5] E. Haber and L. Ruthotto, *Stable architectures for deep neural networks*, Inverse Problems, 34 (2018).

[6] K. He, X. Zhang, S. Ren, and J. Sun, *Deep residual learning for image recognition*, 06 2016, pp. 770–778.

[7] K. Mikula and N. Ramarosy, *Semi-implicit finite volume scheme for solving nonlinear diffusion equations in image processing*, Numerische Mathematik, 89 (2001), p. 561–590.

[8] K. Mikula, J. Urbán, M. Kollár, M. Ambroz, I. Jarolímek, J. Šibik, and M. Šibíková, *An automated segmentation of natura 2000 habitats from sentinel-2 optical data*, Discrete and Continuous Dynamical Systems - Series S, 14 (2021), pp. 1017–1032.

[9] ——, *Semi-automatic segmentation of natura 2000 habitats in sentinel-2 satellite images by evolving open curves*, Discrete and Continuous Dynamical Systems - Series S, 14 (2021), pp. 1033–1046.

[10] K. Mikula, M. Šibíková, M. Ambroz, M. Kollár, A. A. Ožvat, J. Urbán, I. Jarolímek, and J. Šibik, *Naturasat—a software tool for identification, monitoring and evaluation of habitats by remote sensing techniques*, Remote Sensing, 13 (2021).

List of author's publications

- MIKULA, Karol - ŠIBÍKOVÁ, Mária - AMBROZ, Martin - KOLLÁR, Michal - OŽVAT, Aneta Alexandra - URBÁN, Jozef - JAROLÍMEK, Ivan - ŠIBÍK, Jozef. NaturaSat - A software tool for identification, monitoring and evaluation of habitats by remote sensing techniques. In Remote Sensing [elektronický zdroj]. Vol. 13, iss. 17 (2021), online, [19] s., art.no. 3381. ISSN 2072-4292 (2021: 5.349 - IF, Q1 - JCR Best Q, 1.283 - SJR, Q1 - SJR Best Q). V databáze: CC: 000694508100001 ; SCOPUS: 2-s2.0-85114022851 ; DOI: 10.3390/rs13173381. Registrované v databáze: CC, SCOPUS; Kategória publikácie do 2021: ADC

- MIKULA, Karol - KOLLÁR, Michal - OŽVAT, Aneta Alexandra - AMBROZ, Martin - ČAHOJOVÁ, Lucia - JAROLÍMEK, Ivan - ŠIBÍK, Jozef - ŠIBÍKOVÁ, Mária. Natural numerical networks for Natura 2000 habitats classification by satellite images. In Applied Mathematical Modelling. No. 116 (2023), s. 209-235. ISSN 0307-904X (2022: 5.000 - IF, Q1 - JCR Best Q, 1.080 - SJR, Q1 - SJR Best Q). V databáze: SCOPUS: 2-s2.0-85143493733 ; CC: 000694508100001 ; DOI: 10.1016/j.apm.2022.11.021. Typ výstupu: článok; Výstup: zahraničný; Registrované v databáze: SCOPUS, CC; Kategória publikácie do 2021: ADC

- MIKULA, Karol - KOLLÁR, Michal - OŽVAT, Aneta Alexandra - ŠIBÍKOVÁ, Mária - ÈAHOJOVÁ, Lucia. Natural numerical networks on directed graphs in satellite image classification. In Scale Space and Variational Methods in Computer Vision : proceedings of the 9th International Conference on Scale Space and Variational Methods in Computer Vision, SSVM 2023. Santa Margherita di Pula, Italy,

May 21–25, 2023. 1. vyd. Cham : Springer Nature, 2023, S. 339-351. ISSN 0302-9743. ISBN 978-3-031-31974-7. V databáze: DOI: 10.1007/978-3-031-31975-4 26 ; SCOPUS: 2-s2.0-85161217960. Typ výstupu: príspevok z podujatia; Výstup: zahraničný; Registrované v databáze: SCOPUS; Kategória publikácie do 2021: AFC