Methodology of Terrain Classification in Terms of Military Passability

Krzysztof POKONIECZNY, Poland

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SUMMARY

The classification of terrain in terms of passability plays a significant role in the process of military terrain assessment. In presented project, the problem of terrain classification to the respective category of passability was solved (among others) by applying artificial neural networks to generate (calculate) the Index of Passability (IOP). The main methodological assumption of the conducted research was to refer the index of passability of the terrain to the primary fields of various shapes and sizes. The basis for calculating IOP are elements of land cover that exist in the given primary field. This data was inputted into two kinds in neural networks. The results show a comprehensive analysis of the reliability of the neural network parameters, considering the number of neurons, learning algorithm, activation functions and input data configuration. The studies and tests carried out have shown that a well-trained neural network can automate the process of terrain classification in terms of passability conditions. The Author assumed that the values of indices of passability obtained with use of the algorithms may differ, even if the same methods and source data are used, depending on the type of the primary field used, i.e., its shape and size. Considering the above, the Author analyzed the influence of the shape and size of the primary field on the results of automated terrain classification for the purposes of developing passability maps. The Author determined indices of passability for square primary fields of side lengths ranging from 25 m to 10 km. The Author has demonstrated that terrain classification for passability purposes may also be performed with use of not only military data sources.

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1. INTRODUCTION

The aim of classification is to assign each element of the analyzed dataset to a specific class, distinguished by the similarity of the analyzed properties. Objects belonging to the same class should be characterized by the highest possible similarity. At the same time, they should significantly differ from objects belonging to other classes. Classifications are widely used in numerous fields of science, including geodesy and cartography. The notion of classification is commonly used in reference to the classification of satellite images to separate classes of land cover, soils, land management, land usability for specific investments or land accessibility (e.g. for communication purposes). Classification plays an important role in the process of land consolidation and exchange, which involves the search for continuous areas with specific properties. A specific type of classification is terrain classification in terms of passability, which is a more advanced form of communicational or temporal accessibility. Its aim is to identify those fragments of the land that are characterized by similar land cover, relief, water, soil or geological conditions. This issue is vital for land management, particularly in emergency conditions, when it is essential to reach the destination quickly, because deciding on the route to access the endangered area also depends on the types of forces and means that will be directed there. In other words, the access path will be different if roads have not been destroyed than in the situation if, as a result of landslide, flood or acts of war it is necessary to move outside the road network.

In his research, the Author analyses the subject of land passability classification, focusing on its military applications. However, the analyzed problems are deeply rooted in geodesy and cartography, and they refer to: the sizes and shapes of primary fields of reference, the level of detailedness of vector data, data modelling, forms of cartographic presentation and widely understood cartographic modelling. Classification of passability is defined as the capacity of the land to be crossed by vehicles (including such special vehicles as: fire trucks, combat vehicles) in any meteorological conditions, both on roads and off-road. The developed classification is of a statistical-taxonomic nature. The adopted taxonomy is based on the land cover ontologies used in databases containing vector spatial data on land cover and it refers to the military standards established by NATO reference standards. The used statistic classifiers are decision-making rules and perceptrons.

The Author has assumed that classification will be based on the original index of passability (IOP – index of passability) developed by the author and understood as an estimate that reflects the degree of limitation of vehicular speed by land cover elements. As opposed to the previously used division of land into 3 classes (impassable terrain (NO GO), low-passability terrain (SLOW GO) and passable terrain (GO TERRAIN)), the IOP index defines passability in a continuous range, adjusted to the needs and expectations of the decision-makers.

2. INPUT DATA PREPARATION

The main methodological assumption of the conducted research was to refer the index of passability of the terrain to the **primary fields** of various shapes and sizes. The basis for calculating IOP are elements of land cover that exist in the given primary field, including, in particular:

- surface objects (e.g. forests, lakes, built-up areas); - the total surface area of each area found in the given primary field;
- for linear objects (rivers, roads, railways, contours) - the total length of the linear object located within the primary field;
- for singular objects (buildings, enclosures) - the number of objects located within the given primary field.

Additionally, each primary field was assigned the average land denivelation parameter calculated from all points of the numerical model of land inclinations located in the area of the given primary field (Fig. 1).

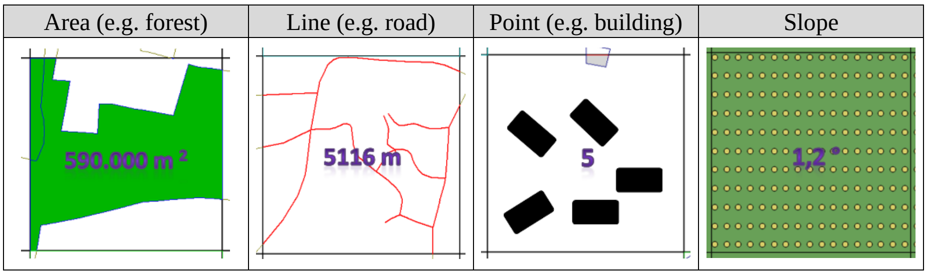


***Fig. 1** Sample visualisations of the parameters obtained for specific land cover elements*

The presented approach is a specific conversion of a vector, discrete data model to a continuous (raster) model (Fig. 2), where the primary field is described by a defined number of parameters (Fig. 3). This way of data organisation enables to carry out statistical analyses, which result in the determination of the index of passability for each primary field.

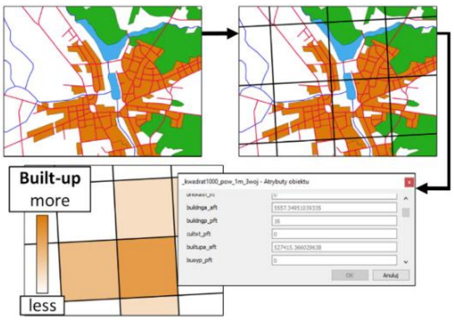


***Fig. 2** Conversion of a vector model based on the example of the "built-up area" category.*

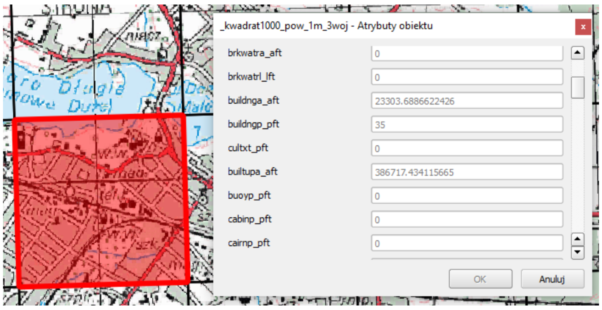


***Fig. 3** Sample land cover parameters for a primary field.*

3. DETERMINING THE INDEX OF PASSABILITY USING NEURAL NETWORKS

The Author assumed that the problem of determining the index of passability may also be solved by using artificial neural networks. Their use is justified by the fact that they are applied in solving problems where we have to deal with a large amount of input data and when the algorithm of solving a problem is unknown or difficult to implement. Such situation is true for the analysed classification, where numerous parameters related to land cover and terrain formation that affect the resulting passability are analysed. Additionally, artificial neural networks fulfil the criteria of fuzzy logic, so that it is possible to determine the passability of a primary field in a continuous range, e.g. from 0 to 1. Moreover, once learned, the neural network may be used to determine the index of passability for any area. The source of input data used was the VMap Level 2, which is a general geographic a vector spatial database, corresponding to a topographic map in the scale of 1:50 000. In his analyses, the Author proposed to apply two types of artificial neural networks: a multi-layered perceptron and SOM – *Self Organizing Maps* by Kohonen.

3.1 Method based on the application of a multi-layered perceptron

In order to determine the index of passability, has been used a perceptron consisting of three layers (Fig. 4):

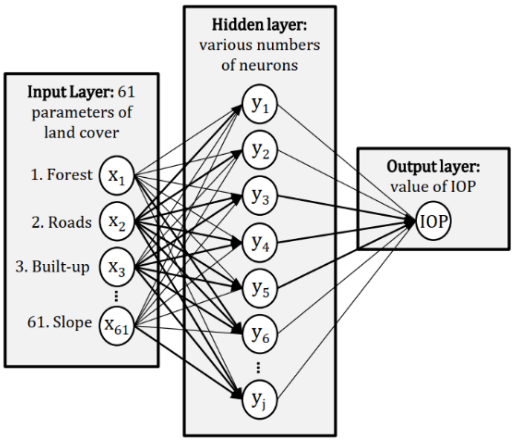


Fig. 4 *Structure of the applied artificial neural network*

The Author proposed an own algorithm of calculating the index of passability with use of a multi-layered perceptron, which is as follows:

- Land cover parameters (e.g. the surface of forests and rivers, length of roads etc.) normalised according to equation (1) are introduced to the input layer.
- A set of learning data, defined as a set of indices of passability, assigned *a priori* to a certain group of randomly selected primary fields, is prepared.

The values of the indices of passability have been determined arbitrarily within the range from 0 to 1 and assigned to 1000 primary fields selected randomly from the whole test area (altogether, the test area contained approx. 81 thousand primary fields, and the learning data accounted for 0.012% of all fields). Tests were conducted for a square primary field of the side length of 1000 and 100 m (Fig. 5).

Primary field 1000 x 1000 m	Primary field 100 x 100 m

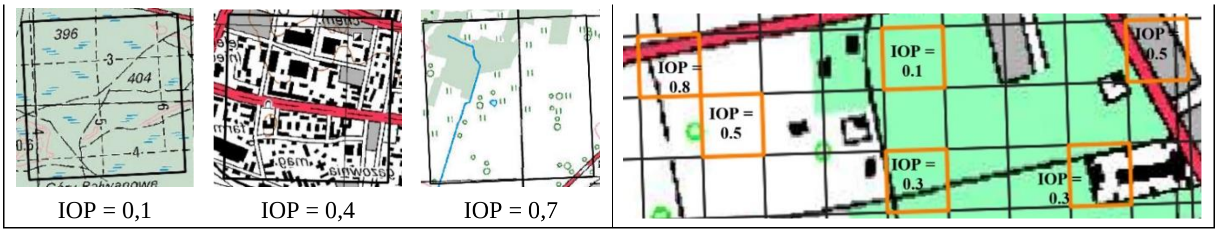


Fig.5 *Sample values of indices of passability assigned arbitrarily to a primary field of the dimensions 100 x 100 m and 1000 x 1000 m.*

- Artificial neural networks are prepared by means of supervised learning with teacher. This process consists in modifying the weight of neuron inputs so that the land cover parameters introduced to the input layer give the so-called expected output of the artificial neural network (in this case, this is the IOP value from the learning data set).
- After the end of the learning process, land cover parameters for all primary fields are introduced to the neural network. In this way, the indices of passability are determined for the whole analysed area.

In order to analyse the influence of selected parameters of the neural network on its effectiveness, the Authors conducted tests, in which he generated over 66 thousand neural networks in various configurations for each prepared neural network a cross-test was conducted. The estimator used to determine the usability of the neural network for the determination of IOP was the "quality" of the network, calculated separately for the learning and validation sets. "Quality" is understood as the Pearson correlation coefficient between the values of the index of passability determined arbitrarily by the analyst and their prediction determined by the neural network.

Tests concerning the applied learning algorithms (Table 1) demonstrated that the highest average sample quality was obtained for the conjugated gradient method and BFGS (Broyden–Fletcher–Goldfarb–Shanno algorithm). On the other hand, the steepest descent method proved to be the least effective (i.e. it generated the lowest "quality" networks).

	1000 x 1000 m		100 x 100 m	
Name of the algorithm	Quality (validation sample)	Quality (learning sample)	Quality (validation sample)	Quality (learning sample)
Conjugated gradients	0,822	0,865	0,957	0,960
Steepest descent	0,796	0,831	0,915	0,919
BFGS	0,766	0,893	0,948	0,969

Table 1. *Average quality values for the learning and validation samples with use of three learning algorithms for two sizes of primary fields.*

The analysis of the efficiency of the applied functions of activation of the neurons (Table 2) demonstrated that the average values of network quality for various activation functions are rather similar. This means that the selected activation function does not have a significant influence on the quality of the resulting neural network. Slightly higher quality values (0.01-0.05) were achieved with use of the sinus function both for the hidden and output layers.

1000 x 1000 m

	Logistic (O)	Tanh (O)	Exponential (O)	Linear (O)	Sinus (O)
Logistic (H)	0,79	0,79	0,75	0,75	0,81
Tanh (H)	0,79	0,79	0,79	0,80	0,83
Exponential (H)	0,79	0,74	0,69	0,70	0,78
Linear (H)	0,83	0,82	0,83	0,83	0,83
Sinus (H)	0,83	0,82	0,83	0,83	0,83
100 x 100 m					
Logistic (H)	0,96	0,95	0,95	0,90	0,95
Tanh (H)	0,96	0,96	0,96	0,96	0,96
Exponential (H)	0,96	0,83	0,93	0,85	0,91
Linear (H)	0,96	0,95	0,96	0,96	0,95
Sinus (H)	0,96	0,95	0,96	0,96	0,96

Table 2. *Average values for the validation sample depending on the activation function applied. (H – hidden layer neurons, O – output layer neurons)*

The conducted research showed that increasing the number of neurons in the hidden layer leads to a decrease in the quality of the generated neural networks (Diagram 1). The highest quality was obtained for 20 to 40 neurons in the hidden layer. On the other hand, in his tests on the influence of learning iterations on network quality (Diagram 2), the Author confirmed a property that is typical of perceptron type neural networks. For the analysed set of learning data, the highest quality of the validation sample was obtained for 20 to 60 learning iterations. Both diagrams demonstrate clearly that the network quality for a 100x100 m field is significantly higher (up to approx. 0.95) than for the 1000x1000 m field (where it slightly exceeds 0.8). This results from the fact that it is possible to determine a less ambiguous IOP than for a larger primary field (1000x1000 m), which may contain more elements that have a negative or positive influence on passability.

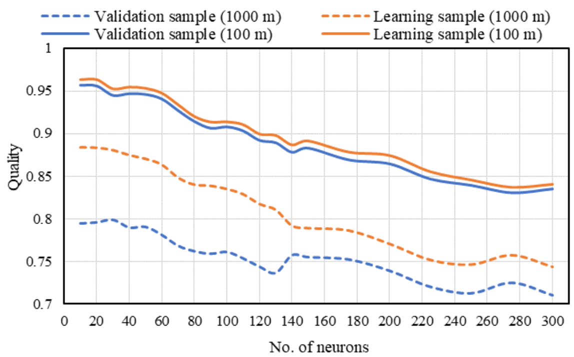


Diagram 1. *Average value of network quality depending on the number of neurons in the hidden layer*

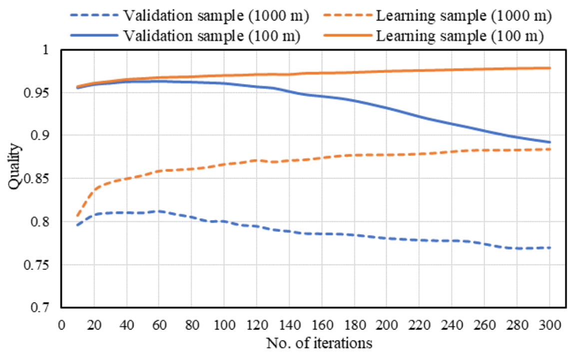


Diagram 2. *Average value of network quality depending on the number of learning iterations*

The cartographic visualisation of the calculated IOP (Fig. 6) demonstrated that the obtained passability maps enable to distinguish natural and artificial terrain obstacles (including forests, built-up areas and rivers) that affect the conditions of movement.

100 x 100 m	1000 x 1000 m

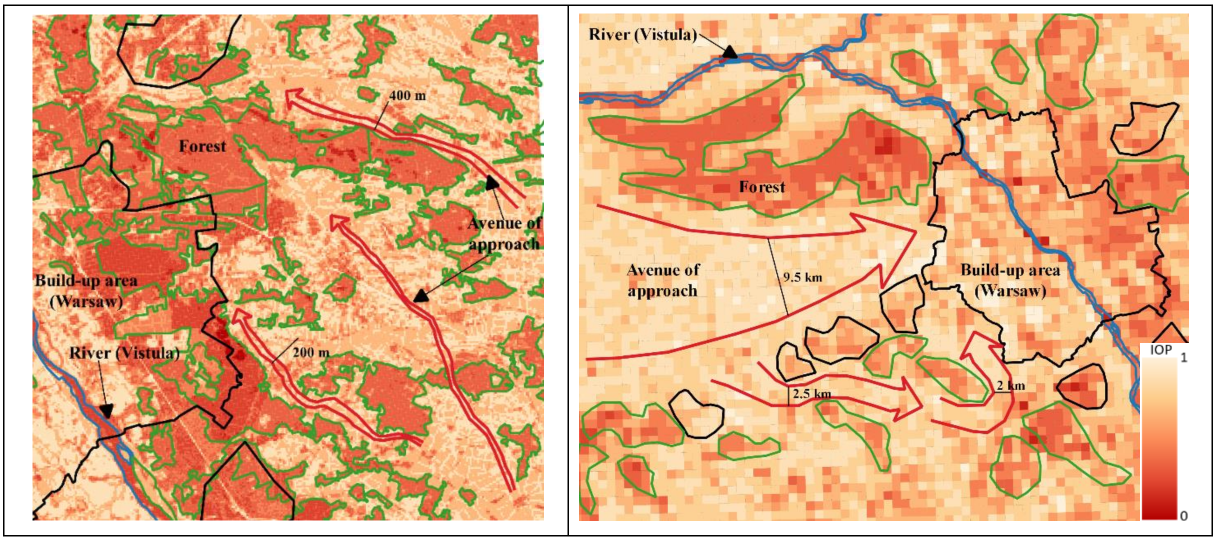


Fig. 61 *Sample visualisations of indices of passability determined with use of the perceptron method for various sizes of primary fields.*

3.2 SOM based method

The presented methodology is based on the application of *Self Organizing Kohonen Maps* for terrain classification. These are two-layer neural networks, in which the neurons in the first layer serve only to introduce the input values to the network. The actual data processing takes place in the neurons of the second (output) layer, organised in form of a two-dimensional grid (so-called map).

This method was used to determine the IOP for the area of three voivodeships in north-eastern Poland, with use of square primary fields of a side length of 1000 m. **The Author developed an algorithm for calculating the index of passability based on the application of SOM**. It consists in:

- Introducing land cover parameters (e.g. the surface of forests and rivers, length of roads etc.) are normalised and inputted to the input layer.
- Conducting the learning process of the neural network. As a result, the process arranges the classification result in such a way that similar patterns in the properties area are represented by neurons of the output layer located close to each other. In this way, the neural network classifies the terrain in terms of input data in such a number of classes that corresponds to the size of the output grid of the network.
- Preparing a set of learning data, defined as a set of indices of passability assigned *a priori* to a certain group of randomly selected primary fields.
- Introducing land cover parameters (forest surface, length of roads, etc.) from the learning dataset to SOM. Assigning each winner (i.e. the neuron characterised by the highest activation value for the introduced data) an index of passability.
- Assigning each neuron in the Kohonen map a final value of the index of passability. This is the average value of the indices obtained while introducing learning data to SOM (Fig. 7)

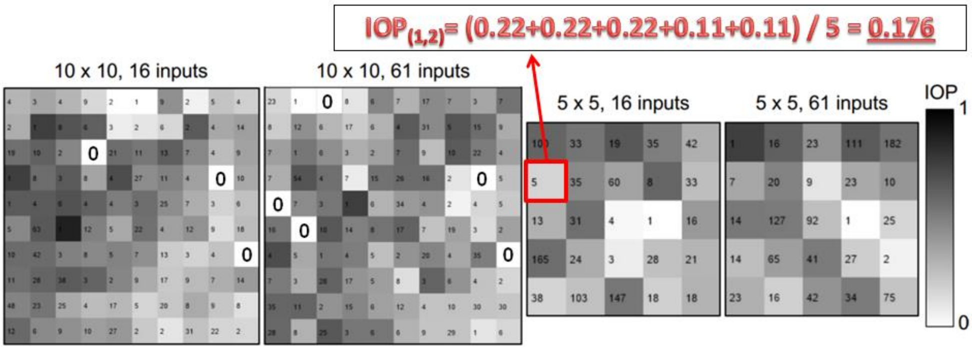


Fig. 7 *Number of winner neurons in the learning set and a visualisation of the determination of the final IOP value of the neuron.*

- Introducing land cover parameters for all primary fields to the neural network and finding the winner neuron for each of them. The IOP value assigned to this neuron then becomes the index of passability for the introduced primary field.

The Author analysed the influence of selected parameters of neural networks on their efficiency. In order to achieve it, he tested the results of SOM operation for two variants of introduced input data. In the first variant, 61 land cover parameters from VMap Level 2 were introduced to the network. In variant 2, the objects were grouped into categories. 16 categories were distinguished altogether.

The Author has also carried out tests for two dimensions of the output map of the neural network. Experiments were conducted for the dimensions of 10 by 10 and 5 by 5 neurons (the terrain was divided, respectively, into 100 and 25 classes).

The comparison of the resulting indices of passability demonstrated (Fig. 8) that there are no significant differences between the IOPs determined with use of 16 and 61 input parameters. This is confirmed by a high Pearson correlation coefficient (0.81 – 0.86) between the calculated indices of passability.

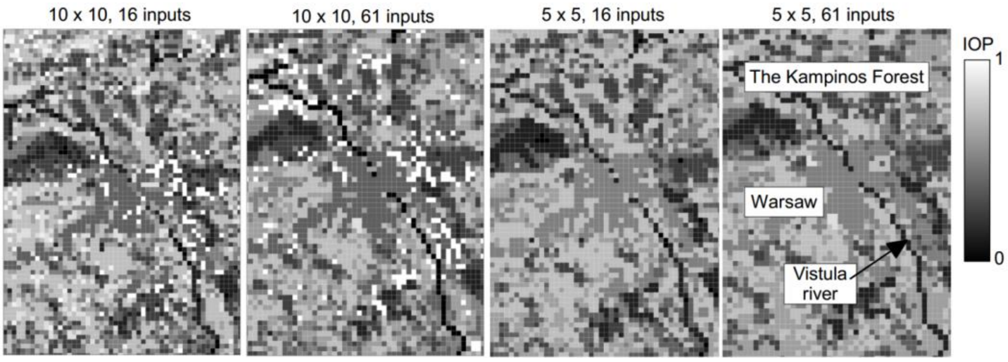


Fig. 8 *Sample visualisations of indices of passability determined with use of the SOM method.*

The visualisation of the obtained indices of passability proves that all 4 neural networks determined the IOP correctly. Impassable areas that cover, among others, forests, rivers and built-up areas were distinguished. Open areas that contain a dense network of roads were assigned high indices of passability, which reflects the actual conditions.

4. THE SHAPE AND SIZE OF THE PRIMARY FIELD

The Author assumed that the values of indices of passability obtained with use of the algorithms described in the previous section may differ, even if the same methods and source data are used, depending on the type of the primary field used, i.e. its shape and size. Considering the above, the Author analysed the influence of the shape and size of the primary field on the results of automated terrain classification for the purposes of developing passability maps.

4.1 Analysis of the shape of primary fields

The analyses of the influence of various shapes of primary fields on terrain classification results were conducted for square, triangular and hexagonal primary fields of a surface area of 1 km^2 (Fig. 9).

Square	Hexagon	Triangle

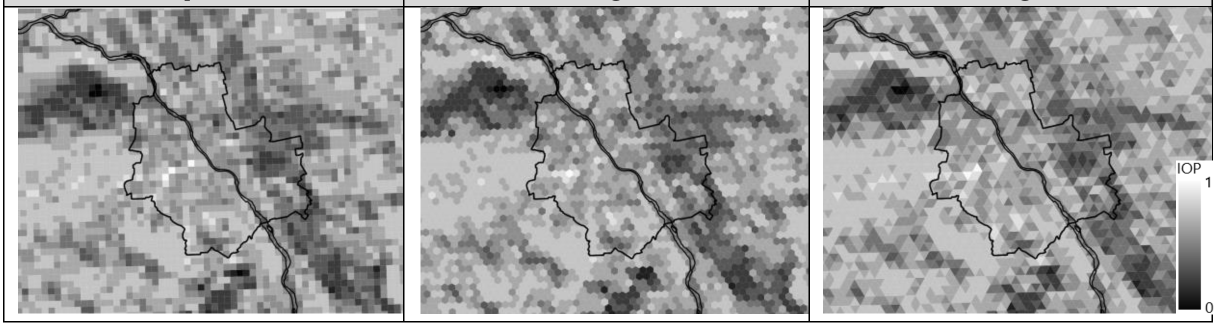


***Fig. 92** Fragments of passability maps created for various shapes of primary fields of the same surface area of 1 km^2*

The analyses conducted by the Author demonstrated that the shape of the used primary field has a slight influence on the terrain classification results, and thus on the information carried by the resulting passability map. This is proven by very high values of the correlation coefficients between the IOPs on the developed maps. These values range from 0.74 to 0.88. For the three analysed shapes of primary fields, 75 to 87% of the indices of passability do not differ by more than 0.1% (i.e. 10% of the whole range). Analysis of the size of primary fields.

4.2 Analysis of the size of primary fields

In order to analyse the influence of the primary field size on the terrain classification results, has been determined indices of passability for square primary fields of side lengths ranging from 100 m to 10 km. The IOPs were determined with use of the VRF method. The visualisation of results in form of passability maps was presented in Fig. 10.

Map in a 1:250 000 scale	Square – size 100 m	Square – size 200 m

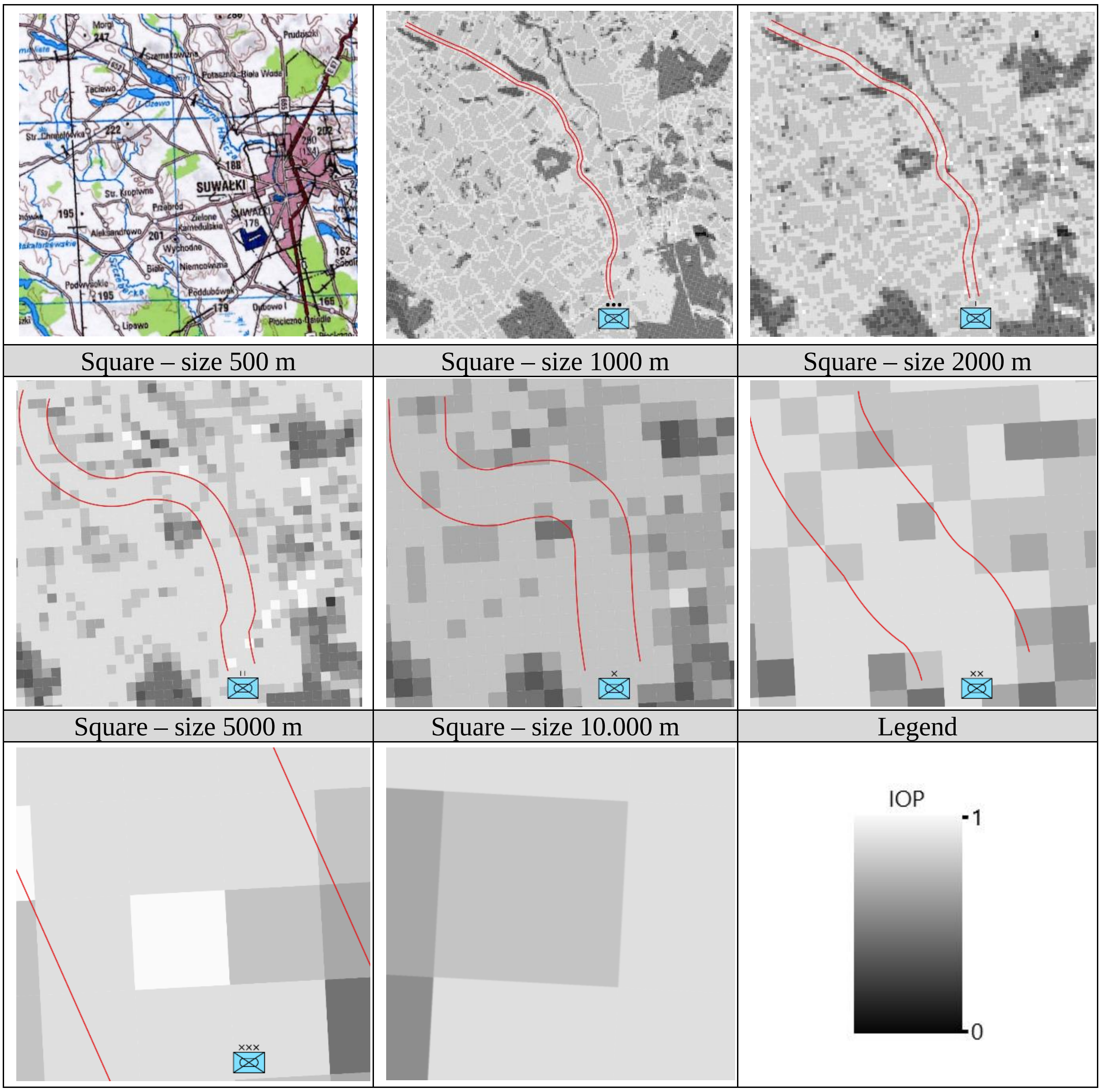


Fig.10 *Fragments of passability maps for various sizes of primary fields.*

On the maps generated for primary fields of 100 m and 200 m sides, the course of roads is noticeable. Roads are essential for passability on the lowest management level (for military applications, this means the tactical level: platoon or company). On the other hand, it was demonstrated that maps based on larger primary fields are more general, with a decreasing number of noticeable terrain details. While maps based on squares of the side of 500 m still allow us to distinguish certain detailed elements of land cover (cf. the topographic map in the 1:250k scale, Fig. 10), in maps based on 2000 m squares the contour of these elements is practically non-existent. For maps generated with use of the largest grid mesh (5000 and 10000 m), the degree of generalisation is so high that their practical application is possible only

on the highest, strategic level of command or management. This results from the fact that such large mesh contains a high number of features that have both a positive and negative influence on passability. Due to that, attempts to unambiguously determine passability in such a large area carries a significant risk of error.
The correlation coefficients between indices of passability calculated for various sizes of primary fields (Diagram 3A), demonstrate that the correlation between indices of passability determined for different primary field sizes decreases with the increase in primary field size. This decrease is linear and the correlation that may be treated as a measure of similarity between the maps, between the extreme values of primary field sizes (100 m and 10000 m squares) is very low (approx. 0.4). This proves that the information carried by maps based on the visualisation of IOP for these primary fields is completely different, although the maps were created with use of the same data and an identical method of calculating the index of passability.
The obtained test results (Diagram 3B) demonstrate that the average index of passability increases with the increasing primary field size. The diagram shows a noticeable drop (decrease) in this average value for the 1000m field. It results from the fact that, starting from this primary field size, the degree of generalisation, manifested as the decrease of the number of distinguishable details on the map, decreases considerably (radically). This means that precisely this primary field size is a "generalisation threshold" that distinguishes detailed maps that contain a large number of terrain features from generalised maps.

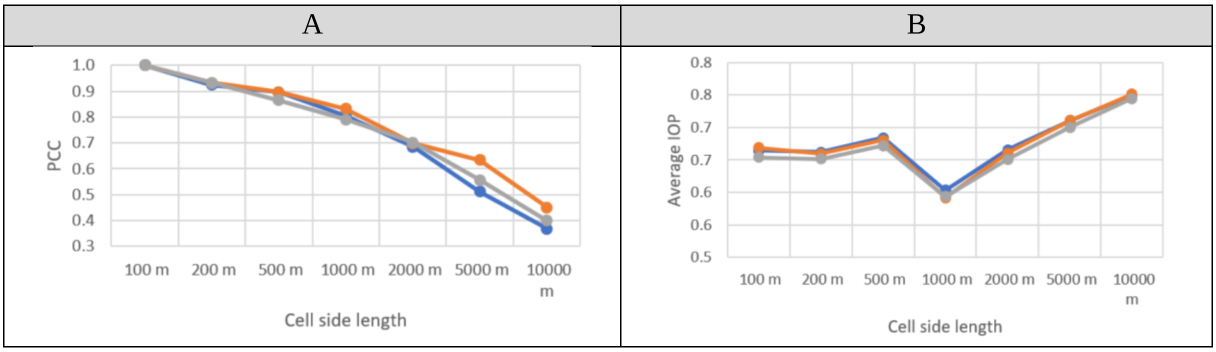


Diagram 3A *– correlation between the correlation coefficient and the primary field size (for a 100 m primary field),* ***B –*** *The correlation between average IOP and primary field size*

5. SELECTION OF DATA SOURCES USED FOR PASSABILITY MAPS

The Author has demonstrated that terrain classification for passability purposes may also be performed with use of various data sources. The analysis included military, public and social spatial databases, such as: VMap Level 2 (VML2), Database of Topographic Objects in a scale of 1:10 000 (BDOT), OpenStreetMap (OSM), VMap Level 1 (VML1), Corine Land Cover (CLC), General Geographic Objects Database (BDOO).
The spatial data used are characterised by various levels of accuracy and thus by various levels of content generalisation. Considering the above, the methodological assumption foresaw applying high-resolution spatial data bases (VML2, BDOT10k, OSM) to create detailed passability maps consisting of the smallest primary fields (100, 200 and 500 m) and the general

databases (VML1, CLC and BDOO) to develop less detailed maps with primary fields of the sizes 1000, 2000 and 5000 m.
The analysis of the schemes of the spatial databases used demonstrated (Diagram 3) that approx. half of the categories in all datasets were classified as not affecting passability. An exception is the Corine Land Cover database, in which all object classes have a non-zero (positive or negative) influence on passability. It was noted for all the applied databases that more object classes had a negative influence on passability than positive.

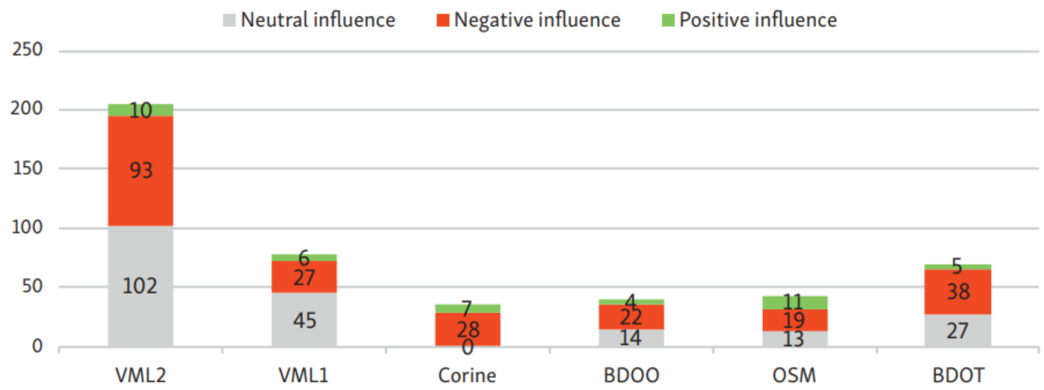
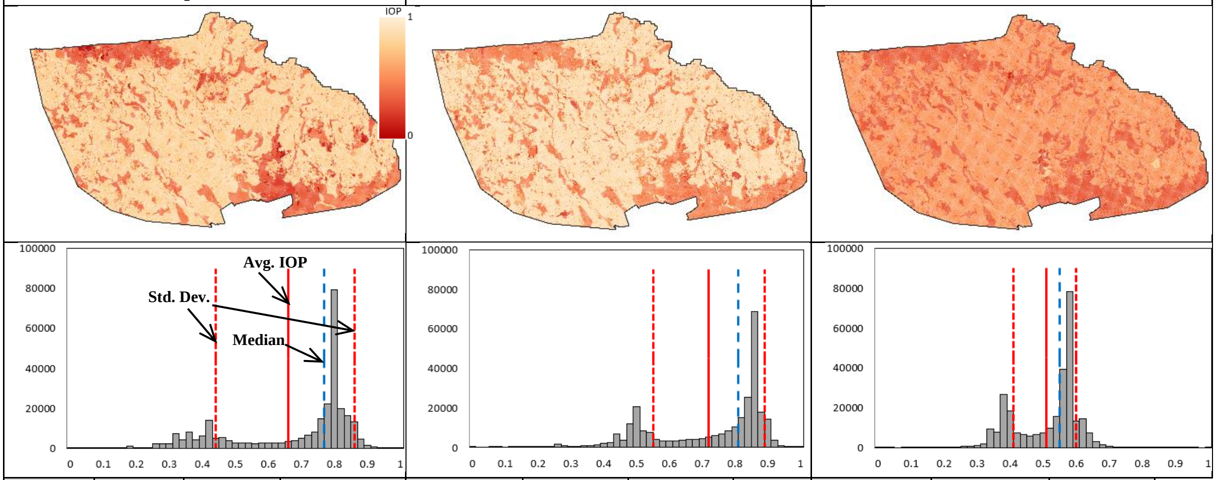


Diagram 3. *Number of object categories that facilitate, hinder or do not affect passability.*

The correlation coefficients between the IOPs calculated for the tested spatial databases (Tables 3 and 4) range from 0.7 to 0.9. This means that the value distribution of the indices of passability is similar in all maps. In spite of that, the analyses of the spatial distribution of differences between the obtained IOPs and the tables of quantity that present the percentage of indices of passability that differ by the absolute values of 0.2 and 0.4 demonstrated that, despite of high values of the Pearson correlation coefficient, a large percentage of primary fields differ significantly. Such case was noted for the comparison of maps generated with use of OSM data with maps based both on VML2 and BDOT. Here, in spite of high correlation coefficients, more than 50% of the IOPs differ by the values from 0.2 to 0.4. On the other hand, it was noted that maps generated from VML2 and BDOT were highly similar (more than 90% of the IOPs did not differ by more than 20%). For the outlook (small-scale) spatial databases (VML1, CLC and BDOO) it was proven that in 70-95% cases the absolute difference in indices of passability did not exceed 0.2, which demonstrates that the maps created with use of these databases are very similar.

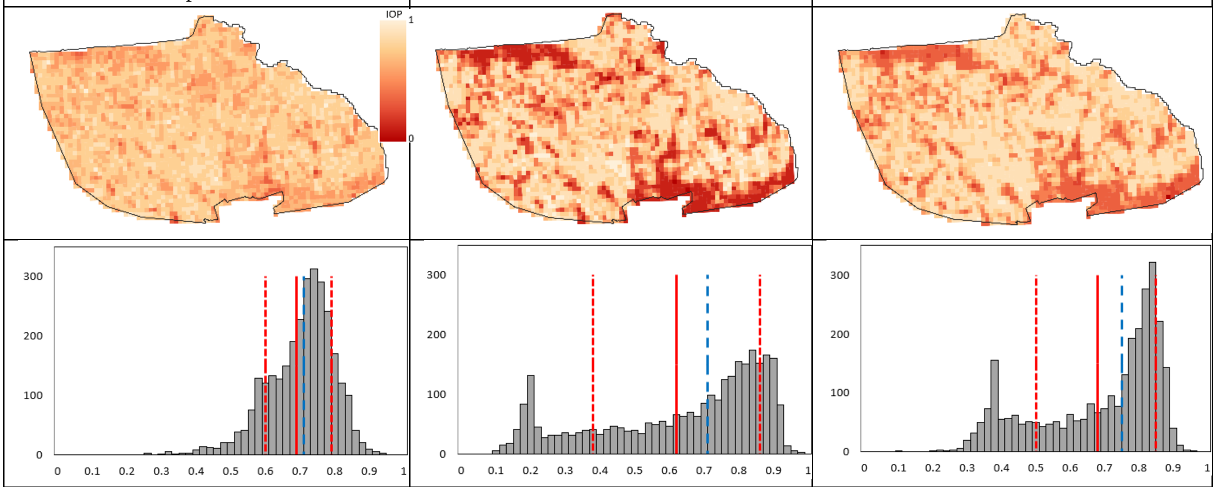
VMap Level 2	BDOT10k	OSM



	Moran I	Median	Variability coefficient	Skewness	Kurtosis	Average	Std. Dev.	VML2	BDOT	OSM
VML2	0,88	0,77	27,78	-1,03	-0,36	0,67	0,19	1	0,87	0,80
BDOT	0,81	0,81	23,44	-0,81	-0,73	0,72	0,17		1	0,83
OSM	0,79	0,55	18,91	-0,62	-0,38	0,51	0,10			1

Table 3. *Visualisation of passability maps, histograms and statistics for 100 by 100 m primary fields*

VMap Level 1	CLC	BDOO



	Moran I	Media n	Variability coefficient	Skewness	Kurtosis	Average	Std. Dev.	VML1	CLC	BDOO
VML1	0,50	0,71	13,64	-0,79	0,97	0,69	0,09	1	0,73	0,79
CLC	0,66	0,71	38,36	-0,70	-0,84	0,62	0,24		1	0,91
BDOO	0,66	0,75	26,32	-0,76	-0,81	0,68	0,18			1

Table 4. *Visualisation of passability maps, histograms and statistics for 1000 by 1000 m primary fields*

The analysis of the obtained results revealed that for maps based on OSM, slight differences between the determined indices of passability were visible. As a result of this phenomenon, impassable areas are less distinctive. A reverse phenomenon is noticeable for maps generated with use of Corine Land Cover data. Here, as the number of separated object classes is low (the objects do not overlap), passability classes are clearly distinguishable, which significantly facilitates using the map. The measure of scattering of the indices of passability is the standard deviation. It was noted that for OSM data it was the lowest for all primary field sizes (Table 3). A considerably higher value of this estimator was noted for data generated with use of CLC database. Table 3 demonstrates that the average index of passability is much lower for OSM data than for the other databases used. This is what causes a noticeable “shift” in the distribution of indices of passability towards lower values. In practice, this leads to the fact that these maps are “darker” than the other ones, with the applied method of cartographic visualisation (see Table 3, compare OSM with other maps).

6. CONCLUSIONS

The presented methods of creating passability maps have been implemented in proprietary software developed by the Author. It enables full realisation and automation of all elements of cartographic modelling, from the preparation and initial processing of input spatial data to the visualisation of the resulting map in the geoportal.
As opposed to currently used methods (division into 3 passability classes), the proposed methodology enables the determination of the index of passability on a continuous scale. In this way, the accuracy with which the passability of a specific area may be defined is incomparably higher and the scope of application of the classification results becomes much broader. The development of a configurable IT system fulfils the requirement to automate the IOP calculating process. It is justified mainly by the changeable and dramatic nature of the situations connected with the potential areas of application of the developed maps (crisis management, planning the movement of military troops). The application of primary fields and the possibility to select their size influences the resolution of the resulting model and thus the level of detail of the carried geographic information.

REFERENCES

Field Manual 34-130 Intelligence Preparation of the Battlefield, 1994, Department of US Army, Washington, DC, USA.

Hofmann A., Hoskova-Mayerova S., Talhofer V., 2013, Usage of Fuzzy Spatial Theory for Modelling ofTerrain Passability. Hindawi Publishing Corporation, Advances in Fuzzy Systems, vol. 2013(506406), Doi: 10.1155/2013/506406.

Hofmann A., Hoskova-Mayerova S., Talhofer V., Kovařík V., 2015, Creation of models for calculation of coefficients of terrain passability. Quality & Quantity, 49 (4), pp. 1679-1691.

Kohonen T., 1982, Self-organized formation of topologically correct feature maps. Biological Cybernetics, 43(1), pp. 59–69, Doi:10.1007/BF00337288.

Pokonieczny K., 2017, Automatic military passability map generation system. Proceedings of ICMT 2017 - 6th International Conference on Military Technologies, Brno, Czech Republic, 31.05.2017–2.06.2017, IEEE, pp. 285–292, Doi: 10.1109/MILTECHS.2017.7988771

Pokonieczny K., 2018, Using a multilayer perceptron to automate the terrain assessment for the needs of the Armed Force. ISPRS International Journal of Geo-Information, 7 (11), 430, Doi: 10.3390/ijgi7110430

Pokonieczny K., 2018, Methods of using self-organising maps for terrain classification, using an example of developing a military passability map. In: Lecture Notes in Geoinformation and Cartography: Dynamics in GIscience, Ed: Springer, Cham, pp. 359-371, Doi: 10.1007/978-3-319-61297-3_26

Pokonieczny K., Mościcka A., 2018, The influence of the shape and size of the cell on developing military passability maps. ISPRS International Journal of Geo-Information, 7(7), 261, Doi: 10.3390/ijgi7070261

Pokonieczny K., 2018, Comparison of land passability maps created with use of different spatial data bases. Geografie, 123/3, pp. 317-352.

Suzuki K., 2013, Artificial Neural Networks - Architectures and Applications", Publisher: InTech, ISBN 978-953-51-0935-8, 264 pages, under CC BY 3.0 license.

BIOGRAPHICAL NOTES

Krzysztof Pokonieczny is specialist in geoinformatics at the Faculty of Civil Engineering and Geodesy of the Military University of Technology. For 8 years he worked at the Military Geographic Centre, where was responsible for military projects associated with geoinformatics. His research work mainly focuses on the use of geostatistics and machine learning algorithms, especially in the military applications of GIS. Currently he is the Director of Institute of Geospatial Engineering and Geodesy.

CONTACTS

Col. Krzysztof Pokonieczny Ph.D. D.Sc. Eng.
Military University of Technology, Faculty of Civil Engineering and Geodesy
Address: gen. Sylwestra Kaliskiego 2 Street
City: 00-908 Warsaw
COUNTRY: Poland
Email: krzysztof.pokonieczny@wat.edu.pl