This research was supported by European Social Fund's Dora Plus Programme

www.emu.ee

Euroopa Liit
Euroopa
Regionaalarengu Fond

Eesti
tuleviku heaks

Eesti Maaülikool
Estonian University of Life Sciences
Põllumajandus- ja keskkonnainstituut
Institute of Agricultural and Environmental Sciences

USING GEOTAGGED PHOTOGRAPHS AND REMOTE SENSING TO EXAMINE VISUAL AND RECREATIONAL LANDSCAPE VALUES IN ESTONIA

Authors

Oleksandr Karasov	**EMÜ, Estonia**
Stien Heremans, PhD	INBO, Belgium
Mart Külvik, PhD	EMÜ, Estonia
Artem Domnich	UT, Estonia

EGU2020: Sharing Geoscience Online 2020

FRAMEWORK

Area: outdoor areas within Estonia

Aim: describe people's activities pattern and link it to landscape attributes

Data:

- Flickr.com (popular photo hosting)
- VK.com (the largest Europe-based social network, 97M users/month (2019)

Methods: machine learning (Clarifai automated image recognition), natural language processing (topic modelling), GIS- and statistical analysis

What is new: time- and cost-effective way of the extraction of meaningful data from geolocated photographs

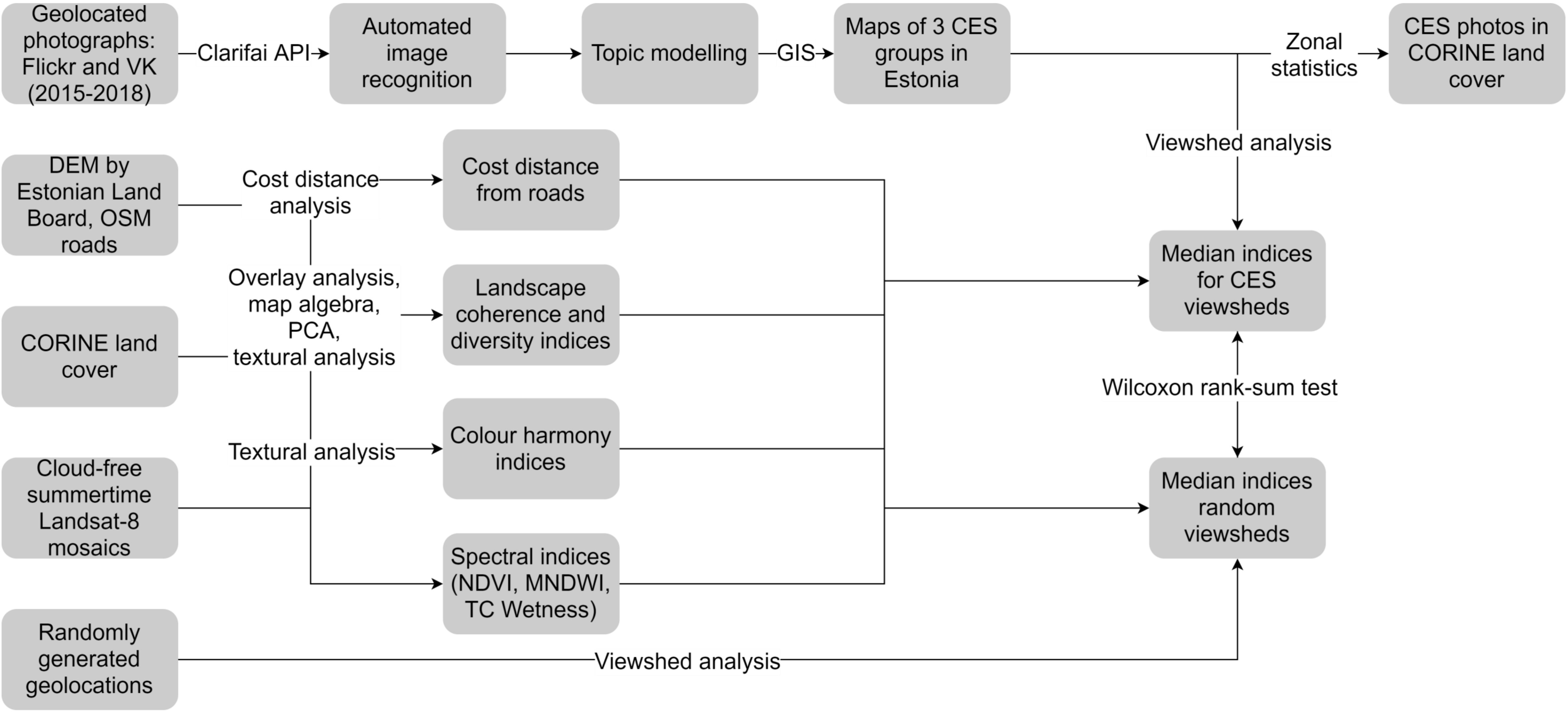
Research questions:

RQ 1. How to improve photo-series and content analysis to map CES flow in Estonia?

RQ 2. What are the main groups of CES, evidenced from social media in Estonia?

RQ 3. What are the remote sensing- and GIS-based indicators, reflecting landscape conditions likely responsible for CES experience?

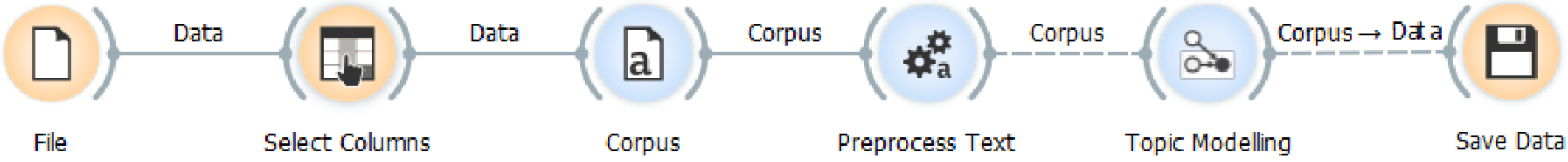
RESEARCH WORKFLOW



RQ 1. IMAGE RECOGNITION + TOPIC MODELLING

GENERAL

beach	0.99	woman	0.94
sea	0.99	landscape	0.94
water	0.99	leisure	0.93
seashore	0.98	sky	0.93
ocean	0.98	sun	0.92
girl	0.96	outdoors	0.92
sand	0.95	relaxation	0.92
travel	0.95	vacation	0.91
nature	0.95	lifestyle	0.89
summer	0.94	people	0.89



Topic modelling (LDA – Latent Dirichlet Allocation (Blei, 2003), Orange software) for Clarifai-derived tags to get CES groups

Latent dirichlet allocation (LDA) is an approach used in topic modeling based on probabilistic vectors of words, which indicate their relevance to the text corpus. LDA randomly ascribes each tag to the topic, and calculates a special score for this word based on the probability that this word will be found in this particular topic in document. LDA then ascribes this same word to another topic and calculates the same score. After many iterations we get a list of words in each topics with probabilities.

https://noduslabs.com/cases/tutorial-lda-text-mining-network-analysis/

RQ 2. CONTENT ANALYSIS FOR SOCIAL MEDIA PHOTOS

Landscape watching: nature, outdoors, landscape, tree, nobody, wood, sky, travel, water, summer

Photos: 6154 (17 taken from wildlife watching)

Outdoor recreation: people, recreation, adult, fun, man, leisure, outdoors, one, sport, action

Photos: 2346 (770 taken from landscape watching, 114 – from wildlife watching)

Wildlife watching: nature, outdoors, nobody, flora, leaf, wild, wildlife, season, animal, growth

Photos: 1485 (124 taken from landscape watching; 2 – from outdoor recreation)

RQ 3. REMOTE SENSING-BASED INDICATORS

Cost distance from roads – the shortest weighted distance from each cell to the nearest source location, TRI as a cost surface. Indicator of accessibility

Landscape coherence

Landscape coherence index (LCI): ratio between Hartley function for composite of TPI-based landforms and CORINE land cover, and summarised Hartley functions applied for landforms and land cover separately

GLCM Angular Second Moment: $\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\{P(i,j)\}^2$, where: *P(i,j)* = the probability of co-occurrence of pixels *i* and *j*, *Ng* = the number of distinct grey levels in the quantised image (64 in this study). Indicator of image orderliness.

GLCM Correlation: $\frac{\sum_i\sum_j(ij)P(i,j)-\mu_x\mu_y}{\sigma_x\sigma_y}$, where: *P(i,j)* = the probability of co-occurrence of pixels *i* and *j*; $\mu_x, \mu_y, \sigma_x, and\ \sigma_y$ = the means and std. deviations of the partial probability density functions. Indicator of linear dependency of pixel pairs

Fragmentation index – number of adjacent pairs of different pixels relative to their maximum possible number – indicator of edge density

Diversity of land cover

Diversity (Shannon entropy, SHDI): *H* =-Σ(*p**ln(*p*)), where: Σ=the sum over all classes in the entire image, and *p*=proportion of each class in the kernel. Indicator of image diversity

Dominance index: *D*=*Hmax*-*H*, where: *H*=Diversity, *Hmax*=maximum diversity=ln(*n*) and *n*=number of different classes present in the kernel. Indicator of lower image variability

Terrain Ruggedness Index (TRI): the mean difference between a central pixel and its surrounding cells, indicator of relief diversity

Colour harmony of land cover

GLCM Homogeneity for Hue – similarity of hues in two-colour combination

GLCM Homogeneity for Saturation – similarity of saturations in two-colour combination

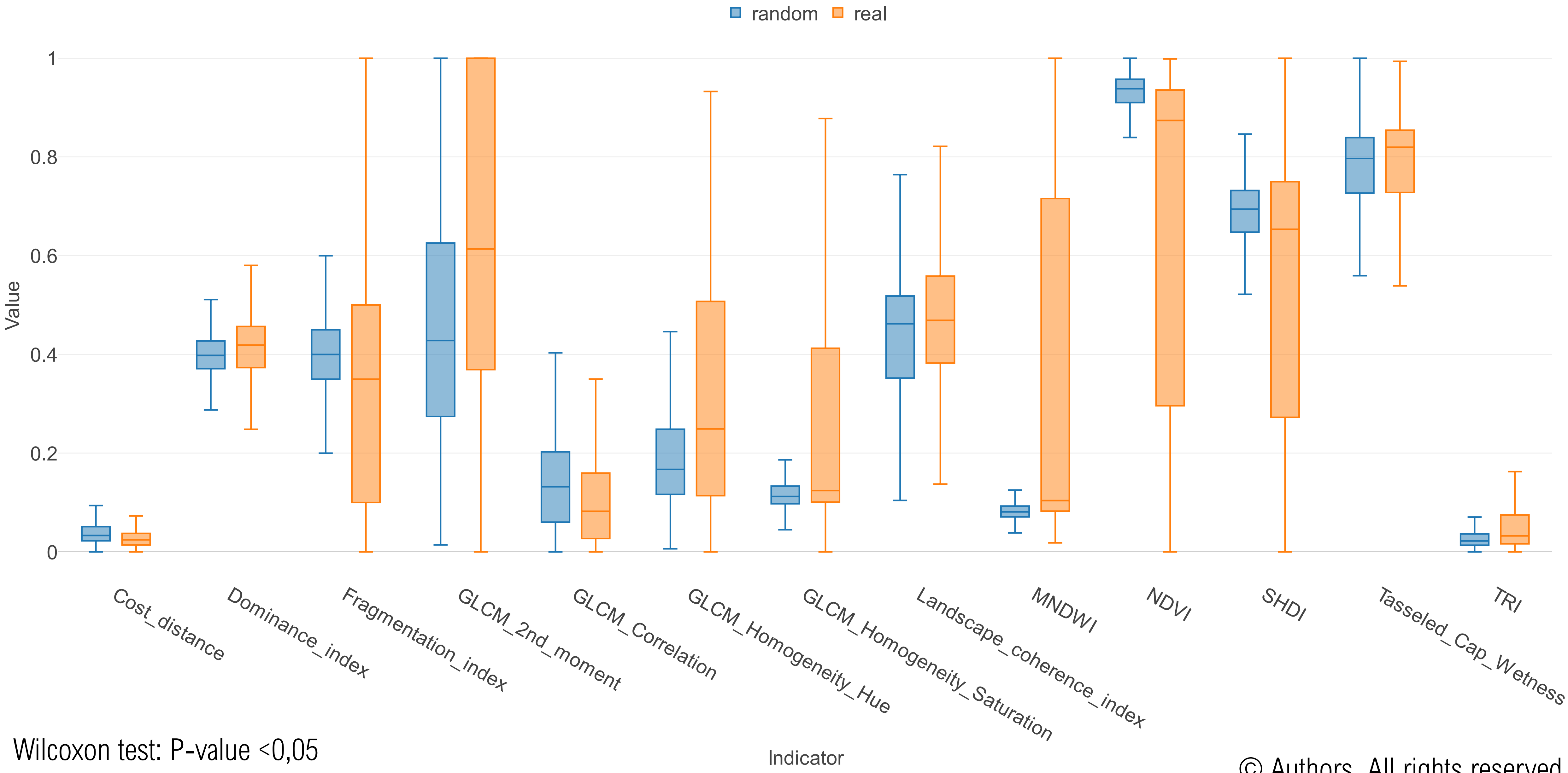
Spectral indices (greenness, moisture conditions)

Normalized Difference Vegetation Index (NDVI): function of Near Infrared and Red bands, indicator of vegetation greenness

Tasseled Cap Wetness: the third output of tasseled-cap transformation, indicator soil or surface moisture

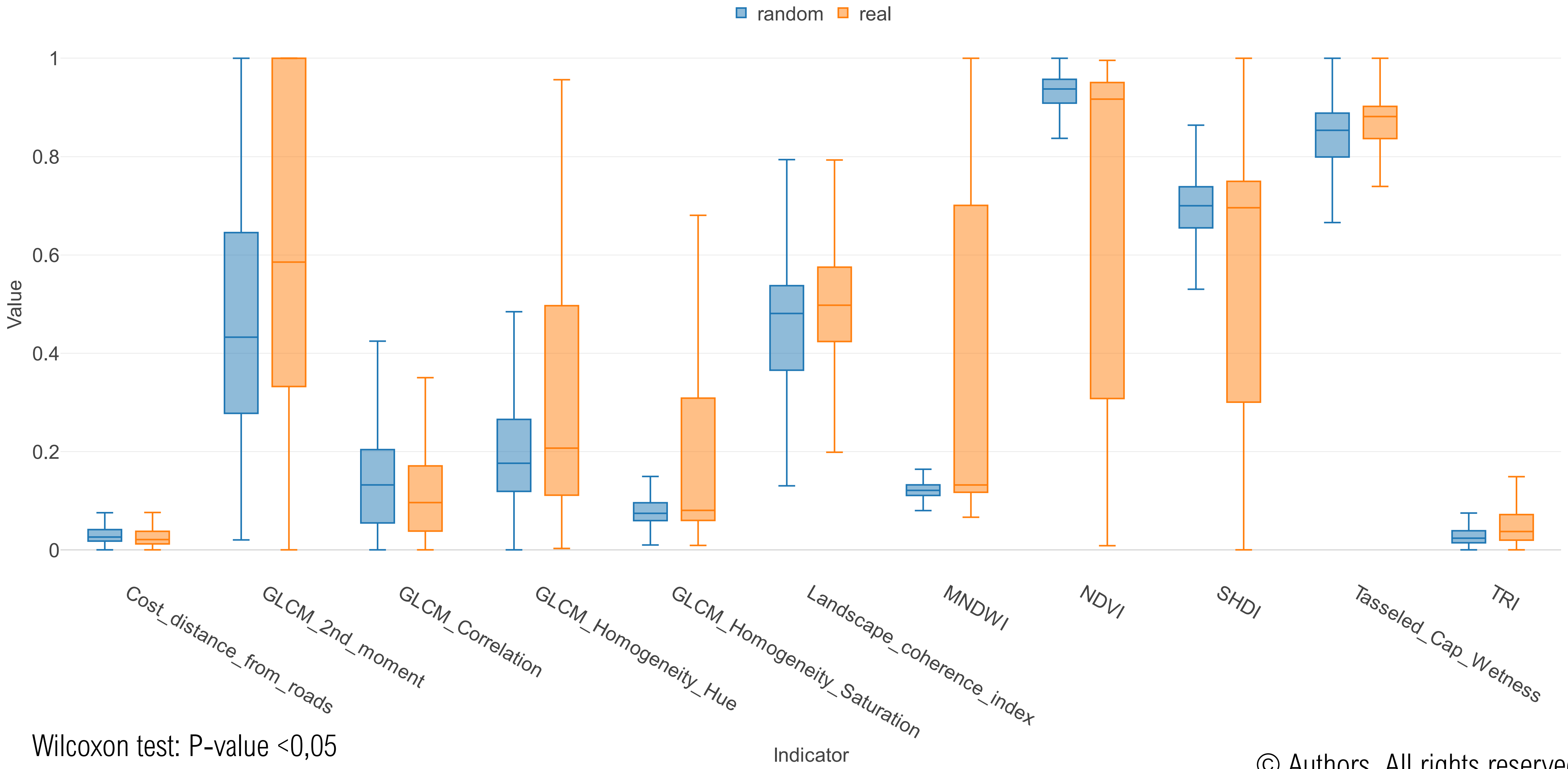
Modified Normalized Difference Water Index (MNDWI): function of Green and SWIR bands, indicator of water presence

LANDSCAPE WATCHING (RESCALED INDICATORS)



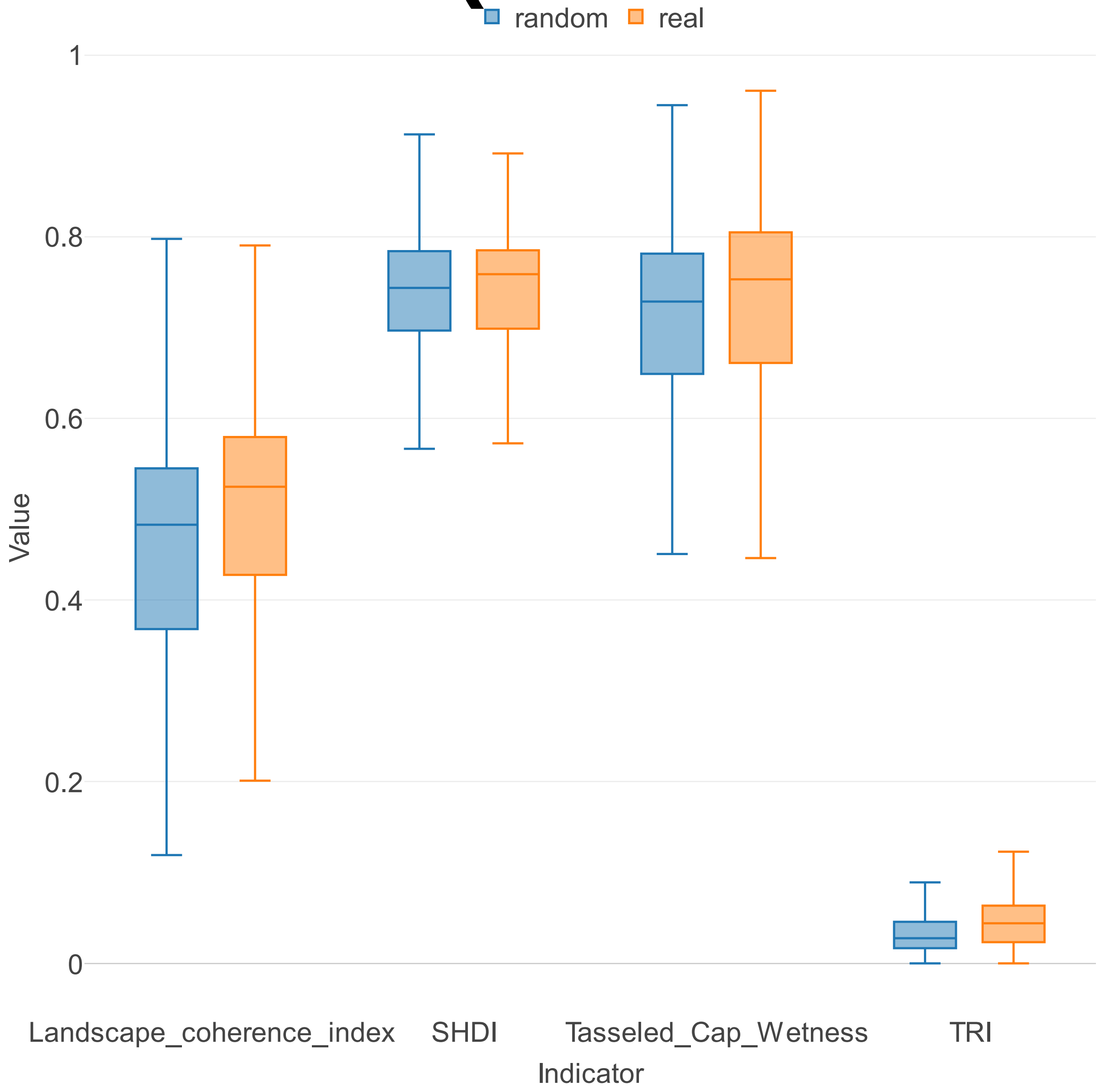
Wilcoxon test: P-value <0,05

OUTDOOR RECREATION (RESCALED INDICATORS)



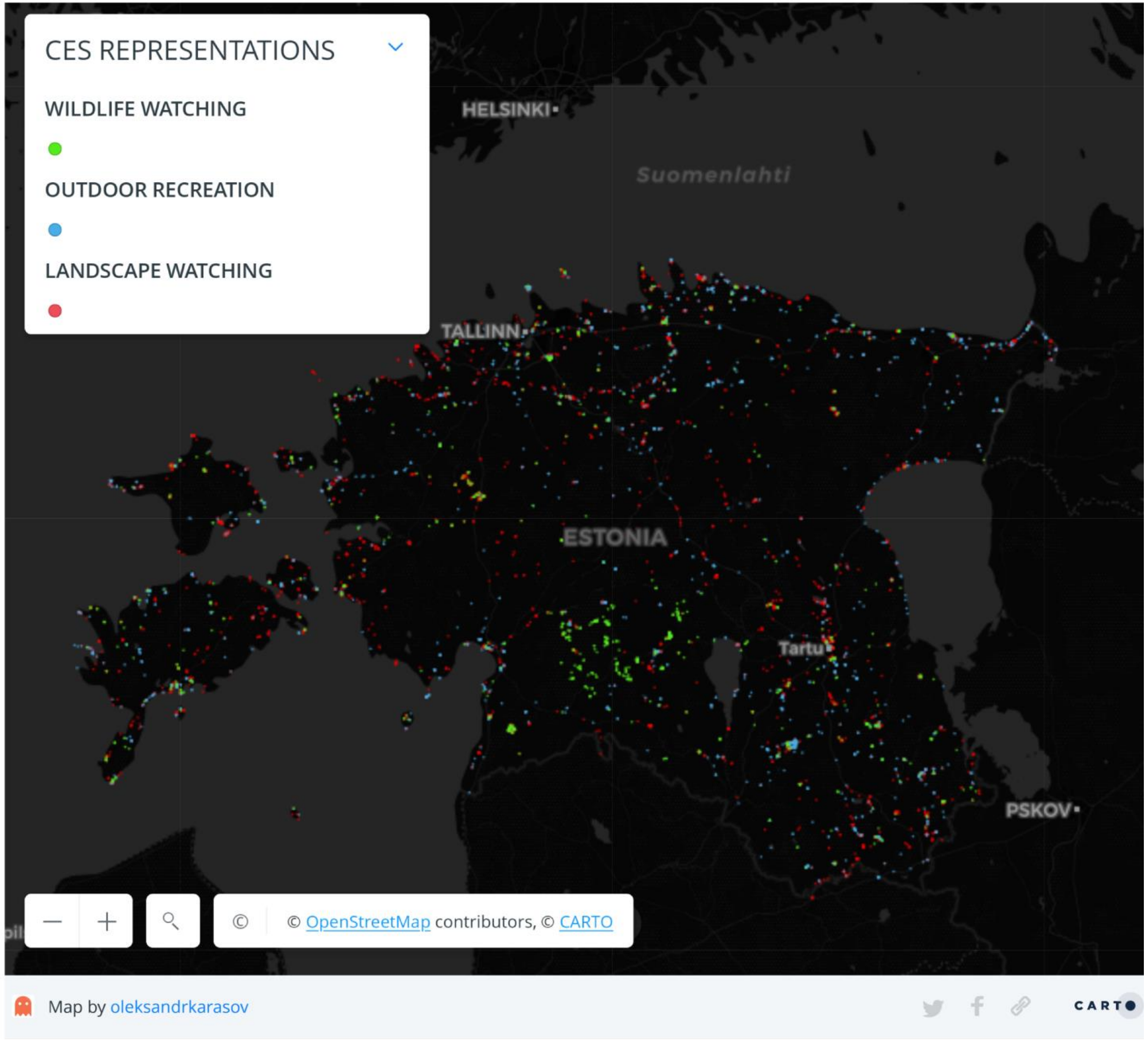
Wilcoxon test: P-value <0,05

WILDLIFE WATCHING (RESCALED INDICATORS)



Wilcoxon test: P-value <0,05

CULTURAL ECOSYSTEM SERVICES IN ESTONIA



1. Water presence, terrain ruggedness, and transport accessibility are the best indicators of recreational experience.
2. Colour harmony of land cover and landscape coherence are moderately higher for actual outdoor photographs.
3. NDVI and to a large extent Shannon diversity index values are lower for actual outdoor photographs
4. Grey Level Co-occurrence Matrix (GLCM) based 2nd moment index, fragmentation index, and landscape coherence index better indicate landscape coherence, than GLCM Correlation index.
5. Landscape watching and outdoor recreation photographs can be indicated with the same metrics
6. Wildlife watching can be indicated with landscape coherence index, Shannon diversity, Terrain Ruggedness Index and Tasseled Cap Wetness only

DISCUSSION

For the first time automated image recognition and topic modelling were used for CES classification based on passively crowdsourced photographs. Previous reports include conjunction of automated image recognition and hierarchical clustering (Richards and Tunçer, 2019)

Conformity with existing research.

1. Photographs of landscape watching, outdoor recreation and organisms occur most commonly (Richards and Friess, 2015).
2. Some colour harmony principles have been confirmed for landscape watching and recreation preferences: hue and saturation similarity (Ou et al., 2018).
3. Landscape coherence shows a weak and place-specific positive influence on landscape watching and recreation, influencing rather photographs of organisms.
4. Terrain ruggedness and accessibility are confirmed as factor of photo taking preferences (Van Zanten et al., 2016)
5. MNDWI and Tasseled Cap Wetness, positively related to landscape preferences, indicate naturalness (Nassauer, 1979)

Contradictions and limitations.

1. Shannon diversity index is unevenly related to landscape preferences (Uuemaa et al., 2013); Shannon diversity has positive association when calculated for green areas only
2. Horizontal landscape coherence, indicated by Correlation index, is lower for actual photoscapes (GLCM Correlation provides almost identical information as provided by autocorrelation methods using Moran’s I, used to indicate ecological landscape coherence (Ode et al., 2008)). GLCM Second Moment index (reflecting orderliness) or suggested vertical landscape coherence index, fragmentation index can be used as landscape coherence indicators instead
3. NDVI values are generally lower for photo taking areas (Vukomanovic et al., 2018)
4. Cumulative viewsheds and data resolution, kernel size to calculate texture metrics (Haralick’s metrics), temporal diversity of summertime Landsat mosaics may bias the results.
5. No social media users’ background was studied.

CONCLUSIONS

RQ 1. Automated image recognition (based on Clarifai general model), used conjunctively with natural language processing (topic modelling) significantly contributed to the efficacy and efficiency of the content analysis for passively crowdsourced outdoor Flickr and VK.com photographs. However, visual post-processing needs to be applied, as automated methods tend to overestimate content of image by expense of its context (photos showing pets were wrongly classified as representing wildlife watching, photos with minor presence of people – as representing landscape watching, etc.).

RQ 2. There are three main groups of cultural ecosystem services, represented in Flickr and VK.com within Estonia: passive landscape watching (photographs of landscapes without people), active outdoor recreation (photographs of outdoor activities or related equipment) and wildlife watching (photographs of organisms). Minor categories of recreation were not extracted.

RQ 3. Textural and spectral indices based on satellite imagery, aesthetic landscape attributes (colour harmony indices), landscape diversity and transport accessibility (the most important variable) indicate cultural ecosystem services use in Estonia, highlighting remote sensing and GIS feasibility and linking ground-based and top-view Earth observations

Applications and further work:

1. Results can be used for developing targets and measures to enhance the visual quality and the recreation potential of landscapes
2. Landscape planners can apply proposed indicators to take into account potential conflicts, synergies and trade-offs involving landscape aesthetics component
3. Areas identified as having a relatively high visual landscape quality should be preserved by avoiding changes that could potentially impair their current value. Also, areas evaluated as having and low medium visual quality should exploit existing opportunities for enhancement.