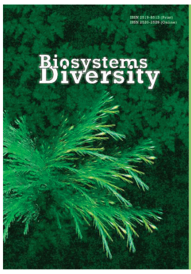

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The effect of technological oil spill in soil within electrical generation substations, analysed by ecological regime in the context of relief properties

O. Potapenko*, O. M. Kunah**, M. P. Fedushko***

**Dnipro State Agrarian and Economic University, Dnipro, Ukraine*
***Oles Honchar Dnipro National University, Dnipro, Ukraine*
****Bogdan Khmelnitsky Melitopol State Pedagogical University, Melitopol, Ukraine*

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Dnipro State Agrarian and Economic University, Sergey Yefremov st. 25, Dnipro, 49600, Ukraine.
E-mail: potapenkoev@dtek.com

Oles Honchar Dnipro National University, Gagarin ave., 72, Dnipro, 49000, Ukraine.
E-mail: kunah_olga@ukr.net
Tel.: +38-098-858-23-79.

Bogdan Khmelnitsky Melitopol State Pedagogical University, Hetmanska st., 20, Melitopol, 72318, Ukraine.
E-mail: marinafedushko@gmail.com

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Technological oil spills within electrical substations are the source of considerable environmental contamination. The aim of this study is to evaluate the relation between phytoindication assessments of ecological factors and geomorphological covariates and investigate the effect of the technological oil spill on ecological regimes within electrical substations. During the fieldwork 175 geobotanical releves were analysed in the years 2016–2017 within Dnipropetrovsk region (Ukraine). Within each electrical substation the geobotanical prospecting was conducted both in plots with undisturbed vegetation cover (control, the plot size 3 × 6 m) and in plots with technological oil spill (pollution, plot size 3 × 3 m). Phytoindication assessment of the following ecological factors was made: soil water regime, soil aeration, soil acidity, total salt regime, carbonate content in the soil, nitrogen content in the soil, radiation balance, aridity or humidity, continental climate, cryo-climate, light regime. HydroSHEDS data were taken for the basis for creating a digital elevation model with resolution of the data layer 15 arcseconds. The phytoindication assessments of the ecological regimes are characterized by correlation of geomorphological properties. The soil humidity is characterized by statistically significant negative correlation with the topographic position index and positive correlation with the vector ruggedness measure. The variability of damping correlates with four geomorphological predictors. This environmental regime has positive correlation with digital elevation model and diffuse insolation and negative correlation with topographic wetness index and direct insolation. The soil acidity of the edaphotope within Dnipropetrovsk region correlates with statistical signiicance with the vector ruggedness measure. The soil humidity of the edaphotope is associated with variation of the topographic wetness index, direct insolation, diffuse insolation and entropy of terrain diversity. The highest carbonate content in the soil correlates with higher risks of erosion, which is characterized by loss of soil and vertical distance to channel network. The nitrogen content in the soil is very sensitive to geomorphological features of the area. This results in the correlation of this indicator with six geomorphological predictors. Obviously, the most favourable supply of the nitrogen content in the soil is formed on upland areas. This allows positive correlation of the phytoindication assessment of the nitrogen content in the soil and the height relief. The use of relief variable as the covariate revealed the nature of the impact of soil contamination on ecological factors. Technological oil pollution leads to deterioration of water regime, reducing the availability of plant available forms of nitrogen and deterioration of soil aeration. There are also changes in microclimatic properties. There are more extreme thermal regimes and greater level of illumination. A key task for further research is to study the influence of relief features on the degree of negative transformation of soil due to technological oil pollution.

Keywords: digital elevation model; environmental regimes; phytoindication; landforms; spatial models.

Introduction

Technological oil spills within electrical substations may lead to a considerable contamination of the environment. Technological oils are the source of polycyclic aromatic hydrocarbons (PAHs) (Wcisło, 1998). Soil contamination by oil is especially dangerous because of the strong toxic effects of PAH (Klamerus-Iwan et al., 2015; Han et al., 2016). PAHs possess mutagenic, teratogenic, or carcinogenic properties (Loick et al., 2009). Polychlorinated biphenyls (PCBs) are commonly present in the dielectric fluid found in electrical transformers and feeder cables, and are often associated with electrical generation stations/substations. Available evidence show significant volumes of PCBs accumulated in electrical equipment (Kukharchik et al., 2007). The PAHs contained in oil penetrate into the soil environment (Lipińska et al., 2013).

The biodegradation time of different hydrocarbon compounds varies greatly under different landscape conditions (Zamotaev et al., 2015). Tobler's "first law of geography" says that everything is related to everything else, but near things are more related than distant things (Tobler, 1970). This law is the foundation of a spatial autocorrelation. Spatial autocorrelation is the similarity between two observations of a measured variable based upon their spatial location (Griffith, 1992; Legendre, 1993; Lennon, 2000). The ability to collect large amounts of data is necessary for the assessment the spatial variability of the ecological regimes. Phytoindication evaluation is quite efficient for this task. Kriging is most often used for interpolation of spatial data (Minasny & McBratney, 2003). But this approach requires the condition of the stationary studied process. As a rule, the implementation of such requirements can be achieved on the spatial level of the single biogeocenosis or landscape (Baljuk et al., 2014). Relief diversity is a source of non-stationary processes on the Earth's surface. Therefore, understanding the nature of relationship between the properties of the relief with the ecological processes is an important condition for spatial modeling of environmental regimes. The relief is a combination of forms and elements of the earth's surface which are different in morphology, genesis and age, and is a reflection of their spatial relations. Relief analyss is a method of the landscape investigation based on the digital elevation model (DEM). The spatial distribution of topographic attributes can be used for indirect measurement of spatial variability of hydrological, geomorphological and biological processes (Moore et al., 1993). The landforms or relief units are important relief parameters, each of which carries information about the physical, chemical and biological processes and properties (Dehn et al., 2001). The topographic indexes have different effects on ecosystem productivity, which are defined by soil and climate conditions (Kravchenko & Bullock, 2000). Position within the landscape (concave or convex areas, slope or thalweg) is a significant factor that affects the wheat yield (Ciha, 1984). Surface relief curvature is an effective option to describe the relationship between yield, topography and weather conditions (Timlin et al., 1998). The relative height of the relief is one of the most important soil and landscape factors that affects the productivity of agro-ecosystems (Cox et al., 2006; Miao et al., 2006). The average yield and average grain moisture greatly depends on the flow field length in surface irrigation conditions (Marques da Silva & Silva, 2006). The slope length to the topographical watershed is the best indicator of the wheat yield in a wide range of scales (Zeleke & Si, 2004). The topographic wetness index enables one to explain from 38% to 48% of the spatial variation of wheat yields in Eastern Colorado (USA) in 1997 (Green & Erskine, 2004).

The impact of the topographic index on productivity of ecosystems is dependent on the weather, especially the rainfall. The water content in the soil is a limiting factor for the production of grain in semiarid and arid regions, where potential evaporation is significantly larger than the amount of rainfall (Chi et al., 2009). The impact of precipitation (snowfall or rain) on productivity can be reinforced as a result of interaction with relief features and soil properties (Timlin et al., 1998; Kaspar et al., 2004). It should be noted that the information in the literature about the nature of the relationship between weather conditions, topography and productivity is extremely controversial (Kravchenko & Bullock, 2000). It was found that fewer topographical features affect the crop in dry years than in wet (Halvorson & Doll, 1991). In another investigation it was found on the contrary that the effect of the topography is greater in wet years than in dry (Simmons et al., 1989). These differences can be explained by distinctions in the soil and climatic conditions in which experiments were performed. Soil wetness conditions are the most important factor that controls the variability of wheat yield and affects the significance of the topographic indexes in the semiarid regions. In dry years, watershed length is the most essential factor that determines yield. In wet years the value of topographical indexes was lower (Chi et al., 2009). The role of geomorphological ecogeographical variables derived by using the Digital Elevation Model created on the basis of Earth remote sensing data is shown as ecological niche weed markers as exemplified by common milkweed (*Asclepias syriaca* L.) (Kunah & Papka, 2016). The spatial distribution of Mute Swan (*Cygnus olor* (Gmelin, 1803)) in the winter conditions of the Sivash Gulf was explained by means of use relief predictors for ENFA-analysis (Andrushenko & Zhukov, 2016). Regression dependence of soil electrical conductivity from the relief height and its derivatives, Landsat vegetation indexes, relief and vegetative cover diversity was found (Zhukov et al., 2016).

Sorption and degradation are key processes that affect the fate and transport of PAHs in the soil (Magee et al., 1991). The speed of pollution dispersion in saturated soil is far greater than in unsaturated soil conditions (Abbasi Maedeh et al., 2017). The soil is the most considerable long-term repository for PAHs (Nam et al., 2003). PAHs can enter plant tissues by partitioning from contaminated soil to the roots (Srogi, 2007). Soil is also considered to be a steady indicator of the state of environmental pollution (Mueller & Shann, 2006). A direct relationship between PAH concentrations in soil and plants was reported (Fismes et al., 2002). PAHs affect the activity of soil enzymes, which can be used to evaluate soil microbial properties (Shen et al., 2006). Accumulation of PAHs in soils may lead to further potential contamination of plants and food chains (Kipopoulou et al., 1999). Oil contamination creates extreme conditions for pedogenesis (Zamotaev et al., 2015). Contamination with hydrocarbons can have a profound effect on soil fauna (Dendooven et al., 2011). Earthworm population density reflected the contamination level of oil-contaminated soils (Klamerus-Iwan et al., 2015). The negative effect of PAHs on the survival and reproduction of earthworms was detected (Brown et al., 2004; Contreras-Ramos et al., 2006). Oil pollution affects soil physical properties (Klamerus-Iwan et al., 2015). Pore spaces might be clogged, which could reduce soil aeration and water infiltration and increase bulk density, subsequently affecting plant growth. Oils that are denser than water might reduce and restrict soil permeability (Abosede, 2013). Grasses and annual herbs have received considerable attention for evaluating the potential of plants to remediate PAH contaminated soils (Davis et al., 2002). Oil contamination with PAHs modified the physical properties of soils and oil had a negative impact on enzyme activity in soil (Klamerus-Iwan et al., 2015).

The Didukh phytoindication scales indicate the specific ecological factors that are measured in specific units. For example, the rate of the soil humidity allows one to measure the productive soil water content during the vegetation season. The damping variability rate indicates the level of unevenness of damping and the soil acidity indicates pH (Didukh, 2011). The approaches were developed for the application of the catena method to the study of the soil animal community diversity of the river arena landscape of the Dnieper Valley (within the Dnieper-Orylskiy Nature Reserve) by means of phytoindication evaluation of the main trends of environmental conditions (Zhukov et al., 2016).

The aim of our research is to establish a link between phytoindication assessments of ecological factors and geomorphological covariates and evaluate the effect of the technological oil spill effect on ecological regimes within electrical substations.

Materials and methods

Electrical network objects including electrical substations are located throughout Dnipropetrovsk region (Ukraine). The ramified structure entails interaction with the environment. The important aspect of ecological estimation of territories of electric substations is determination of their role as local refugia of biological diversity. These territories are regime objects that to a great extent are screened from a whole series of external influences. They can be considered as elements of a territorial mosaic that form cells, exposed to less agrotechnical influence (Potapenko, 2016). During the fieldwork 175 geobotanical releves were analysed in Dnipropetrovsk region on territories of 74 electric substations in 2016–2017 (Zhukov & Potapenko, 2017; Potapenko, 2018). Within each electrical substation, the geobotanical prospecting was conducted both in plots with undisturbed vegetation cover (control, the plot size 3 × 6 m) and in plots with technological oil spill (pollution, the plot size the 3 × 3 m).

Geobotanical prospecting has come to form the basis for phytoindication of environmental regimes. Didukh (2011) distinguishes the following edaphic and climatic phytoindication scales. Soil water regime (Hd), variability of damping (fH), soil aeration (Ae), soil acidity (Rc), total salt regime (Sl), carbonate content in soil (Ca), nitrogen content in soil (Nt) belong to edaphic scales. The scales for the next four factors belong to climatic scales. There are radiation balance (Tm), aridity or humidity (Om), cryo-climate (Cr) and continentality (Kn). In addition, the scale of light regime (Lc) is allocated as the microclimate scale. We can assume that edaphic scales and the scale of light regime will be light-sensitive properties of soil variability at a single point, which can be the basis for the application of phytoindication scales for large-scale mapping. Thermal properties of soils are indicated by the radiation balance scale; hydrothermal properties of soils are indicated by aridity scale (Didukh, 2012). Phytoindication scales are presented by Didukh (2012). Phytoindication assessment of gradations of environmental factors is presented by Buzuk (2017).

HydroSHEDS data were taken for the basis for creating a digital elevation model (Lehner et al., 2006). The resolution of the data layer was 15 arcseconds. The vector file outline of Dnipropetrovsk region was obtained from the resource DIVA-GIS (http://diva-gis.org). The list of derivatives from digital elevation model data layers was used as environmental factors predictors measured from phytoindication.

Topographic wetness index. The concept of Topographic wetness index (TWI) was proposed by Beven & Kirkby (1979) for the first time. Topographic wetness index is calculated by the formula: $TWI = \ln(a/\tan\beta)$, Topographic wetness index is calculated by the formula: TWI = ln(a/tanβ), where a is a drainage area (catchment are calculated per unit length locking circuit), β is the local slope angle (Moore et al., 1993; Kunah & Papka, 2016; Zhukov & Andryushchenko, 2017).

Topographic position index. Topographic position index (TPI) is the difference between the absolute height of the point in space and an average height of points in a certain buffer around the starting point. TPI positive values correspond to the earth's surface convexity; its negative values correspond to decreases. Values close to zero may indicate both the flat surface and the middle part of the slope (Guisan et al., 1999).

Mass Balance Index. Mass Balance Index reveals topographic prerequisites for destruction and entrainment of soil. This indicator allows identification of areas with a high degree of probability of landslip processes (Moeller et al., 2008). Negative indexes indicate areas with accumulation of geomass, such as relief depression or floodplains. Positive values indicate areas with high erosion risk. A value close to zero indicates areas with loss of geomass balance and gain (Kunah & Papka, 2016).

Erosion factors. Loss of soil LS is one of the components of the universal equation of soil erosion (Universal Soil Loss Equation – USLE). LS is the product of L- and S-factors. L-factor determines the value of slope length, S-factor determines the value of slope steepness. The universal soil erosion loss equation (USLE), or Wischmeier-Smith's equation was established in the US as a method of quantifying annual soil loss through summarizing the results of observations with a slope of 9%, conducted at more than 8,000 sites (Kunah & Papka, 2016). In the first edition USLE, the tangent was used for describing the influence of slope steepness. A constant equal to 0.5 was used for level value of slope length. Later, the tangent of surface inclination angle was replaced with a sinus, because it was found that this function more accurately reflects the impact of an event on more than 3 slopes (Wischmeier & Smith, 1978). Erosion soil loss is much more sensitive to changes in slope steepness than the change of length, so the improved model USLE – RUSLE was aimed at the most accurate assessment of slope steepness factor (McCool et al., 1994).

Direct and diffuse insolation. Direct and diffuse insolation belongs to the category of topoclimatic indicators (Boehner & Antonic, 2009). The most distinctive variations in climatic patterns occur because of topoclimatic processes in the boundary layer of the earth that have the characteristic dimension of no more than 10^1 km (meso β-scale) till 10^{-3} km (micro β-scale). The scale levels are shown by Orlanski (1975). Topoclimatology is the part of climatology which studyies the impact of the earth's surface on climate. The earth's surface primarily controls the spatial differentiation of surface atmospheric processes and associated climate variations (Boehner & Antonic, 2009). Solar radiation that falls on the earth's surface consists of two components – shortwave and longwave. We must take into account of the direct and diffuse components assessment in order to calculate the wavelength component (Boehner & Antonic, 2009).

Altitude above channel network. Altitude above channel network or Vertical Distance to Channel Network (VDTCN) is the difference between the height relief and channel network height (Olaya & Conrad, 2008). It is a reliable marker of ground water and can be used for mapping soil (Bock & Köthe, 2008).

Vector Ruggedness Measure (VRM) estimates variance of the vectors which are orthogonal to the surface relief. The VRM value is low for flat terrain and steep terrain, but it is high for steep and rugged terrain (Sappington et al., 2007). Rugged terrain is understood as unevenness of surface (Kunah & Papka, 2016).

The procedure for landform classification was performed on the basis of digital terrain models by Iwahashi & Pike (2007). 16 relief forms were allocated. These are gentle slope, coarse texture, low convexity; gentle slope, fine texture, low convexity; gentle slope, coarse texture, high convexity; gentle slope, fine texture, high convexity; moderate slope, coarse texture, low convexity; moderate slope, fine texture, low convexity; moderate slope, coarse texture, high convexity; moderate slope, fine texture, high convexity; steep slope, coarse texture, low convexity; steep slope, fine texture, low convexity; steep slope, coarse texture, high convexity; steep slope, fine texture, high convexity; very steep slope, coarse texture, low convexity; very steep slope, fine texture, low convexity; very steep slope, coarse texture, high convexity; very steep slope, fine texture, high convexity. The relief forms' variety entropy was calculated after classification of the forms by Shannon with 3 pixels assumption window.

The geographic database was prepared in ArcMap 10.4.1. Calculations of the geomorphologic layers were implemented in the program Saga-GIS (Olaya & Conrad, 2008). The regression analysis and extrapolation of values assessed within the regression model on the territory of the region is executed in an environment of statistical calculations R (R Core Team, 2017) using kernlab library (Karatzoglou, 2004).

Results

The soil humidity level varies between 8.77 and 20.48 by the phytoindication assessment (Table 1), which corresponds to the favourable conditions from sub-xerophytes to sub-hydrophytes by Didukh (2011). The most common conditions are those favourable for hyhro-mesophytes. The histogram analysis of the environmental factors' distribution points to the sample heterogeneity (Fig. 1). This conclusion is also confirmed by the values of asymmetry (positive value indicates a shift of the distribution to the left) and kurtosis (a negative value indicates a bimodal distribution). Accordingly, the predominant regimes are those that are favourable for hygro-mesophytes, hygropytes and sub-hydrophytes.

Table 1
Descriptive statistics of the environmental factors obtained after phytoindication and ANOVA of the oil contamination effect

Phytoindication scale	Indicator value (x ± SE)		ANOVA	
	uncontaminated	oil contaminated	*F*-ratio	*p*-level
Hd	14.59 ± 0.24	14.18 ± 0.27	1.31	0.25
fH	7.30 ± 0.10	7.75 ± 0.11	8.91	<0.001
Rc	7.73 ± 0.12	7.88 ± 0.12	0.78	0.38
Sl	9.14 ± 0.19	9.12 ± 0.25	0.01	0.93
Ca	8.73 ± 0.16	8.92 ± 0.17	0.64	0.43
Nt	8.54 ± 0.20	6.89 ± 0.23	29.10	<0.001
Ae	7.65 ± 0.05	7.55 ± 0.07	1.53	0.22
Tm	10.21 ± 0.10	9.96 ± 0.12	2.66	0.10
Om	12.27 ± 0.09	11.65 ± 0.11	19.65	<0.001
Kn	9.29 ± 0.15	9.86 ± 0.19	5.25	0.02
Cr	8.19 ± 0.09	7.77 ± 0.12	7.31	0.01
Lc	6.49 ± 0.21	7.61 ± 0.21	14.55	<0.001

Note: Hd – soil humidity, fH – variability of damping, Rc – soil acidity, Sl – total salt regime, Ca – carbonate content in soil, Nt – nitrogen content in soil; Ae – soil aeration, Tm – thermal climate, Om – humidity, Kn – continental climate, Cr – cryo-climate, Lc – light regime.

The contrast regime of humidity conditions ranges from hemi-hydrocontrastophobes to hydrocontrastophiles. The most common conditions are such that are favourable for hemi-hydrocontrastophiles. The histogram analysis of the environmental factors' distribution points to the sample heterogeneity. This conclusion is also confirmed by the values of asymmetry (positive value indicates a shift of the distribution to the left) and kurtosis (a negative value indicates a bimodal distribution). Accordingly, the predominant regimes are such that are favourable for hemi-hydrocontrastophobes and hydrocontrastophiles. Statistical distribution of phytoindication acidity assessments is close to normal. The most common conditions are such those favourable for sub-acidophiles. However, the acidity conditions vary from favourable for acidophiles to sub-bazophiles. Total salt regime assessments are distributed symmetrically. The most common conditions are those favourable for eutrophes. The total salt regime varies in conditions from semi-oligotrophes to glycotrophes. Carbonate content in the soil creates the most favourable conditions for hemi-carbonatophiles.

The investigated sample is heterogeneous in terms of phytoindication assessment estimates of digestible forms of nitrogen. It is a mixture of normal distributions. The most common conditions are such that are favourable for hemi-nitrophiles and eunitrophiles. The mode of soil aeration creates favourable conditions for hemi-aerophobes. In general, the conditions of soil aeration vary from sub-aerophilic to sub-aerophobic. Vegetation communities indicate thermal climate, which corresponds to the energy balance 2110.1 MJ • m^2 • year^{-1}. This estimate varies in the range of 1567.9–2706.6 MJ • m^2 • year^{-1}. Distribution of thermal climate phytoindication assessment is symmetric and close to the normal distribution. Humidity is characterized quantitatively by the relationship between rainfall and evaporation. We can determine in accordance with phytoindication estimates that this figure is –193.2 mm, which corresponds to the sub-aridophytic conditions. The humidity assessment varies from –603.1 (mezo-aridophytic conditions) to +242.3 mm (sub-ombrophytic conditions).

The region's climate may be classified as sub-continental with variation from hemi-oceanic to continental according to phytoindication assessments. The cryo-climate is characterized quantitatively by the temperature of the coldest month of the year. Phytoindication assessments of this indicator are characterized by an asymmetrical distribution with the cells to the right. The commonest cryo-climate estimate is –7.53 ºC corresponding to moderate/mild winters. The range of cryo-climate variation estimates is from –19.02 to +3.16 °C. The vast majority of sites where geobotanical descriptions were conducted are characterized by the highest level of lighting, which is favourable for heliophytes. But the range of lighting levels varies from scyophytic to heliophytic conditions.

The height of the relief within Dnipropetrovsk region varies within 51–211 m. The most typical height is located in the range of 65–155 m (Table 2). The average height of the relief is 109 m. The range of heights where geobotanical descriptions were made is 30–179 m. The average is 88.9 m. The digital elevation model is the basis for the calculation of derived information layers, exposing various aspects of the earth's surface as a factor of redistribution of climatic conditions. The topographic wetness index is the marker geomorphological soil moisture. TWI varies in Dnipropetrovsk region within 6.9–25.1. The average one is 11.8. TWI value varies within 8.5–21.6 at the points where the geobotanical description of vegetation was conducted. The average one is 12.5.

Table 2
Descriptive statistics of the relief morphometric properties

Morphometric properties	x ± SE	Median	Minimum	Maximum
Elevation (m, DEM)	88.96 ± 2.69	74.00	30.00	179.00
Topographic wetness index (unitless, TWI)	12.46 ± 0.22	11.89	8.54	21.54
Topographic position index (unitless, TPI)	0.18 ± 0.09	0.29	–2.04	2.98
Mass Balance Index (unitless, 10^{-2}, MBI)	0.46 ± 0.09	0.07	–1.37	3.79
Erosion factors (unitless, LS)	0.14 ± 0.01	0.06	0.00	0.66
Vector Ruggedness Measure (unitless, 10^{-4}, VRM)	0.21 ± 0.03	0.00	0.00	3.00
Direct insolation (kWh/м^2 10^2, Dir)	12.56 ± 0.01	12.57	12.33	12.72
Diffuse insolation (kWh/м^2, Diff)	174.61 ± 0.07	174.21	173.02	177.07
Vertical Distance to Channel Network (m, Vert)	18.99 ± 1.50	13.15	0.00	85.09
Shannon diversity (Bit/pixel)	1.29 ± 0.02	1.30	0.72	2.04

The earth's surface shapes within the Dnipropetrovsk region vary from convex (index of topographic position of TPI, a positive value to 4.3) to concave denotations (TPI negative takes the value to –4.3). It is natural that the figure is close to zero (0.02) on average. Geobotanical descriptions are situated within a slightly smaller range of relief conditions (TPI from –2.0 to +2.9, on average, 0.2). The vast majority of the pixels are characterized by the values of mass balance index (MBI) between –0.029 and +0.036. The points of geobotanical descriptions are characterized by MBI values from –0.014 to +0.036. The vast majority of areas are characterized by small field marker levels of loss of soil LS, although this figure may reach values of 1.27. For 95% of geobotanical descriptions, erosion LS factor value does not exceed 0.49. Vector ruggedness measure (VRM) varies from 0 to 9.8 × 10^{-4}.

Direct insolation is 1201–1341 kWh/м^2 for the period 1 April to 31 October within Dnipropetrovsk region. The average one is 1254 kWh/м^2. Diffuse insolation is 171–178 kWh/м^2. Its average value is 174.9 kWh/м^2 in the same period of time. The level of direct insolation at the locations of geobotanical descriptions is 1233–1270 kWh/м^2. Its average value is 1255 kWh/м^2. The level of diffuse insolation is 173–177 kWh/м^2. Its average value is 174.6 kWh/м^2. The vertical distance to channel network varies from 0 to 131 m. Its average value is 29.2 m. Geobotanical descriptions are placed in habitats where the vertical distance to channel network does not exceed 85.1 m, on average it does not exceed 18.9 m.

The 16 types of the earth's surface were selected by the Iwahashi & Pike (2007) procedure (Fig. 1). Each of these types is 1.5–21.9% of the surface. The type moderate slope, coarse texture, high convexity occupies the lowest part of surface. The types steep slope, fine texture, high convexity and very steep slope, fine texture, high convexity occupy the largest part of the surface. The entropy of terrain diversity by Shannon varies from 0 to 2.35 bit/pixel. Its average value is 1.16 bit/pixel. The geobotanical descriptions were made at the locations, their diversity varies from 0.72 to 2.04 bit/pixel. The average diversity is 1.28 bit/pixel.

The phytoindication assessments of the ecological regimes are characterized by correlation of geomorphological properties. The soil humidity is characterized statistically by significant negative correlation with the topographic position index and positive correlation with the vector ruggedness measure. The variability of damping correlates with four geomorphological predictors. This environmental regime has positive correlation with digital elevation model and diffuse insolation and negative correlation with topographic wetness index and direct insolation. The soil acidity of the edaphotope within the Dnipropetrovsk region statistically significantly correlates with the vector ruggedness measure. The soil humidity of the edaphotope is associated with variation of the topographic wetness index, direct insolation, diffuse insolation and entropy of terrain diversity. The highest carbonate content in soil correlates with higher risks of erosion, which are characterized by loss of soil and vertical distance to channel network. The nitrogen content in soil is very sensitive to geomorphological features of the area. This results in the correlation of this indicator with six geomorphological predictors. Obviously, the most favourable supply of the nitrogen content in the soil is formed on the upland area. This is consistent with positive correlation of the phytoindication assessment of the nitrogen content in soil and the height relief.

Experimental results revealed no statistically significant pairwise correlations between the soil aeration and geomorphological predictors (Fig. 2). The thermal climate variation (geomorphological correlation with four predictors) is most geomorphologically deterministic among the climatic scales. The humidity variation is the least deterministic. This is correlation with one predictor.

It can be assumed that the relationship between phytoindication assessments of environmental regimes and geomorphological predictors is more complex than described quantitatively pairwise correlation coefficients. In order to test this hypothesis, we used multiple regression analysis where phytoindication assessments are considered as the dependent variable. A set of geomorphic indicators are considered as a predictors.

Regression models can explain 11–42% variability of phytoindication assessments of environmental regimes (Table 3). The soil humidity and the nitrogen content in the soil are the most geomorphologically dependent. The variability of damping and humidity are the least dependent. The digital elevation model and direct insolation (four statistically probable regression coefficients) are the most valuable predictors for edaphic environmental regimes. Loss of soil, direct insolation and topographic wetness index (two statistically significant regression coefficients) are the most valuable predictors for climate regimes (Table 4). The entropy of terrain diversity is a statistically significant predictor for humidity, nitrogen content in soil and thermal climate.

Linear regression models that established a link between phytoindication assessments of the environmental regimes and geomorphological predictors are characterized by a certain explanatory power. The linear model allows quite clear interpretation of the installed links. Some connections are obvious to a lesser extent and are trivial. Thus, the regression model indicates that the greater the height of the terrain, the less the soil humidity, which is quite expected. Some links show more subtle interaction between relief, vegetation and environmental regimes. The relationship of such synthetic properties of terrain as diversity relief elements and phytoindication assessments of humidity, nitrogen content in soil and thermal climate is of particular interest. This indicates that not only local conditions but also the influence of spatial context on the development of ecological processes which determined the appropriate modes.

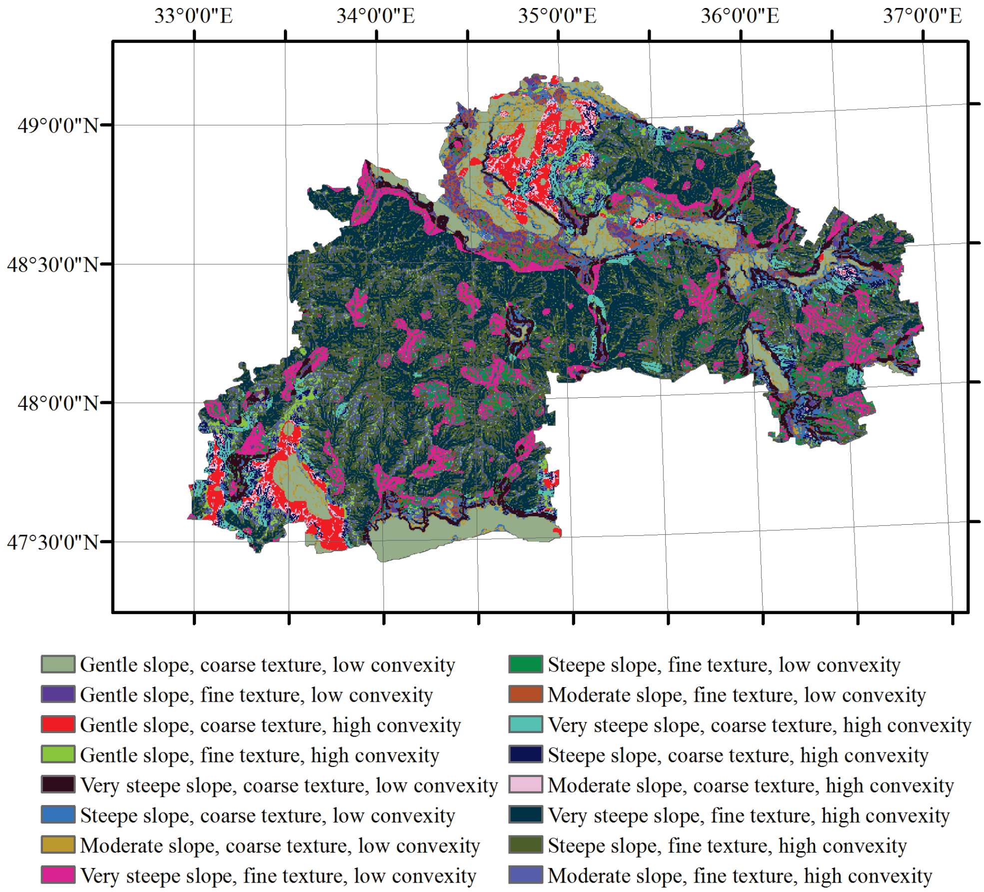

Fig. 1. The landforms classification within Dnipropetrovsk region by Iwahashi and Pike (Iwahashi & Pike, 2007)

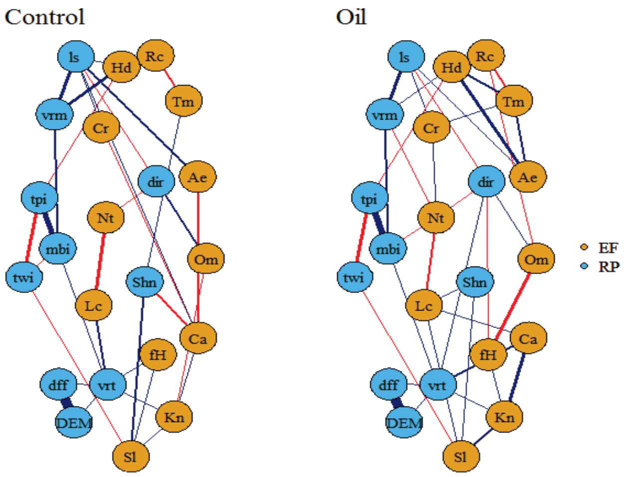

Fig. 1. Regularized partial correlation network of the phytoindicator estimation of the ecological factors and relief properties without contamination (control) and under oil contamination (oil): Ecological factors (EF): Hd – soil humidity, fH – variability of damping, Rc – soil acidity, Sl – total salt regime, Ca – carbonate content in soil, Nt – nitrogen content in soil, Ae – soil aeration, Tm – thermal climate, Om – humidity, Kn – continental climate, Cr – cryo-climate, Lc – light regime; Relief properties (RP): DEM – digital elevation model; TWI – topographic wetness index; TPI – topographic position index; MBI – mass balance index; LS – loss soil; VRM – vector ruggedness measure; DIR – direct insolation; DIFF – diffuse insolation; VERT – vertical distance to channel network; Shannon – entropy of terrain diversity

Discussion

In some cases only, we can give value of markers of causation to the established regression dependencies. At the local level, the impact of the relief on ecological processes can be defined by certain multiple processes, whose composition and intensity of impact can vary significantly in different parts of space. However, it is possible to consider the fact that at the regional level a monotonic relationship can be set between phytoindication estimated environmental regimes and geomorphological predictors.

The linear component connection reflects a real relationship between the study variables only very generally. The undoubted advantage of the linear model is the convenience of its interpretation. But rather superficially derived interpretations show ties in climate topography and vegetation. Linear regression requires a functional connection. Deviation from it is random in both directions of the projected hypothetical value function response. But the vast majority of ecological relationships obey the limiting factor, so that a deviation from the functional relationship is asymmetrical. The studied variable can be less (or more) predicted, but never more (or conversely, never less). Where other sources show such a relationship can be described by a Gaussian bell curve, then mathematical description can be applied depending on specific mathematical procedures (ter Braak, 1986). The β-function can be applied in the case of asymmetric dependence (Austin, 1976). These models are suitable for describing dependence, but their use is difficult to forecast, and consequently to the extrapolation. A regression model is a flexible method for support vector (Karatzoglou, 2004). This regression can find dependencies that pretty well describe the complex relationships in nature, but unlike the linear model. Support methods cannot be used to interpret the obtained results. The resulting spatial models are characterized by a high degree in formativeness.

Table 3
General linear models of the dependence of edaphic regimes on geomorphological predictors (regression coefficients ± SE)

Predictors	Edaphic regimes						
	Hd	fH	Rc	Sl	Ca	Nt	Ae
DEM	–4.70 ± 2.12*	–2.42 ± 2.12	6.51 ± 2.35*	1.19 ± 2.21	–3.10 ± 2.31	4.87 ± 1.88*	–2.90 ± 2.18
TWI	–0.12 ± 0.09	–0.10 ± 0.09	0.36 ± 0.10*	–0.26 ± 0.09*	–0.04 ± 0.09	–0.11 ± 0.08	0.09 ± 0.09
TPI	–0.42 ± 0.11*	0.07 ± 0.11	0.21 ± 0.12	0.00 ± 0.12	–0.04 ± 0.12	–0.07 ± 0.10	–0.16 ± 0.11
MBI	0.09 ± 0.12	–0.03 ± 0.12	0.15 ± 0.13	–0.04 ± 0.12	–0.06 ± 0.13	–0.34 ± 0.10*	0.25 ± 0.12*
LS	0.14 ± 0.09	0.03 ± 0.09	–0.02 ± 0.10	–0.13 ± 0.09	0.03 ± 0.10	0.11 ± 0.08	0.45 ± 0.09*
VRM	0.36 ± 0.09*	–0.15 ± 0.09	–0.28 ± 0.10*	0.07 ± 0.09	0.14 ± 0.10	–0.19 ± 0.08*	–0.10 ± 0.09
DIR	0.09 ± 0.08	–0.24 ± 0.08*	–0.10 ± 0.08	0.13 ± 0.08	–0.05 ± 0.08	–0.15 ± 0.07*	0.22 ± 0.08*
DIFF	4.73 ± 2.12*	2.67 ± 2.12	–6.38 ± 2.34*	–0.83 ± 2.20	2.87 ± 2.31	–4.47 ± 1.88*	2.92 ± 2.18
VERT	–0.12 ± 0.11	0.12 ± 0.11	–0.02 ± 0.12	–0.18 ± 0.11	0.54 ± 0.12*	–0.13 ± 0.09	–0.15 ± 0.11
Shannon	–0.04 ± 0.07	0.02 ± 0.07	0.01 ± 0.08	0.42 ± 0.08*	–0.17 ± 0.08*	–0.07 ± 0.07	0.11 ± 0.08
Contamination	–0.14 ± 0.06*	0.31 ± 0.06*	0.07 ± 0.07	–0.06 ± 0.07	0.00 ± 0.07	–0.37 ± 0.06*	–0.27 ± 0.07*
R^2_{adj}	0.27	0.27	0.11	0.21	0.14	0.42	0.23

Note: Hd – soil humidity, fH – variability of damping, Rc – soil acidity, Sl – total salt regime, Ca – carbonate content in soil, Nt – nitrogen content in soil, Ae – soil aeration, Tm – thermal climate, Om – humidity, Kn – continental climate, Cr – cryo-climate, Lc – light regime, DEM – digital elevation model; TWI – topographic wetness index; TPI – topographic position index; MBI – mass balance index; LS – loss of soil; VRM – vector ruggedness measure; DIR – direct insolation; DIFF – diffuse insolation; VERT – vertical distance to channel network; Shannon – entropy of terrain diversity; * – statistically significant coefficients for P < 0.05.

Table 4
General linear models of the dependence of climatic regimes on geomorphological predictors (regression coefficients ± SE)

Predictors	Climatic regimes				
	Tm	Om	Kn	Cr	Lc
DEM	0.37 ± 2.30	–3.92 ± 2.24	–1.36 ± 2.21	1.21 ± 2.33	–4.42 ± 1.90*
TWI	–0.12 ± 0.09	–0.08 ± 0.09	–0.07 ± 0.09	–0.13 ± 0.09	0.07 ± 0.08
TPI	–0.43 ± 0.12*	0.14 ± 0.12	–0.06 ± 0.12	0.01 ± 0.12	0.13 ± 0.10
MBI	0.18 ± 0.13	–0.15 ± 0.12	–0.06 ± 0.12	–0.17 ± 0.13	–0.07 ± 0.10
LS	–0.08 ± 0.10	0.11 ± 0.09	–0.15 ± 0.09	0.25 ± 0.10*	–0.16 ± 0.08*
VRM	0.21 ± 0.10	0.08 ± 0.09	0.11 ± 0.09	0.12 ± 0.10	0.20 ± 0.08
DIR	0.11 ± 0.08	0.35 ± 0.08*	–0.12 ± 0.08	0.02 ± 0.08	–0.04 ± 0.07
DIFF	–0.31 ± 2.30	3.88 ± 2.23	1.39 ± 2.20	–1.03 ± 2.32	3.78 ± 1.89*
VERT	–0.08 ± 0.11	–0.10 ± 0.11	0.50 ± 0.11	–0.13 ± 0.12	0.67 ± 0.09*
Shannon	0.25 ± 0.08*	0.04 ± 0.08	0.10 ± 0.08	–0.05 ± 0.08	0.15 ± 0.07*
Contamination	–0.16 ± 0.07*	–0.33 ± 0.07*	0.18 ± 0.07*	–0.19 ± 0.07*	0.33 ± 0.06*
R^2	0.14	0.19	0.21	0.12	0.42

Note: Tm – thermal climate, Om – humidity, Kn – continental climate, Cr – cryo-climate, Lc – light regime, DEM – digital elevation model; TWI – topographic wetness index; TPI – topographic position index; MBI – mass balance index; LS – loss soil; VRM – vector ruggedness measure; DIR – direct insolation; DIFF – diffuse insolation; VERT – vertical distance to channel network; Shannon – entropy of terrain diversity; * – statistically significant coefficients for P < 0.05.

Two groups of indicators, digital elevation models and their derivatives, and vegetation indices derived using remote sensing of the earth are usually used as predictors in order to solve the problems of describing the spatial variation of ecological characteristics (Brygadyrenko, 2016; Ließ et al., 2016). This approach is suitable for areas where there is remaining natural or artificial naturalized vegetation (Zhukov et al., 2016). Within Dnipropetrovsk region, a considerable part of the territory is transformed anthropogenically (Brygadyrenko, 2015; Zhukov et al., 2017). Monocenoses, which are formed within agricultural fields, cannot be applied for carrying out synphytoindication. Vegetation communities of electrical substations are distinguished by a certain level of diversity. These sites with their fragmented communities of natural ecosystems can be used for phytoindication of environmental regimes But for purposes of extrapolation within the region, the data digital elevation model and its derivatives can be applied only. Vegetation indices also reflect the effects of anthropogenic transformation that are inextricably linked to the dynamics of ecological processes, but cannot be used as predictor variables.

Conclusions

The digital elevation model and information derived from it in the form of spatial data layers (topographic wetness index, topographic position index, mass balance index, loss of soil, vector ruggedness measure, direct insolation, diffuse insolation, vertical distance to channel network, entropy of terrain diversity by Shannon) are valuable information covariates (predictors) of environmental regimes which are evaluated using the phytoindication method. The procedure of spatial extrapolation of phytoindication assessments at regional level can be performed based on regression models by the method of support vectors. This approach is flexible and takes into account the specific environmental interactions in the system topography and vegetation and environmental regimes. We found that soil pollution by technological oil within the territories of electrical substations leads to the transformation of environmental regimes. Such changes can be clearly shown using the phytoindication method. The soil properties were revealed to be subjected to a considerable transformation. Technological oil pollution leads to deterioration of water regime, reducing the availability of plant available forms of nitrogen and deterioration of soil aeration. There are also changes in microclimatic properties. There are more extreme thermal regimes and greater level of illumination. An important task for further research is to study the influence of relief features on the degree of negative transformation of soil due to technological oil pollution.

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