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Session 06: Mitigation effects of natural disasters – tools and methods

Quantitative assessment and mapping of hydrological risk using Landsat data

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Risk assessment: methodological challenges

Problem of risk assessment is the problem of:

correct quantification of multi-source data;

correct mapping of prospect data with various spatial and temporal parameters;

correct uncertainty management;

correct calculation of spatial and temporal heterogeneities in distributions of key parameters;

correct global-local inter-interdependencies analysis;

operation of integrated assessments for adequate decision making;

An approach to integrate satellite observation data, ground measurements, modeling of heat & mass exchange in natural systems is required to construct a quantitative risk assessment model

Risk assessment: Data assembling approach

Satellite observation, ground calibration, and modeling data may be represented in framework of formalization "information – response" in security management systems

General definition of risk in these terms: $$R(I^*, d^*) = \int \min_{a \in A} l(a, \theta)\, p(\theta)\, d\theta$$

I – information obtained from direct ground measurements and modeling, *θ* – state of observed system or object

$H_I(i|\theta)$ - probability distribution function of *I*

Decision making could be formalized as the reaction to input information by decision function *d(I)*.

$$l(b, \phi(i^*)) = \min_a l(a, \phi(i^*)) \quad d^*(i^*) = b$$

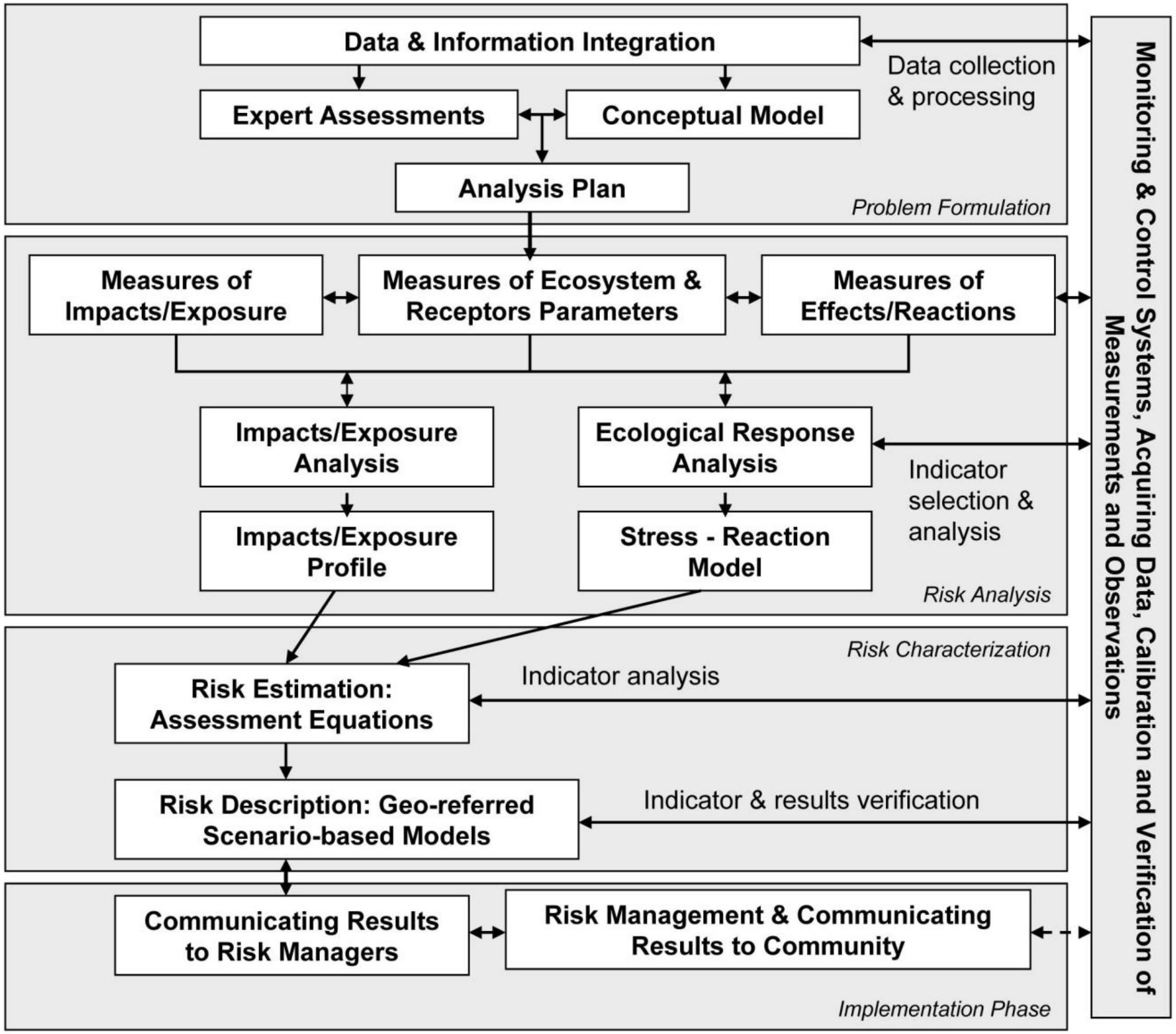
ϕ *(i*)* – state of observed system

For decision function d the expected losses or risks could be defined through minimization of optimal decision function, for example Bayes' function, *d*(I)*. risks in this case are determined by implementation of decisions d from strategy A, based on information received.

We analyze set of data *I* (ground and modeling data) and *i** - information, which optimize decision function *d* to *d**, and so minimize corresponding risk. So this additional (in our case - information from satellite observations) made information I nominally full (*I**)

Risk Analysis: Conceptual Approach

Ecological risk assessment framework

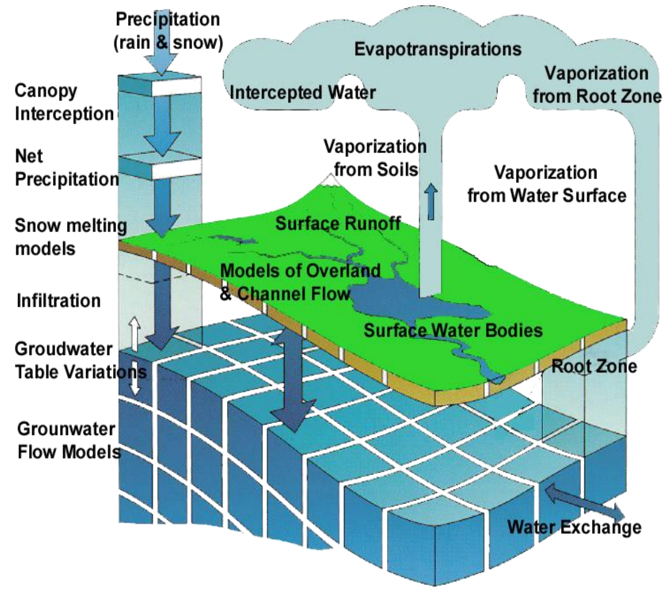


Water balance basin model

Model of water catchment area with varied sources

$$q(t) = \left[A_1(t) k \frac{dH}{dx} \right] + \left[A_2(t) \cdot P_a(t) \right] + \left[A_3 P(t) \right]$$

A1(t) – square of total saturation; *A2* – horizontal projection of total saturation area; *A3* – water resistant area; *Pa(t)* – precipitation intensity (including snow); *k* – filtration coefficient; *H* – hydraulic coefficient



Surface runoff with precipitation

$$\frac{\partial h}{\partial t} + \frac{\partial q}{\partial x} = P - F; \qquad q = \alpha h^{\beta}; \qquad h(0,t) = h(x,0) = 0$$

x – spatial coordinates *t* – time, *h* – depth of undersurface flow, *q* – water debit, *P* – precipitation intensity, *F* – filtration intensity, *α* and *β* – empiric coefficients. For laminar flow *α=8gi/kγ*, *β*=3, for turbulent *α*=i0,5/n i *β*=5/3

Undersurface runoff

$$n \frac{\partial h_g}{\partial t} + \frac{\partial q_g}{\partial x} = f, \qquad q_g = k_f h_g \left(i_g - \frac{\partial h_g}{\partial x}\right),$$

$$q_g(o,t) = 0, h_g(D_s,t) = h_r, h_g(x,0) = h_g^o(x)$$

n – soil porosity, *hg* – intensity of undersurface flow, *qg* – efficiency of flow, *ig* – angle of flow, *kf* – horizontal filtration coefficient, *Ds* – length of flow, *hr* – river water level, *h0g* – initial intensity of flow. For low gradients: *qg=kfighg/m*

Groundwater balance model

Model of the site inundation

$$ds_1 = A(s_1, s_2)dt + B(s_1, s_2)dW_t$$

$$\alpha = LE_p / 2wu$$

L – integrated size of area studied, E_p – evapotranspirastion w – average atmospheric humidity, u – average wind speed

$$ds_2 = C(s_1, s_2)dt + D(s_1, s_2)dW_t$$

$$Q_1(s_1) = k_s s_1^b$$

$$\langle dW_t \rangle = 0$$

$$\langle dW_t dW_{t'} \rangle = 1$$ if $t = t'$

та $dWt = 0$ else

dW_t – Viner increment for evatranspiration and precipitation fluctuations description

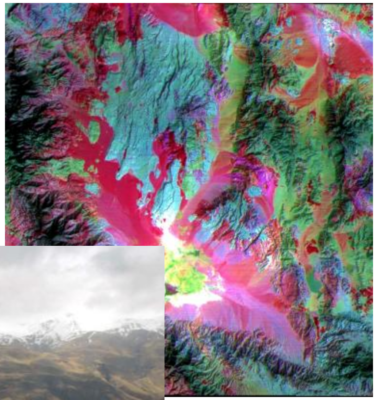
$$Q_2(t) = (\frac{1 - f_g}{f_g})\frac{k_s}{J}\int_{-\infty}^{t} s_1^b(t-\tau)e^{-\tau/J}d\tau$$

$$A(s_1, s_2) = \frac{P_a}{nz_r}\{1 + \langle\alpha\rangle[(1 - f_g)s_1^c + f_g s_2^c]\}(1 - \varepsilon s_1^r) - \frac{E_p s_1^c - k_s s_1^b}{nz_r}$$

$$B(s_1, s_2) = \frac{P_a}{nz_r}[(1 - f_g)s_1^c + f_g s_2^c](1 - \varepsilon s_1^r)\sigma$$

$$C(s_1, s_2) = \frac{P_a}{nz_r}\{1 + \langle\alpha\rangle[(1 - f_g)s_1^c + f_g s_2^c]\}(1 - \varepsilon s_2^r) - \frac{E_p s_2^c - Q_2(t)}{nz_r}$$

$$D(s_1, s_2) = \frac{P_a}{nz_r}[(1 - f_g)s_1^c + f_g s_2^c](1 - \varepsilon s_2^r)\sigma$$



Daily evapotraspiration

$$E_p = \{\frac{[f(A)+1]\{R_n - G]\Delta}{[\sigma f(A)+1]C_p\rho} + [f(A)+1]\frac{\rho_2^* - \rho_2}{r_a}\} \times \{\frac{r_a + r_x}{r_a} + \frac{[f(A)+1]L_v\Delta}{[\sigma f(A)+1]C_p\rho}\}^{-1}$$

Data Analysis: Direct Regularization

Required regularization may be provided by different ways. If we able to formulate stable hypothesis on distribution of reliability of regional archives data in the framework of defined problem we may to propose relatively simple way to determine investigated parameters distributions $\boldsymbol{x}_t^{(x,y)}$ towards distributions on measured sites $\boldsymbol{x}^m{}_t$ basing on *Fowler, Kilsby, O'Connell (2003)*:

$$x_t^{(x,y)} = \sum_{m=1}^{n} w_{x,y}(\tilde{x}_t^m) x_t^m$$

where weighting coefficients $w_{x,y}(\tilde{x}_t^m)$

determined as: $$\min\{\sum_{m=1}^{n} \sum_{x_t^m \in R^m} w_{x,y}(\tilde{x}_t^m)(1 - \frac{x_t^m}{\tilde{x}_t^m})^2\}$$

Here m – number of records/points of measurements or observations; n – number of observation series; $\boldsymbol{x}^m{}_t$ – distribution of observations data; R^m – set (aggregate collection) of observations; and

$\tilde{x}_t^m$ - mean distribution of measured parameters

This is the simple way to obtain a regular spatial distribution of analyzed parameters over the study area, on which we can apply further analysis, in particular temporal regularization

Further regularization should take into account both observation distribution temporal non-linearity (caused by imperfection of available statistics) and features of temporal-spatial heterogeneity of data distribution caused by systemic complexity of studied phenomena – natural and technological disasters

Data Analysis: Non-Linear Approach

Proposed method is based on modified kernel principal component analysis (KPCA) (*Scheolkopf, Smola, Muller, 1998; Mika, Scheolkopf, Smola, et al., 1999; Romdhani, Gong, Psarrou, 1999*). In the framework of this approach the algorithm of non-linear regularization might be described as following rule:

$$x_i = \sum_{i=1}^{N} \alpha_i^k \tilde{k}_t(x_i, x_t)$$

the coefficients *α* selected according to optimal balance of relative validation function and covariance matrix, for example as (Lee, Yoo, Choi, et al, 2004):

$$C^F v = \frac{1}{N} \sum_{j=1}^{N} \Phi(x_j)\Phi(x_j)^T \cdot \sum_{i=1}^{N} \alpha_i \Phi(x_i)$$

Where non-linear function of input data distribution *Φ* determined as (*Scheolkopf, Smola, Muller, 1998*):

$$\sum_{k=1}^{N} \Phi(x_k) = 0$$

$\tilde{k}_t$ - is mean values of kernel-matrix $\mathbf{K} \in R^N \quad [\mathbf{K}]_{ij} = [k(\mathbf{x}_i, \mathbf{x}_j)]$

Vector components of matrix determined as $\mathbf{k_t} \in R^N \quad [\mathbf{k_i}]_j = [k_t(\mathbf{x_t}, \mathbf{x_j})]$

Matrix calculated according to modified rule of (*Christianini, Shawe-Taylor, 2000*) as:

$$\mathbf{k}_t(\mathbf{x}_i, \mathbf{x}_t) = \left\langle \rho_{j,t}^{x_j} (1 - \rho_{j,i})^{x_j} \right\rangle$$

Here *ρ* – empirical parameters, selected according to the classification model of study phenomena (*Villez, Ruiz, Sin, et al, 2008*)

Using described algorithm it is possible to obtain regularized spatial-temporal distribution of investigated parameters over whole observation period with rectified reliability

Risk Assessment: Probability of Stress

Way to analysis of **hydrological and hydrogeological risk**

$$SRI_{\tau} = f(\lambda)_{\tau} \qquad SRI^{*}_{\tau} = \frac{\max\{SRI_{\tau}\} - SRI_{\tau}}{\max\{SRI_{\tau}\} - \min\{SRI_{\tau}\}}$$

$$P(\Delta SRI^{*}(x,y) \mid Q_{stress}) = \frac{P_s(x,y) \cdot \prod_{N} P_N(\Delta SRI^{*} \mid Q_{stress})}{\int_{x,y} P_N(\Delta SRI^{*} \mid Q) dP_s(x,y)} =$$

$$\lim_{x,y,\tau}(P_S(x,y)_{\tau} + P_0(x,y)_{\tau}) = 1$$

$$= \frac{P_S(x,y) \cdot P_N(\Delta SRI^{*} \mid Q_{stress})}{P_N(\Delta SRI^{*} \mid Q_{stress}) P_S(x,y) + P_N(\Delta SRI^{*} \mid Q_0) P_0(x,y)}$$

$$P_S(x,y) = P_{\min} + (P_{\max} - P_{\min}) \cdot e^{d_s^2 / 2\sigma_p^2}$$

For regional calibrated Landsat TM/ETM data:

$$P_S(x,y) = 0{,}01 + 0{,}26 \cdot e^{d_s^2 / 1{,}69}$$

P_{max} – max possible probability of current stress in site (which depends of sensor type, local geomorphologic features and land covers), for example for Northern-West of Ukraine P_{max} for TM and ETM sensors of Landsat satellites might be assessed as 0,25 – 0,3; P_{min} – min probability, which can be assessed for similar conditions as 0,01); $d_s(x,y)$ – geometrical distance to nearest place where stress was detected; σ_p – empirical factor (for sensors TM and ETM of Landsat satellite for Northern-West of Ukraine σ_p is about 1,1 – 1,5 km for hydrological stresses).

Indicators of Threat: Biomass Distribution & State

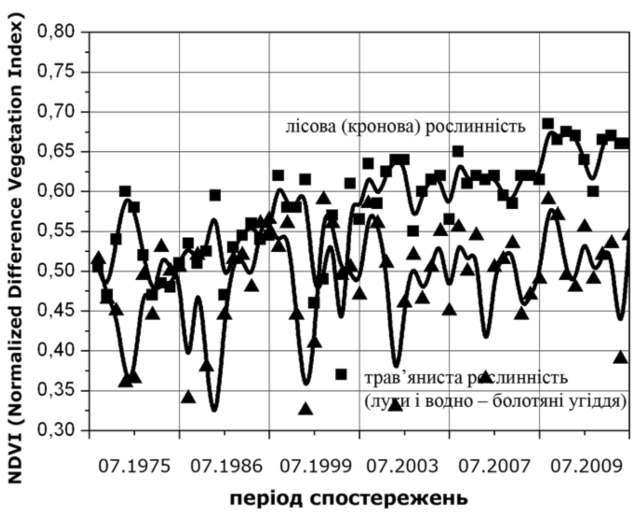
Normalized Difference Vegetation Index (NDVI): horizontal distribution of biomass, state of biota, state of chlorophyll

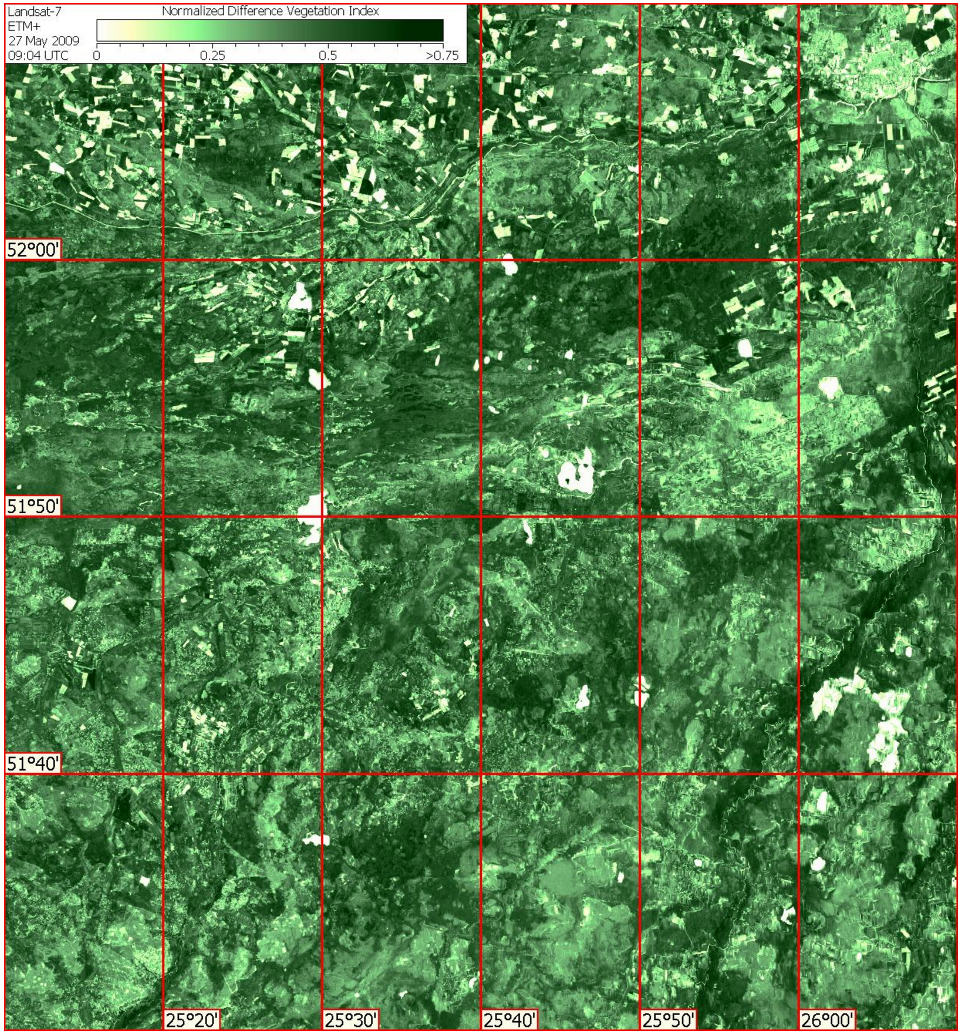
$$NDVI = \left(\frac{\lambda_{0.800} - \lambda_{0.680}}{\lambda_{0.800} + \lambda_{0.680}}\right) / g$$

$$NDVI^{MSS} = \left[\int_{0.70}^{0.80} I d\lambda - \int_{0.60}^{0.70} I d\lambda\right] \Big/ \left[\int_{0.70}^{0.80} I d\lambda + \int_{0.60}^{0.70} I d\lambda\right]$$

Atmospherically Resistant Vegetation Index (ARVI): reduced to atmosphere effect

$$ARVI = \frac{\lambda_{0.800} - (2\lambda_{0.680} - \lambda_{0.450})}{\lambda_{0.800} + (2\lambda_{0.680} - \lambda_{0.450})}$$





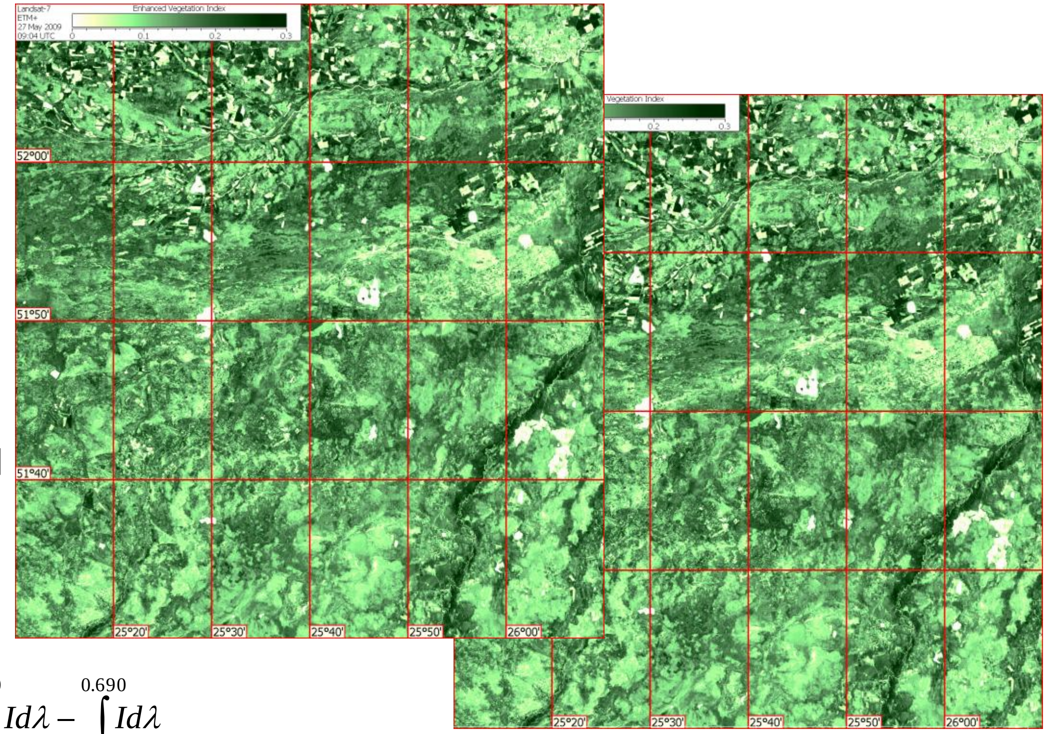
Indicators of Threat: Biomass Distribution & Stresses

Enhanced Vegetation Index (EVI): sensitive to volume (vertical) distribution of biomass, heat and water stresses impact to photosynthesis

$$EVI = 2{,}5\left(\frac{\lambda_{0.800} - \lambda_{0.680}}{\lambda_{0.800} + 6\lambda_{0.680} - 7{,}5\lambda_{0.450} + 1}\right) / g$$

$$EVI^{ETM} = 2.5\left[\int_{0.760}^{0.900} I d\lambda - \int_{0.630}^{0.690} I d\lambda\right] \Big/ \left[\int_{0.760}^{0.900} I d\lambda + 6\int_{0.630}^{0.690} I d\lambda - 7.5\int_{0.450}^{0.515} I d\lambda + 1\right]$$

Structure Intensive Pigment Index (SIPI): ecosystem stress reaction



$$SIPI(a)^{ETM} = \left[\int_{0.760}^{0.900} I d\lambda - \int_{0.450}^{0.515} I d\lambda\right] \Big/ \left[\int_{0.760}^{0.900} I d\lambda - \int_{0.630}^{0.690} I d\lambda\right.$$

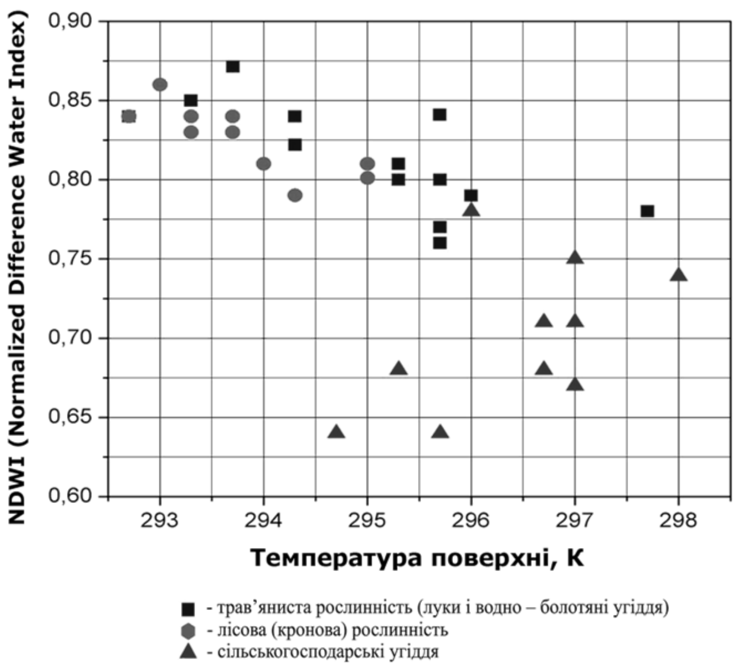
$$SIPI = \frac{r_{800} - r_{445}}{r_{800} - r_{680}}$$

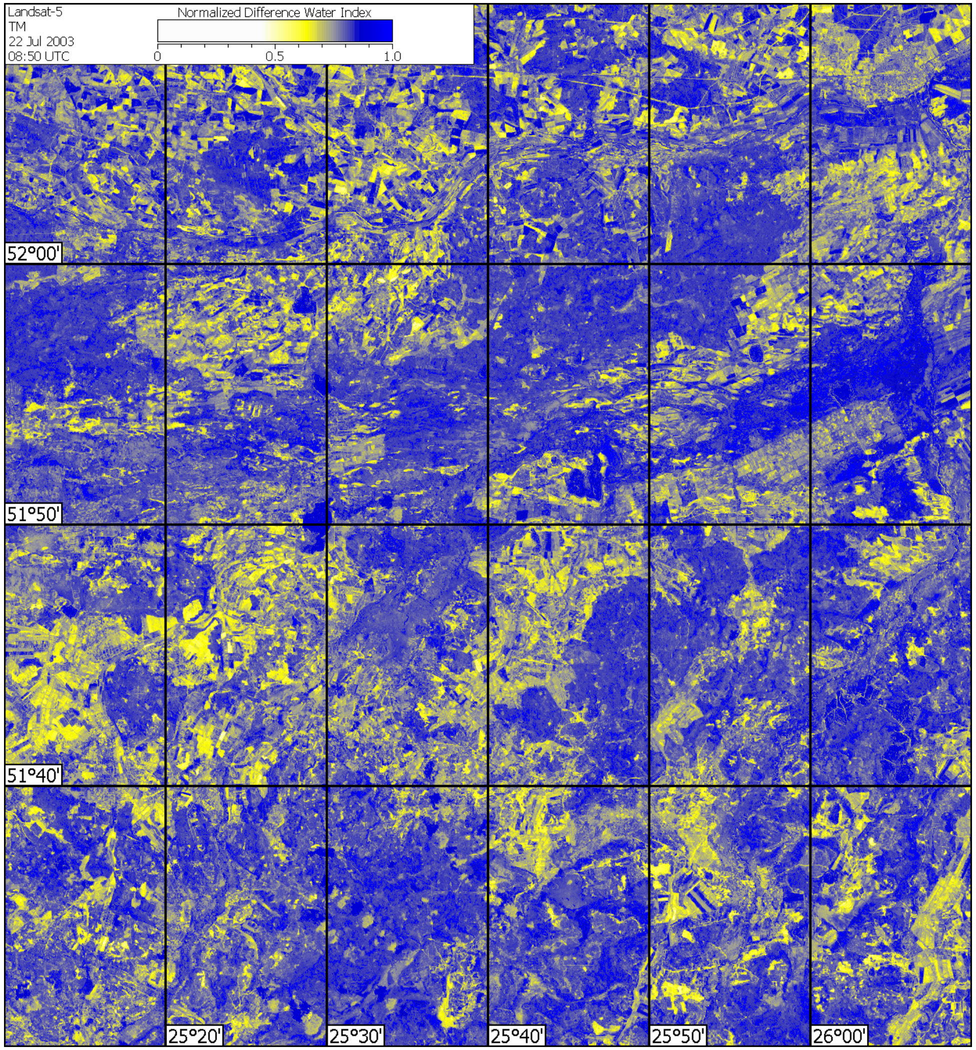
Indicators of Threat: Ecosystem Stresses

Normalized Difference Water Index (NDWI): site water load / water stress reaction index

$$NDWI = \left(\frac{\lambda_{0.857} - \lambda_{1.241}}{\lambda_{0.857} + \lambda_{1.241}}\right) / g$$

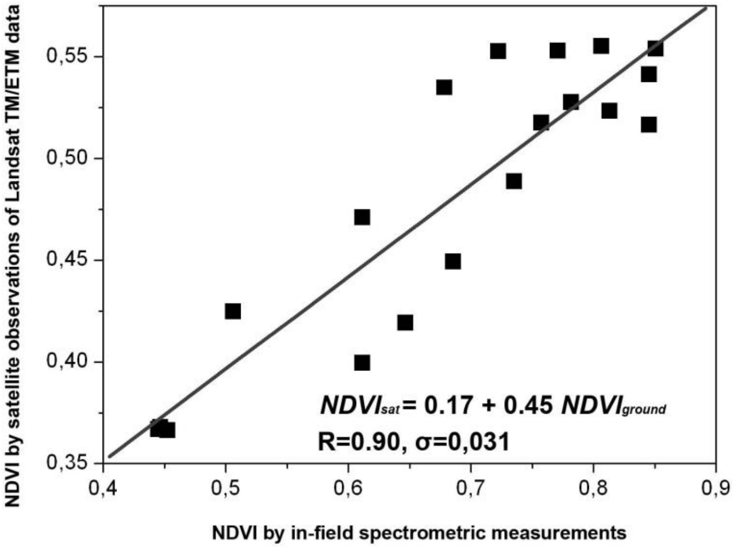
$$NDWI^{TM/ETM} = \left[\int_{0.76}^{0.90} Id\lambda - \int_{1.55}^{1.75} Id\lambda\right] \Big/ \left[\int_{0.76}^{0.90} Id\lambda + \int_{1.55}^{1.75} Id\lambda\right]$$



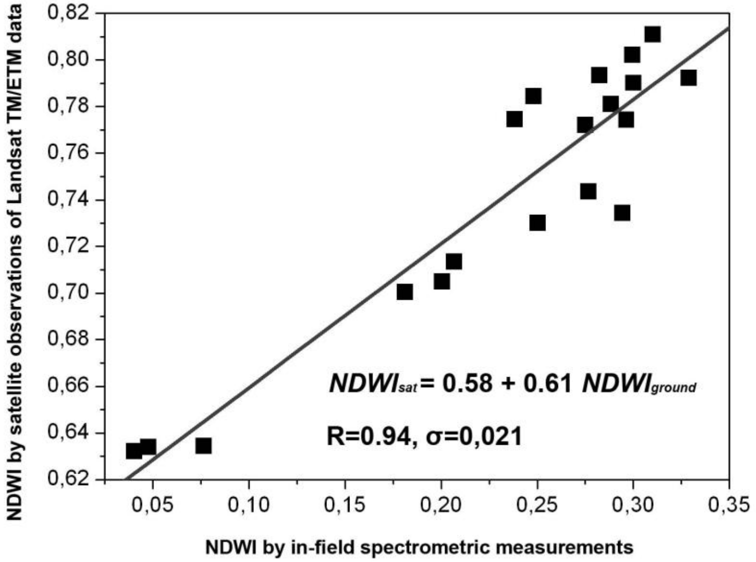


Calibration & Validation

Comparisons of distributions of *NDVI* satellite and ground derived index



Comparisons of distributions of *NDWI* satellite and ground derived index

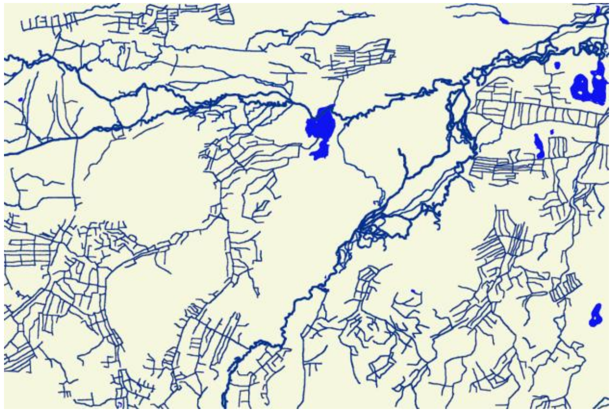


$$C_{cl(j)} = \eta \cdot e^{\mu \cdot SRI}$$

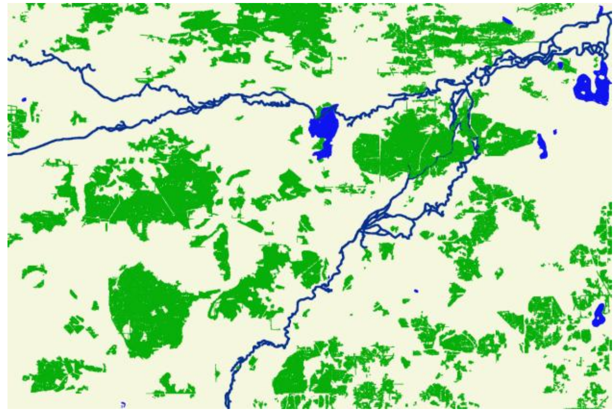
(j) \ *SRI*	*NDVI*	*ARVI*	*EVI*
Chlorophyll *a*	η = 9,41	η = 7,87	η = 7,92
	μ = 4,59	μ = 4,57	μ = 4,58
Chlorophyll *b*	η = 7,59	η = 6,91	η = 7,12
	μ = 4,31	μ = 4,18	μ = 4,27

Satellite images classification

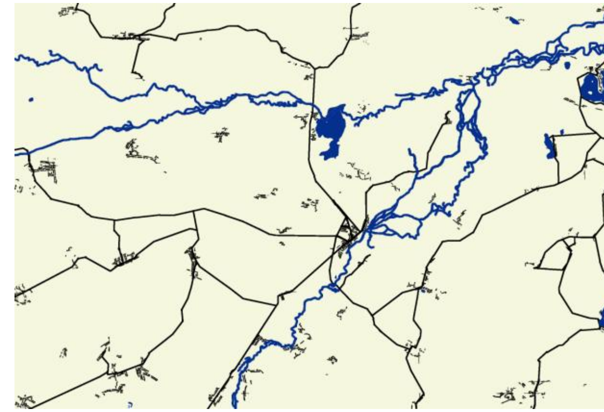
Hydrographic network

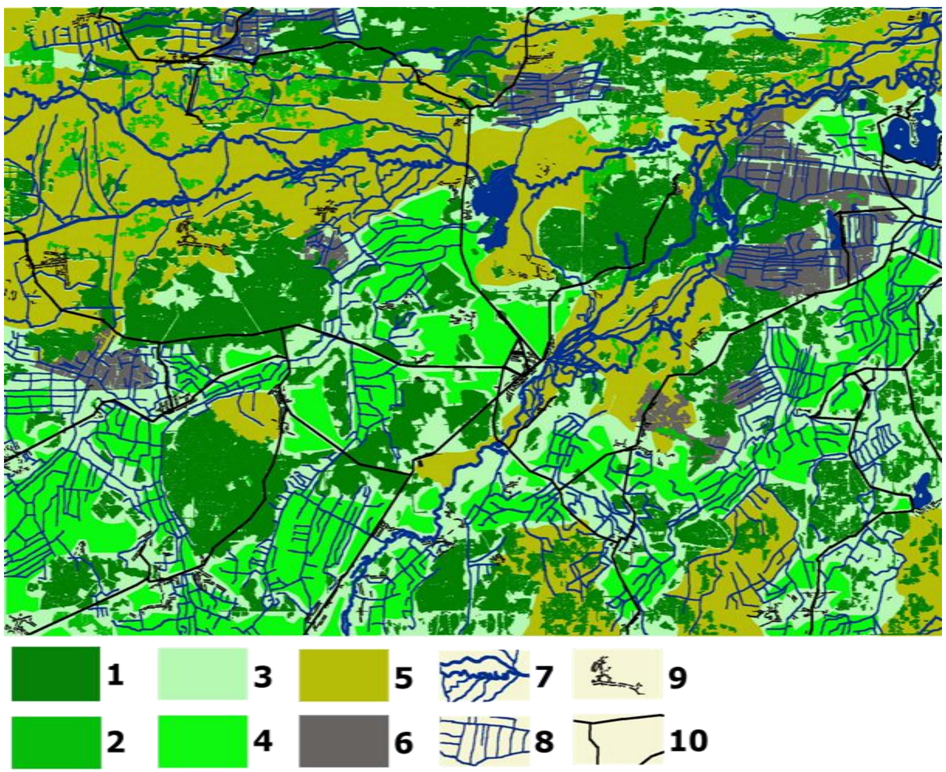


Forestry



Infrastructure

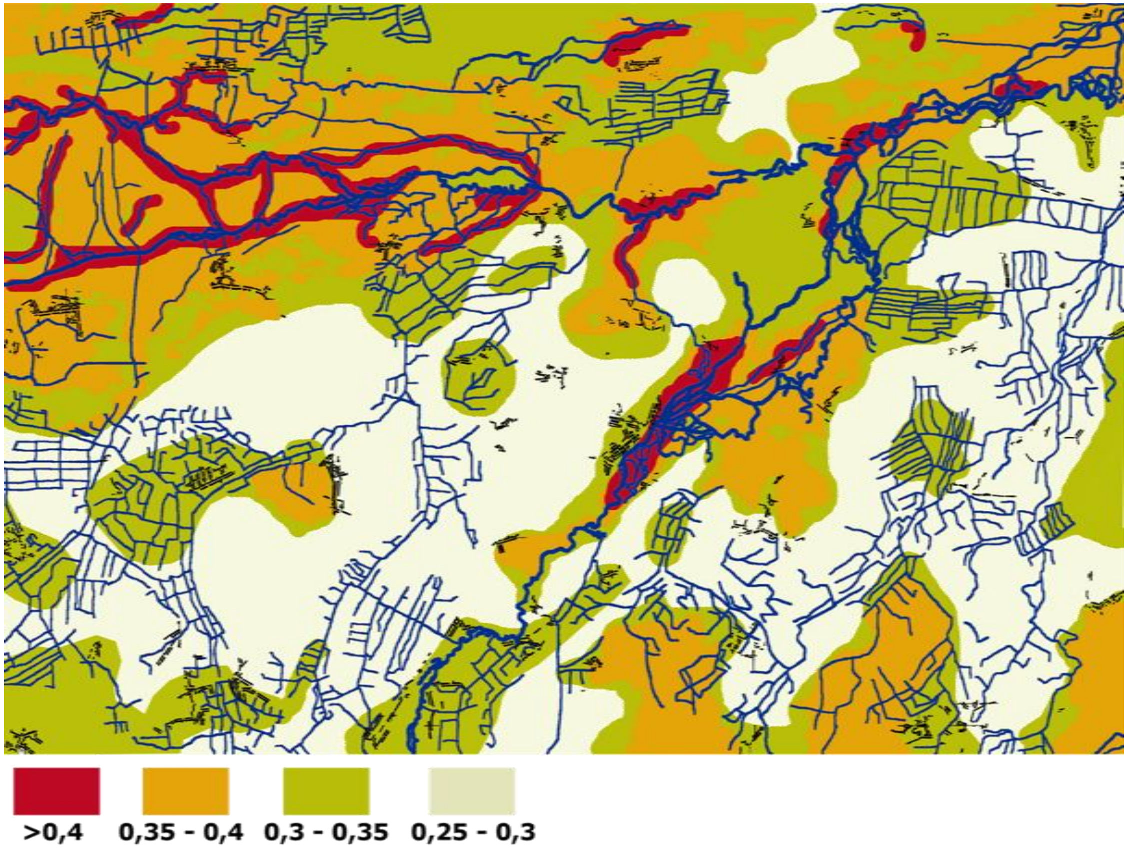




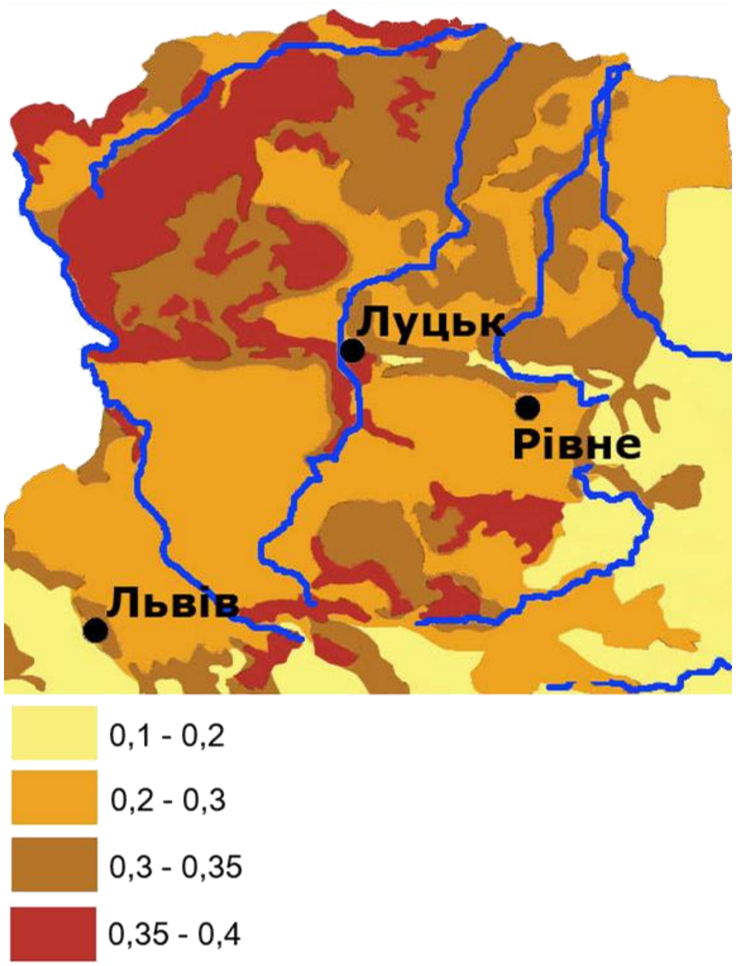
Legend: 1 – woods (average for period 2003 – 2009); 2 – bush (2003 – 2009); 3 – meadows (1999 – 2009); 4 – agricultural sites (2007 – 2009); 5 – bogs and overmoistured sites (1999 – 2009); 6 – peat-bogs and peatery (1999 – 2009); 7 – natural water objects (2009); 8 – man-made water objects (2009); 9 – built-up sites (2009); 10 – roads and bridges (2009).

Regional and Local Flooding Risk Assessment

Local flooding risk calculated for Prypyat river middle basin (Northern-West part of Ukraine) for period March – June 2011. Data used: Landsat TM& ETM, MODIS.



Regional flooding risk calculated for Northern-West part of Ukraine for period March – June 2011. Data used: Landsat TM& ETM, MODIS.



General conclusions

In our opinion the great potential of satellite observation techniques would be realized more effective using advanced interpretative approaches and sophisticated analytical tools.

We propose to utilize existing satellite data in the framework of comprehensive approaches to integrated modeling of ecosystems and data non-linear optimization. It allows to minimize the probability of misinterpretations and to activate important correlations between phenomenological parameters of ecosystems at data analysis.

To increase the applicability of results we propose to apply the advanced risks analysis approach, which allows to consider systems heterogeneities and uncertainties. As it was demonstrated it is the optimal way to operate with spatial-temporal distributed data in long-term perspective.

The results presented are indicate the way to construct the scientific base for sustainability oriented policy making, and demonstrate high capabilities of Earth observation for coupled analysis of socio – ecological risks.



Thank you for all your courtesies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