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A Remote Sensing and GIS based Approach for Vulnerability, Exposer and Landscape Trajectories in Olomouc, Czech Republic

By Mukesh Singh Boori & Vít Voženílek
Palacky University Olomouc, Czech Republic

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Keywords: remote sensing, gis, tourism, land cover classification, landsat etm+/tm, land use/cover, change trajectories, image classification, vulnerability index, exposer index, sensitivity index, adaptive capacity index, spatial principal component analysis (spca), environment vulnerability introduction.

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A Remote Sensing and GIS based Approach for Vulnerability, Exposer and Landscape Trajectories in Olomouc, Czech Republic

Mukesh Singh Boori [α] & Vít Voženílek [σ]

Abstract- Olomouc with Jeseníky mountains tourism in Czech Republic is unique for its floristic richness, which is caused mainly by the altitude division and polymorphism of the landscape; climate and oil structure are other important factors. This study assesses the impacts of tourism on the land cover in the Jeseniky mountain region by comparing multi-temporal Landsat imagery (1991, 2001 and 2013) to describe the rate and extent of land-cover change throughout the Jeseniky mountain region. This was achieved through spectral classification of different land cover and by assessing the change in forest; settlements; pasture and agriculture in relation to increasing distances (5, 10 and 15 km) from three tourism site. The results indicate that the area was deforested (11.13%) from 1991 to 2001 than experienced forest regrowth (6.71%) from 2001 to 2013. In first decay pasture and agriculture areas was increase and then in next decay it was decrease. The influence of tourism facilities on land cover is also variable. Around each of the tourism site sampled there was a general trend of forest removal decreasing as the distance from each village increased, which indicates tourism does have a negative impact on forests. However, there was an opposite trend from 2001 to 2013 that indicate conservation area. The interplay among global (tourism, climate), regional (national policies, large-river management), and local (construction and agriculture, energy and water sources to support the tourism industry) factors drives a distinctive but complex pattern of land-use and land-cover disturbance.

As Olomouc is a unique and complex landmark with widespread forestation and land use. This research work was conducted to assess important and complex land use change trajectories in Olomouc region. Multi-temporal satellite data from 1991, 2001 and 2013 were used to extract land use/cover types by object oriented classification method. To achieve the objectives, three different aspects were used, that is: (1) Calculate the quantity of each transition; (2) Allocate location based landscape pattern (3) Compare land use/cover evaluation procedure. Land cover change trajectories show that 16.69% agriculture, 54.33% forest and 21.98% other areas (settlement, pasture and water-body) were stable in all three decade. Approximately 30% of the study area maintained as a same land cove type from 1991 to 2013. Here broad scale of political and socio-economic factors also affects the rate and direction of landscape changes. Distance from the settlements was the most important predictor of land cover change trajectories. This showed that most of landscape trajectories were caused by socio-economic activities and mainly led to virtuous change on the ecological environments.

This research work also focus on vulnerability and exposer intensity due to land use change in Olomouc, Czech Republic. Assessment of vulnerability with exposer intensity to land use change is an important step for enhancing the understanding and decision-making to reduce vulnerability. This research work includes quantification of Exposure Index (EI), Sensitivity Index (SI) and Adaptive Capacity Index (AI). EI is based on intensity of land use change, SI and AI based on natural factors such as elevation, slope, vegetation and land cover. Vulnerability Index (VI) derived on the quantification of SI and AI and compared among three decades from 1991, 2001 and 2013. Comparing of EI and VI for last three decades, water have lowest vulnerability index and settlements have highest vulnerability index due to high socio-economic activities. Agriculture has highest exposer index and second highest vulnerability, which show its high rate of exploitation and production. In the study areas, vulnerability tends to increase with the increase of exposure to land use change, but can peak off once the land use start to benefit socio-economically from development. Only in this way we can enhance the adaptive capacity of study area to use change of land.

In the research work remote sensing (RS) and geographical information system (GIS) technology were used to develop an environmental numerical model for vulnerability evaluation based on spatial principle component analysis (SPCA) method. Based on environmental numerical modal an environmental vulnerability index (EVI) for the year of 1991, 2001 and 2013 of the study area were calculated. This numerical model has five thematic layers including height, slope, aspect, vegetation and land use/cover maps. The whole area vulnerability is classified into four classes: slight, light, medial and heavy level based on cluster principle. Results show that environmental vulnerability integrated index (EVSI) was continuously decreased from 2.11 to 2.01 from the year 1991 to 2013. The distribution of environmental vulnerability is vertical and present heavy in low elevation and slight in high elevation. The overall vulnerability of the study area is light level and the main driving forces are socio-economic activities and human interferences.

Keywords: remote sensing, gis, tourism, land cover classification, landsat etm+/tm, land use/cover, change trajectories, image classification, vulnerability index, exposer index, sensitivity index, adaptive capacity index, spatial principal component analysis (spca), environment vulnerability introduction.

Author α σ: Palacky University Olomouc, Olomouc, Czech Republic. e-mails: mukesh.boori@upol.cz, vit.vozenilek@upol.cz

I. Introduction

The Olomouc Region has a rich diversity of activities capable of pleasing even the most demanding visitors. This is a place for enthusiasts

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of historical and natural monuments, winter sports, and bicycle tours. The Jeseníky Mountains offer a paradise full of natural treasures and hundreds of well-marked routes for hikers and cyclists, along with countless educational trails, caves, waterfalls and viewing towers. The natural centre of the Olomouc region is the city of Olomouc with its distinguished monument, the Holy Trinity Column, which is inscribed on the UNESCO World Heritage List [1]. Its area is 5,267 km^2 (January 1, 2006), 6.7 % of the national territory, making it the 8th largest region in the country. As of H1 2009 there are 642,080 inhabitants (6.1 % of the population of the Czech Republic, the 6th most populated region in the country). Its 397 communities make up for 6.4 % of all communities in the country [2]. Olomouc, the regional capital with a population of 100,168 is the 5th largest city in the Czech Republic. There are 13 towns and cities with populations exceeding 5,000 in the region [3] and most attractive place for tourism [4].

The early 1990s produced a boom in tourism for Czech Republic, as the country of architecture and rich culture were 'rediscovered' by Western Europeans curious to visit a country formerly hidden behind the Iron Curtain and the tourism boom brought US$ 4 billion per annum to the state budget [1] with almost no marketing and promotion. Prior to the collapse of communism, the service sector (and hence the tourism industry) in the Czech Republic was weakly developed [5, 6]. The universal right to work, common to all ex-communist countries, favored employment in heavy industries and/or collective agriculture. Neither, private ownership of enterprises nor NGO activity was permitted [7]. As in the rest of Eastern Europe, since the fall of the Iron Curtain in 1990 the economy underwent rapid transition, most notably the collapse of the primary sector and consequently rising unemployment. Between 1980 and 2000, the contribution of secondary industries to the GDP fell from 63% to 43%, while the contribution of tertiary industries increased from 30% to 53% [8].

Last five decades agriculture and forested landscapes have been transformed by economic and social development [9, 10]. These transformations are important components of land cover disturbance and global environmental change [11, 12]. The most rapid and significant include deforestation as a consequence of urbanization, agricultural expansion, logging, and pastoral expansion [13]. A theoretical framework to explain the nature of resource use by the tourism industry is the Von Thunen model [14]. Von Thunen's theory suggests that resource extraction decreases with increasing distance from settlements due to the costs of transport [15]. This premise has been outdated for industrialized parts of the world due to improved infrastructure [16].

Land cover disturbance and environmental impact of tourism is particularly critical in mountain regions [17]. Mountain communities are typically less affluent than their counterparts in lowland regions, and poverty is still a fact in many mountainous areas [18]. Infrastructure development is hampered by difficult access and harsh climate [19]. The drawing of policies and plans is less effective in mountain areas, because historically these areas have been of marginal concern for decision-makers, and therefore neglected in development priorities [20]. Moreover, policy implementation is undermined by political instability, which often characterizes mountain areas due to their proximity to national and international borders [21]. On top of these factors, there are peculiar conditions of mountain areas that make them more vulnerable, such as land cover disturbance, environmental fragility and tourism seasonality. High-altitude ecosystems are inherently fragile and characterized by low resiliency, and therefore they are particularly susceptible to human interference, such as soil and vegetation trampling, disturbance to native wildlife, and waste dumping [22, 23]. High altitude recreation sites are characterized by extreme seasonality, because accessibility and favorable climatic conditions are restricted to the short summer season. Consequently, human-induced disturbances on the land cover and environment are concentrated in this period that is also the peak season for several biological processes, such as mating, vegetation growth, migration, spawning, etc [24].

Socio-economic activities have been one of the most important factors for land cover change trajectories. In place of two dates of change in satellite imageries, researchers are more focus on temporal land cover change trajectories [25]. In European Union (EU) 43% land is farmland and 26% arable. For Czech Republic it`s 54% and 37% respectively [26]. Only 17% of farmland is farmed by the landowners and this is the second lowest in EU [26]. These growing environmental problems in recent decades frequently ensue from two dominant trends in the current use of agricultural land within Europe [27]: intensification and specialization in some areas accompanied by marginalization and abandonment in others. Earlier land cover change in Czech Republic have analyzed by many authors. These studies focused on the influence of extreme fragmentation of agricultural land ownership as an important driver of homogenization of rural landscape patterns were presented by [28] and [29]. Historical maps reaching back to the mid-18th century were used by [30] to analyses long-term land-cover changes in 21 cadastral units of Central Bohemia. They mention that 18% to 5% permanent grassland and 6% to less than 1% surface water area were decrease.

Trajectory analysis is a new method for land cover change research based on each pixel`s in time series. [31] developed a trajectory-based hierarchical decision tree to delineate warm season grass (WSG) and cool season grass (CSG) for long term WSG/CSG mapping. Temporal trajectory is using to discover land

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use/cover change trends by constructing the 'curves' or 'profiles' of multi-temporal data [32]. The concept of trajectory to change has attracted some attention from a theoretical viewpoint [33]. These trajectories defined as trends over time among the relationships between the factors. These factors shape the changing nature of human–environment relation and their effects within a particular region [34]. This takes widely different forms and depends on circumstances, regional contexts, and government policies. These studies have further highlighted the importance of understanding landscape dynamics for sustainability and conservation purposes [35].

Remote sensing data are particularly useful due to the cost and time associated with traditional survey methods [36, 37]. These techniques have become viable alternatives to conventional survey and ground-based mapping methods [38]. Remote sensing and geographic Information Systems are powerful and effective tools for assessing the spatial and temporal dynamics of landscape trajectories [39]. Remote sensing data provide valuable multi-temporal information of the processes and patterns of land cover change. GIS is useful for mapping and analyzing these patterns [40]. In addition, retrospective and consistent synoptic coverage from satellites is particularly useful in areas where changes have been rapid [41]. Furthermore, since digital archives of remotely sensed data provide the opportunity to study historical land use/cover changes, the geographic pattern of such changes in relation to other environmental and human factors can be evaluated. In addition, accurate and comprehensive land cover change trajectories statistics are useful for devising sustainable development and planning strategies [42]. It is therefore very important to estimate the rate, pattern and type of land cover change trajectories in order to predict future changes for sustainable development.

This research present land cover change trajectories analysis for forest, agriculture and others (settlement, pasture and water body) for three decades (1991, 2001 and 2013) in the Olomouc, Czech Republic. This research seeks to: (1) Capture the spatio-temporal variability of landscape change trajectories in Olomouc, (2) Comparing RS, GIS and socio-economic factors in Olomouc. Pre- and post-classification comparison techniques have been extensively used [43]. In the pre-classification approach procedure such as image differencing [44], band rationing [45], change vector analysis [46], direct multi-date classification [47], vegetation index differencing [48] and principle component analysis [49] have been developed [50]. These techniques are useful for locating the change but they are unable to identify nature of change [51].

In Olomouc, Czech Republic highly productive regions with high density of population are most exploited areas. These areas are experiencing various environmental impacts and climate change associated with local, regional and global issues. These areas are highly vulnerable to threats from both natural processes and socio-economic activities [52]. Present research on vulnerability is focus on natural disasters and climate related impacts such as droughts, floods, see level rise and cyclones [53], but not on non-climatic parameters such as elevation, slope, aspects, vegetation and socio-economic activities [54]. Maximum vulnerability studies are on national and continental level but at small level, local factors along with socio-economic activities such as land use change and pollution, might have more profound impacts than global climate change.

In this research work we used three terms (exposure, sensitivity and adaptive capacity) inside the vulnerability. While there is considerable heterogeneity in both the potential impacts of environmental changes, and the adaptive capacity to cope with these impacts, this assessment shows that study area in particular will be vulnerable to natural parameters, ecosystem and land use change [55]. Projected economic growth increases adaptive capacity, but is also associated with the most negative potential impacts. The potential impacts of more environmentally oriented developments are smaller, indicating an important role for both policy and society in determining eventual residual impacts [56].

Economic growth directly effect on land use change because a large part of forest and agriculture area convert in urbanization and industrial areas. Recent studies shows, that there is a positive feedback between landscape urbanization and economic growth in Czech Republic [57], indicating the existence of a strong driver for land use conversion from forest and agriculture to urban use [58]. This conversion some time cause of excessive exploitation of natural resources and their regional imbalance. These changes are main cause of different types of vulnerability and their transfer from one to other type of vulnerability. As the objective of this research is to develop a module with an indicator system to compare vulnerability due to exposed of land use change, using the concepts of exposure, sensitivity and adaptive capacity [59]). The results are showing relationship between vulnerability, exposure and land use change. In last we compare results for last three decades for 1991, 2001 and 2013.

Environmental vulnerability evaluation is characterizing the vulnerability and resilience of socio-ecological systems exposed to environmental hazards. Previous research developed many methods such as fuzzy evaluation method [60], the gray evaluation method [61] along with the artificial neural-network evaluation method [62], and the landscape evaluation method [63]. These methods are based on quantitative analysis and their variables are not easy to acquired or operated in the model. However, advancement in remote sensing, GIS and numerical modelling

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techniques is a powerful tool for environmental vulnerability assessment [64].

Since last three decades in Olomouc from 1991 to 2013, land cover has transformed dramatically due to socio-economic activities and extraction of natural resources [65]. Unlimited or unwanted exploitation of natural resources reduces their sustainability limit and this has become a cause of serious concern for the government and the people of Czech Republic. Recently land use/cover studies have attracted wide variety of researcher, ranging from those who are modelling the spatial and temporal patterns of land conversion, to those who try to understand the causes and consequences of land use changes [66, 67].

Remote sensing, GIS and numerical modelling techniques played a great role in extraction and preparation of the environmental vulnerability evaluation attributes [68]. The major objective of this study is to evaluate the environmental vulnerability in a typical mountainous region characterized by apparent vertical-belt features. Both natural and human induced attributes were considered [69]. The land use and vegetation cover maps were derived from landsat TM and ETM+ data with a resolution of 25-30m through classification and interpretation of the land cover features [70]. Terrain characteristics namely slope; elevation and aspects were derived from Digital Elevation Model (DEM). The specific objectives of this study were to (i) measure the quality and quantity of LUCC; (ii) evaluate the vulnerability of environment during three intermediary periods from 1991 to 2013; (iii) elucidate changing trends of vulnerability in terms of location, intensity and the nature of the threats; (iv) an environmental numerical evaluation model was set up supported by GIS; (v) the spatial principal component analysis (SPCA) was developed to build an environmental vulnerability index (EVI) model and the computed result is classified using the cluster principle; (vi) the spatial distribution and its change of environmental vulnerability were analysed and driving forcing for change are discussed. (vii) the regionalization is worked out as the basis for environmental rebuilding planning [80].

II. Materials and Methods

a) Study Area

The study area cover Olomouc Region, which is located in north-eastern Czech Republic between 49°45´ N, and 17°15´ E (Fig. 1). The border between the Olomouc region and Poland in the north is 104 km long. The other neighbours are the Moravskoslezský Region in the east, the Zlín Region and the Jihomoravský Region in the south and the Pardubický Region in the west. The geographical layout of the region is rather unusual. There are lowlands at the Polish borders, followed by the Jeseníky mountain range with Praded (map) as highest mountain (1.492 m above sea level), while the southern part (again) comprises lowlands – the flat and fertile land of Haná. This region is one of the most fertile areas of the Czech Republic. Its elevation is 219 m (719 ft) and total area is 103.36 km^2. Its total population is 101,003 with 987/km^2 density.

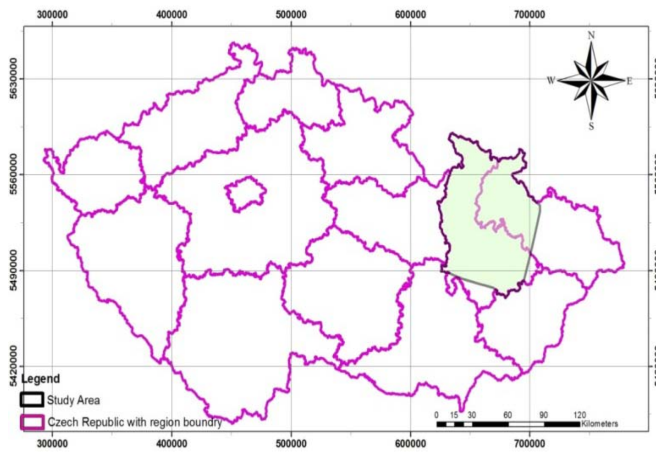

Fig. 1 : Study area: Jeseniky mountain region, Olomouc

This region is characterised by coniferous forest (Pinus sylvestris L.and Picea abies L. Karst.) and large aapa mires. Deciduous trees mainly Betula spp. occur to a lesser extent and located in the northern boreal vegetation zone. Highest fells and alpine vegetation are found in the north-western part of the study region in the Jeseniky mountain area. A large number of lichen pastures with forest are located in the eastern and north-eastern mountainous part of the Olomouc region. The most important late winter pastures with arboreal lichens are located in the western, central and southern parts of the Olomouc Region [81]. Summer and autumn pasture with vegetation are consisting in mires, lake and riversides. Moist forest and fresh forest are present in the north-eastern, south-western, eastern and western parts of the Olomouc Region [82].

b) Data

NASA Landsate TM and ETM+ data (1991, 2001 & 2013) were used for vulnerability evolution. ArcGIS 10.1 software was used for all image preparation, spatial analysis and mapping. The data of land use and vegetation is derived from landsat data by user-computer interactive interpreting method. Elevation and slope maps were generated from DEM. Topographic database provides the most accurate and uniform information for map products, which covering the entire country, so geographic corrections were performed on the base of topographic sheets and then registered (UTM WGS84) all images. 26 ground control points (GCPs) were used for registration. All GCPs were dispersed throughout the scene, yielding a RMS error of less than 0.5 pixels. The photographs were acquired with a frame camera that was designed to support mapping, charting and geodesy in addition to two high-resolution cameras. The ground-truth data required for

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visual interpretation and accuracy assessment of IRS images was collected from the field in April, 2014. Socio-economic information and natural resource use pattern of the local communities was generated using questionnaire method.

One Landsat 5 TM and two Landsat 7 ETM+ images (WRS II Path 190, Row 25; 9 Oct. 1991, 14 April 2001, 24 September 2013) were used for this research. Which were selected for their clarity and being at least 10 years apart. ArcGIS 10.1 software was used for all image preparation, spatial analysis and mapping. Topographic maps served as the base maps and was rectified (UTM WGS84) to the roads layer with a nearest-neighbour resampling (RMSE< 0.5 pixels, or <15 m). Image-to-image registration was performed on the other images. After completing the registration, each image was radiometrically calibrated to correct for sensor related, illumination, and atmospheric sources of variance (Green et al., 2005). The ancillary data used in this research includes:

- Photos and field notes recorded in 2013 during a trek around the study area
- Google Earth images used as reference data during the classification and validation phases of the analysis
- GIS layers of the study area, which includes roads, rivers, ecology and boundaries, and a land-cover map obtained from the European Space Agency (ESA) and the United States Geological Survey.

c) *Field Data Collection*

Field work was conducted to determine ambiguous land-cover classification and to visit area of major change to determine causes of the changes with both observation and informal interviews of local people. This also provided a secondary validation of the classification accuracy for the most current image date. A *Trimble* hand-held GPS with an accuracy of 10 meters was used to map and collect the coordinates of important land use features during pre- and post-classification field visits to the study area in order to prepare land-use and land-cover maps.

d) *Normalized difference Vegeatation Index (NDVI) calculation and change detection*

The Normalized Difference Vegetation Index (NDVI) is calculated as (NIR - red) / (NIR + red), where red corresponds to Landsat TM band 3 and near-infrared to band 4. Continuous NDVI values range from -1 to +1. High values closer to +1 are associated with healthy green vegetation and standing biomass. NDVI was calculated for each image date and using these images we then calculated standard normal deviates (Z-scores) to minimize the influence of seasonal variation and inter-annual differences [83]. The use of the standard normal deviates reduces much of the potential effect of inter-annual climate variation, which is necessary even when using anniversary dates and calibrated imagery, in a region influenced so heavily by rainy season precipitation amounts.

e) *Image Classification*

In this research work, first was used unsupervised classification and after field visit and identification of land cove classes, supervised classification was used on the basis of training sites. Forest was defined as >30% tree canopy closure to separate the dense forest area from scrub and agriculture lands. Non forested land includes an aggregation of the other land covers water, pasture (which at this time of year includes agriculture, which presents as bare soil, within this cover), built, and scrub. The DEM was used to separate the high and low elevation area.

Three tourist sites (Olomouc, Rymarov and Jesenilk) were identified to access tourism effect, using the field notes as a guide and spatially located as a point GIS layer. A gradient of tourism proximity was generated using the ArcGIS “multi-ring buffer” tool to produce three concentric circles placed 5 km apart around each of the tourism facilities. Then proximity zone were overlaid on land cover change layer, and statistics for each tourism facility and proximity zone. This was further analysed to calculate the net percentage change in forest, agriculture, pasture, settlements and regression analysis was used to identify trends in change and tourism proximity. This analysis was applied for all three tourism facilities combined, the Olomouc, Rymarov and Jeseniky facilities for 1991, 2001 and 2013 (Fig. 2).

f) *Land use/cover analysis*

After pre-processing and geometric correction, all satellite images used for classification to know changes in between two dates in the study area. A number of methods are available for temporal land use change detection, including: (i) post-classification comparison, (ii) classification of multi-temporal data sets, (iii) principal components analysis (PCA), (iv) temporal image differencing and rationing, (v) change vector analysis and (vi) spectral mixture analysis. The main emphasis of the study was on change in natural forest cover (i.e. deforestation) and areas under intensive cultivation. In satellite image classification, vegetated area was comprised mixture of surface materials such as different canopy components, bare soil, water and shadow. The spectrum measured by the sensor was therefore a mixture of each of these components [84].

This research work report the finding of post-classification comparison between two dates images in the study area. First unsupervised classification and then supervised maximum likelihood classification (MLC) were used to obtain the best results from remotely sensed data. Gaussian distribution [85] was

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applied in each image. In supervised classification training sites were based on reference data and ancillary information. In last, post-classification refinement was used to improve the accuracy of classification. Three major land cover classes were identified: forest, agriculture and others (water body, pasture and settlements). In this research work three land cover classes for three time nodes were used in the trajectory analysis to monitor land use/cover change dynamics.

We used simple metrics for quantifying the landscape structure and their behavior predicated across all evaluation [86]. In ArcGIS, an iterative multi-objective land allocation procedure was used to resolve conflicts decision heuristic and carried out change trajectories over the landscape. The definition of forest cover was minimum 30% canopy coverage which provides a distinct delineation between scrub areas and dene forest. Follow-up field work was conducted in October 20013 and February 2014, to determine ambiguous land-cover classification. Visit study area to determine major changes and there causes by observations and informal interviews of local people. This also provided a secondary validation of the classification accuracy for the most current image date.

The terrain complexity complicates the interpretation of spectral signatures in land use/cover mapping and changes. Which were influenced by elevation, aspect, and slope; this could lead to similar objects showing different reflectance and/or the different objects presenting the same reflectance, especially in dark shadow areas [87]. So in visual image interpretation techniques, it's used a combination of subjective and objective methods. Ground truth information was used in doubtful areas during image interpretation. The hydrological DEM was generated from contour and drainage layers in ArcInfo using topogrid tool. Slope and aspects were derived from the DEM and then changes were studied along all the topographic parameters using matrix functions [88].

Table 1 : Land cover areas (km^2) changes for 1991, 2001 and 2013

	1991		2001		2013		1991-2001		2001-2013		1991-2013	
Class	Area	%	Area	%	Area	%	Area Diff.	% Diff.	Area Diff.	% Diff.	Area Diff.	% Diff.
Water	209.85	10.49	243.77	12.19	298.85	14.94	33.92	1.70	55.08	2.75	89.00	4.45
Forest	804.02	40.20	581.49	29.07	715.61	35.78	-222.53	-11.13	134.12	6.71	-88.42	-4.42
Settlement	29.87	1.49	26.42	1.32	43.55	2.18	-3.45	-0.17	17.13	0.86	13.68	0.69
Pasture	213.03	10.65	301.75	15.09	160.09	8.00	88.72	4.44	-141.66	-7.08	-52.94	-2.64
Agriculture	743.23	37.16	846.57	42.33	781.90	39.09	103.34	5.17	-64.67	-3.23	38.67	1.93
Total	2000.00	100.00	2000.00	100.00	2000.00	100.00	Land use/cover changes					

Agriculture and forested land makes up the largest percent of the study area with 35%, 40%, area in 1991 and vice versa in 2013 (Table 1). Forest makes up the largest land-cover, and occurs predominantly in the more upland areas with greater relief (Fig. 2). Forest area was decrease (222.53 km^2) slightly during the first half of the study period but then increase (35.78 km^2) during the second half of the study. Water makes up less than 15% of the upland landscape for all years of the study. Table 1 provides the areas of each class. The total area of the study was 2000 km^2. From 1991 to 2001, there has been a net decrease of forest is 11.13%. But in 2001 to 2013, 6.71% forest area was added. Pasture and agriculture was added 4.44% and 5.17% respectively from 1991 to 2001 but both area reduce (7.08% and 3.23% respectively) from 2001 to 2013. From 1991 to 2013 forest and pasture area was reduces (4.42% and 2.64% respectively). Where agriculture and settlements increased 1.93% and 0.69% from 1991 to 2013, here total water body area was highest increased around 4.50% from 1991 to 2013 (Fig. 2). These changes show governmental protection of forest area in between 2001 to 2013. Table 1 show that no change in number of settlements from 1991 to 2001 but for next decay settlements and water body area was increased.

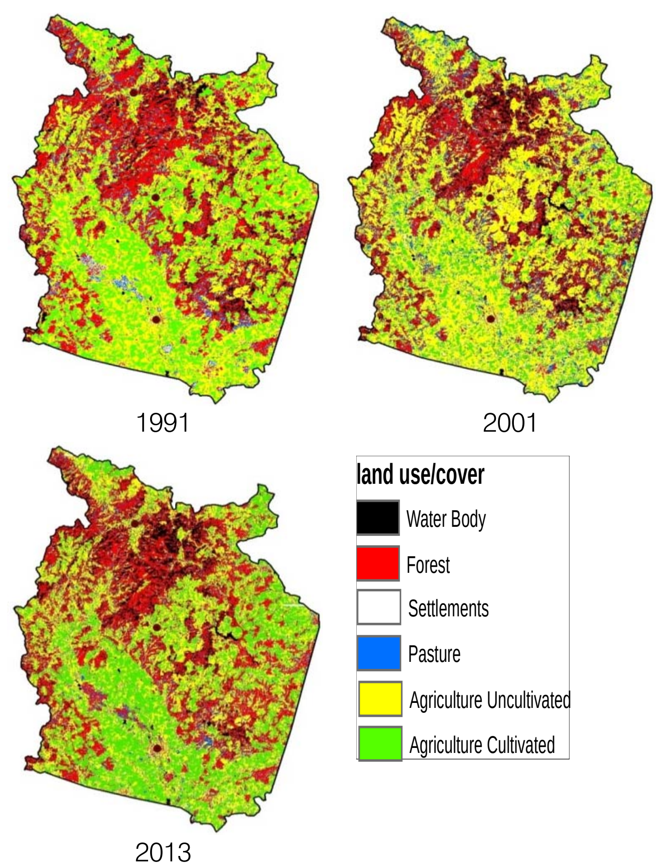

Fig. 2 : Land Cover change for 1991, 2001 and 2013

g) Vulnerability concept

The vulnerability is a function of the character, magnitude and rate of natural resources change and variation to which a system is exposed, its sensitivity, and its adaptive capacity. Landscape condition is determined the susceptibility of a community to the impact of hazards, the degree to which a system is susceptible to, or unable to cope with, adverse effects

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on natural resources, including variability and extremes. So we can say vulnerability is a function of exposure, sensitivity and adaptive capacity [89]. Where potential impacts are a function of exposure and sensitivity therefore, vulnerability is a function of potential impacts and adaptive capacity (Fig. 3).

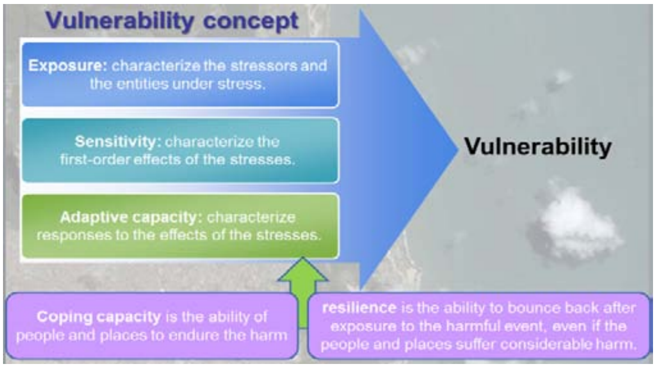

Fig. 3 : Vulnerability concept (Mukesh Singh Boori PhD thesis)

As vulnerability include the three dimensions: exposure, sensitivity, and adaptive capacity. Where exposure components characterize the stressors and the entities under stress, Sensitivity components characterize the first order effects of the stresses, and adaptive capacity components characterize responses to the effects of the stresses (fig. 3). These measures can be quantitative (e.g., precipitation variability, distance to market) or qualitative (e.g., political party affiliation, environmental preservation ethic). Another slightly different view favored by the hazards and disasters research community is that adaptive capacity consists of two subcomponents: coping capacity and resilience. Coping capacity is the ability of people and places to endure the harm, and resilience is the ability to bounce back after exposure to the harmful event, even if the people and places suffer considerable harm. In both cases, individuals and communities can take measures to increase their abilities to cope and bounce back; again depending on the physical, social, economic, spiritual, and other resources they have or have access to [90].

Another basic issue for the evaluation a model is to assign weights to each factor according to its relative effects of factors considered on the vulnerability in a thematic layer. The analytic hierarchy process, a theory dealing with complex technological, economical, and socio-political problems [91, 92], is an appropriate method for deriving the weight assigned to each factor. The degree of membership within different levels of different indices was integrated using weight and the total degree of membership for different thematic layers was used to calculate the whole study area vulnerability. The application of subjective weightings on the one hand gives us some indication of how the relative importance of different factors might vary with context, and can also tell us how sensitive vulnerability ratings are to perceptions of vulnerability in the expert community.

h) *Standardised the indicators*

This study is based on the quantification of sensitivity and adaptive capacity. Here various indicators are define and measure sensitivity and adaptive capacity such as elevation, slope, vegetation and land use. In this study, adaptive capacity is defined as the ability of the natural resources to adapt to a changing environment caused by land use change, which depends on natural factors. Land use change is a spatial manifestation of human activities, associated with regional planning, land management and economic development. High intensity of land use may present a potential threat to local ecosystem or community. Land use change may impact on geology, geomorphology, soil, vegetation, surface water body, quality of water and create disturbance in ecosystem and sometime cause of natural disasters [93]. All are important factors for sensitivity due to land use change. Sensitivity of an area was reflected in the following aspects: (1) the extent of natives' discontent with contaminated living environment. Along with the progress of land use change, natural vegetation around villages were destroyed, but population and industry increased a lot, making sewage and garbage beyond the purification capacity of ecosystem. So the natives would be dissatisfied and suffer psychological and economic losses. (2) The percentage of occupied farmlands with the expansion of industrial and residential areas. (3) The percentage of lack of fresh water resource by the reason of flow reduction and pollution. While flow reduction is the result of occupation of catchment areas and river ways by waterproof buildings, and pollution is the result of excessive industrial waste. Since aquiculture and agriculture both depended on fresh water, farmers have been severely affected. (4) The degree of unemployment. It is much serious in farmers because of farmland loss. (5) The rate of loss of traditional culture. In a changing environment, the traditional culture always fades away to exchange for economic opportunity, such as traditional architecture. Adaptive capacity is the ability of human sectors to handle change, which is determined by various factors such as economic development, technology and infrastructure, information, knowledge and skills [94].

It is important to note that each designated indicator system is inevitably subjective (Fig. 4). It presents only one possible result of vulnerability assessment. Therefore, it is more meaningful to use these indicators to compare relative values across study area as well as longitudinal comparison within the same area, rather than trying to make sense of the absolute values of indices. In view of different dimensions and magnitudes of the indicators, a standardization of the

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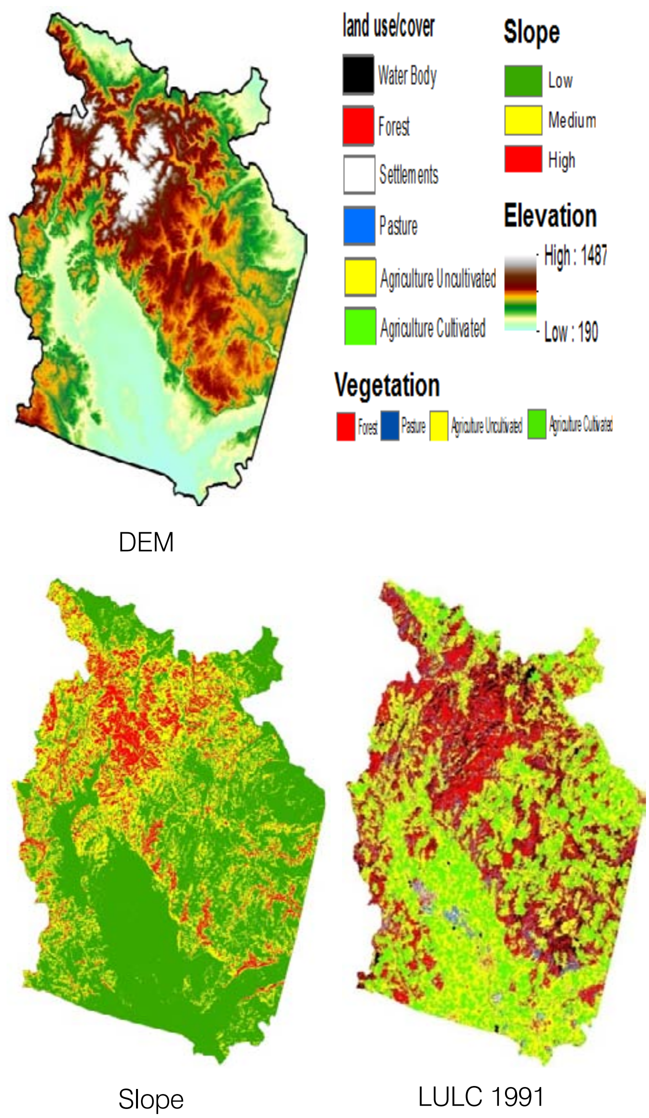
initial value is required. For indicators associated with the target index, make

$$y_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \; (i\mathcal{E}[1,m], j\mathcal{E}[1,n]) \qquad (1)$$

Where y_{ij} is the standardized value of indicator; x_{ij} is the initial value of indicator, i is the serial number of the study area, j is the serial number of the indicator, m is the number of study areas, n is the number of indicators (Fig. 4).



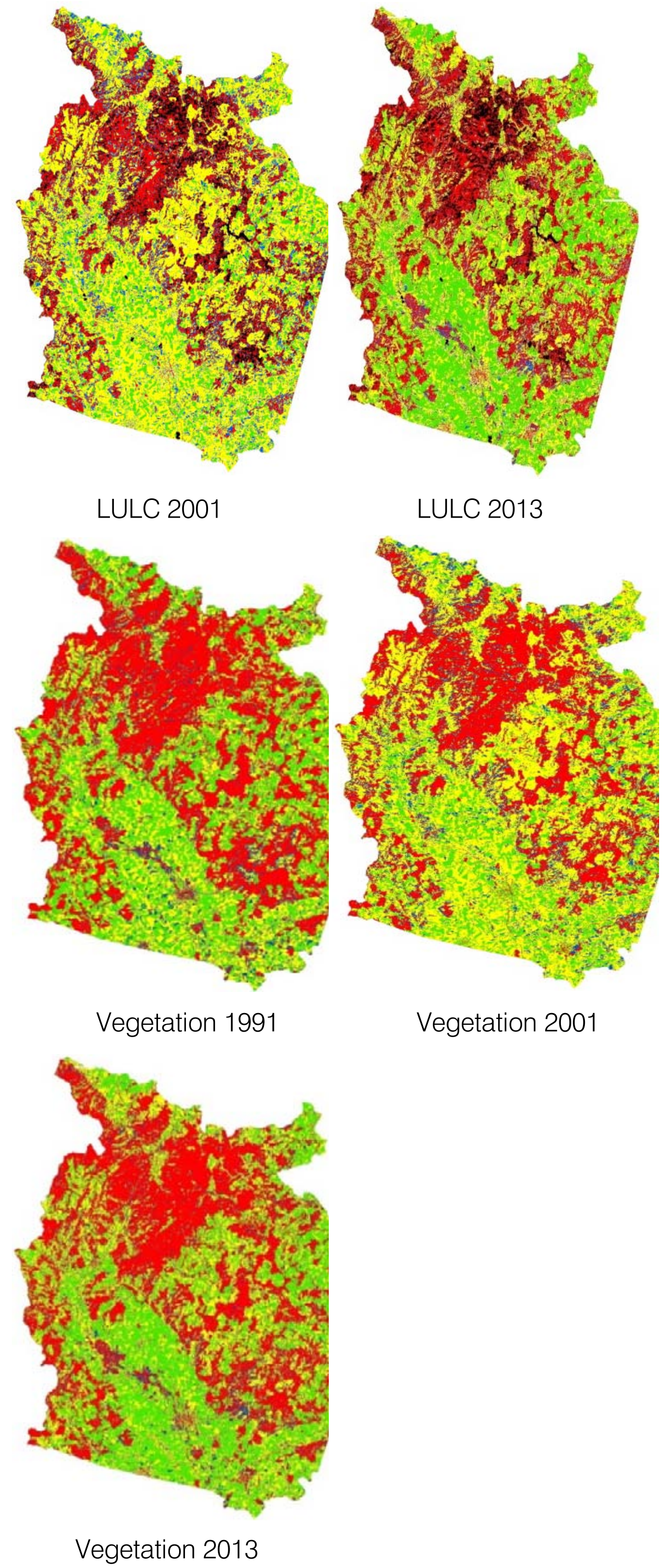


Fig. 4 : DEM, Slope, vegetation and land use/cover maps

After the standardization, SI and AI can be calculated based on Eq. (2), equal to the geometric mean of its standardized indicators. In this way the information of every indicator is contained by the target

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index, and each indicator is given the same weight, simple but clear. We choose the geometric mean algorithm because its result is eclectic and smoother than that of arithmetic mean, especially when some indicators of an object are unusually large or small.

$$SI_j \text{ or } AI_j = \left(\prod_{i=1}^{n} y_{ij}\right)^{1/n} \quad (2)$$

We used equation 6 to generate Vulnerability Index (VI). VI is proportion to sensitivity index (SI) and adaptive capacity index (AI). SI indicates negative effect of land use change and AI show positive effects. Here exposure is not including in the equation, but there relationship is the core of this study.

$$VI = \frac{SI}{AI} \quad (3)$$

Where VI is Vulnerability Index, SI is Sensitivity Index, and AI is Adaptive Capacity Index. Vulnerability maps of the study area for 1991, 2001 and 2013 are shown in figure 5.

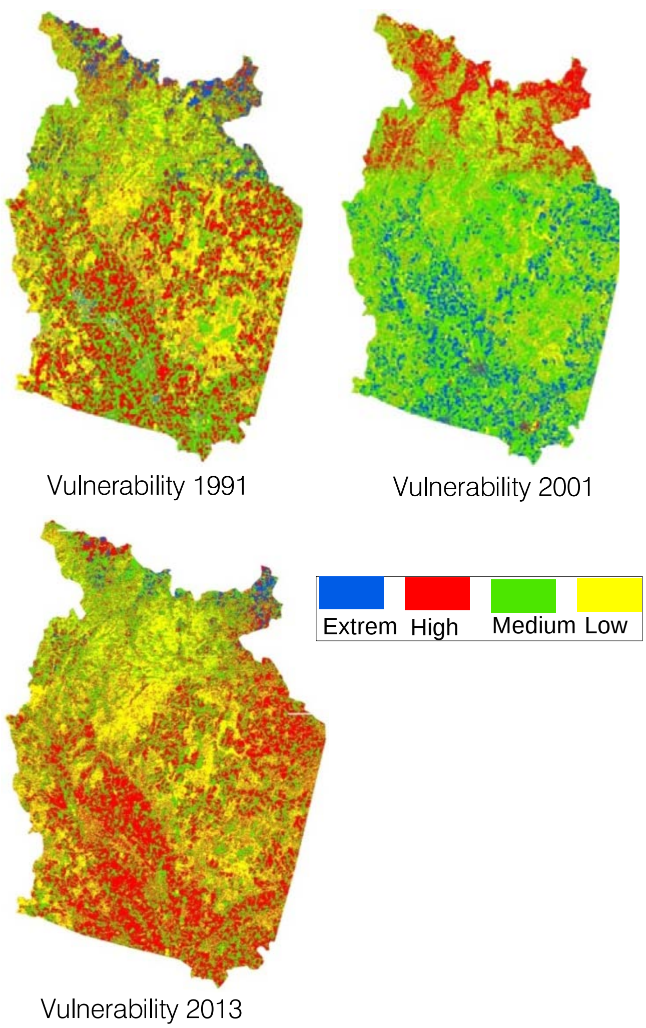


Fig. 5 : Vulnerability maps of the study area.

Figure 5 shows that extreme vulnerability was very less in 1991 but it was very high in 2001 due to degradation of forest and then 2013, its recover due to governmental protection. High vulnerability is present in areas, which is related to socio-economic activities. Low and medium vulnerability present in stable forest or low human impact areas.

i) Exposer intensity based on land use change

Since land use change was defined as the exposure of land classes in this study, we constructed Exposure Index (EI) based on land use intensity, which reflects the degree of human impact on natural land, containing information on patterns and their proportions of land use (Liu, 1996).

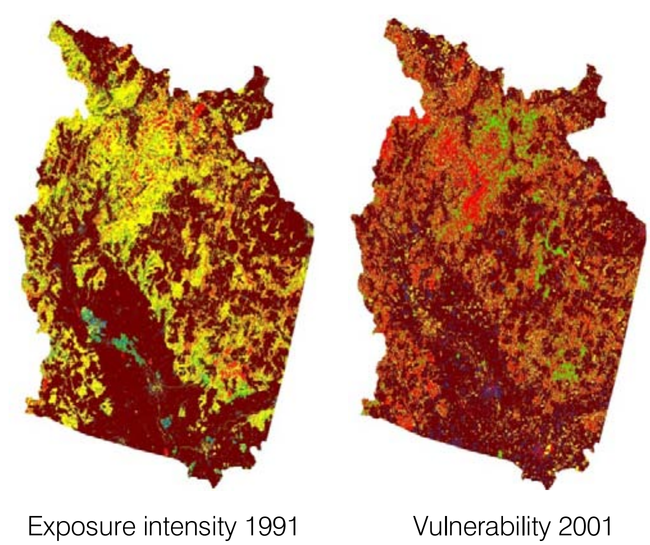
$$EI = \frac{i * c_i}{10} \quad (4)$$

Where EI is the Exposure Index, i is the rank of land use, Ci is the area percentage of land use of rank i. EI can be calculated according to Eq. (4) and Table 2. We make n = 4 in Table 2.

Table 2 : Correspond between types and ranks of land use

Types of land use	Rank (i)	Example
Limited used	1	Forest
Low impact used	2	Agriculture land
Medium impact used	3	Pasture and water body
High impact used	4	Settlements, tourism, industry, transport

Figure 6 show the exposer intensity of the study area. In all three decades exposer index is high in agriculture and socio-economic activities area, where human interaction is high. In protected forest area, exposer intensity is low due to less human interaction or less exploitation.



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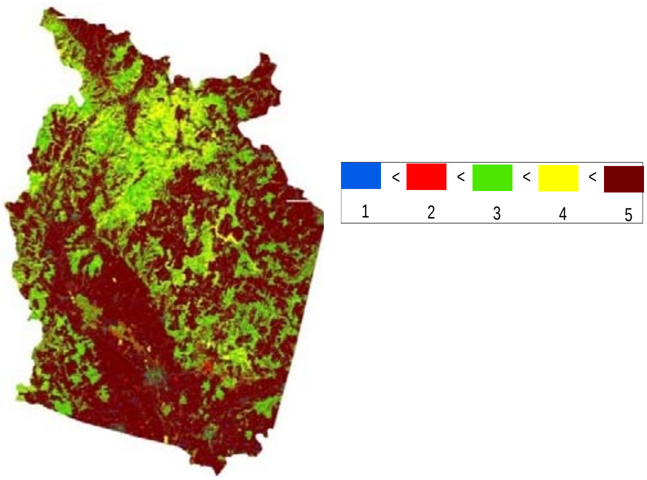

Vulnerability 2013

Fig. 6 : Exposer intensity maps of the study area

j) Evaluation principle and factors

For environmental vulnerability assessment, there is a need to determine the factors which pose negative impact on ecosystem and make sensitive the system. Following thematic layers were used for environmental vulnerability analysis: slope, aspects, height, vegetation and land use/cover maps. The whole vulnerability analysis work grouped in two parts first data preparation and second evaluation model. In first part: standardised maps were reclassified and recorded in raster maps. The principal component analysis (PCA) method, which using coefficients of linear correlation were used for the possibility weight of contributed factors [95, 96]. This study has developed an environmental vulnerability evaluation (EVE) model by spatial principal component analysis (SPCA) method, which is a modified PCA approach, whose schematic representation is shown in Fig. 7.

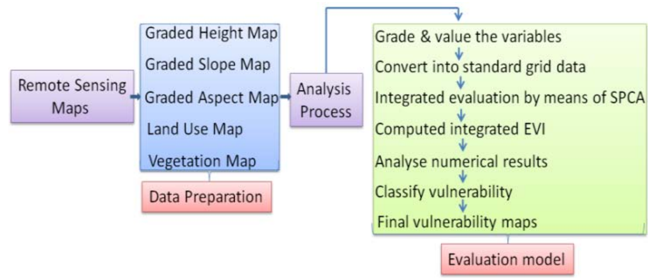

Fig. 7 : Schematic representation of numerical model of environmental vulnerability evaluation by means of spatial principal component analysis

The processes of environmental vulnerability evaluation by SPCA method are explained as follows: (1) to standardize primary data; (2) to establish a covariance matrix R of each variable; (3) to compute an eigenvalue λ_i of matrix R and its corresponding eigenvectors α_i; (4) to group αi by linear combination and put out *m* principal components. According to the cumulative contribution of principal components, the number of components was affirmed 6 and SPCA was accomplished. Then, an evaluation function [97] was setup for computing an integrated evaluation index on the basis of selected components shown as below:

$$E = \alpha_1 Y_1 + \alpha_2 Y_2 + \cdots + \alpha_m Y_m \qquad (5)$$

Where, Y_i is no. i principal component, and α_i is its corresponding contribution.

According to each component's weight and generated stack, the algebra computation is worked out and evaluation indexes are put out pointing the situation of regional environmental vulnerability, defined in this paper as environmental vulnerability index (EVI). The higher the EVI value, the more vulnerable environment is.

Table 3 : The results of spatial principal component analysis in the study
Selected principal components

	I	II	III	IV	V	VI
1991						
Eigenvalue	366.88	23.77	10.31	1.06	0.62	.05
Percent of Eigen Values	81.10	5.90	2.56	0.26	0.15	0.01
Accumulative of Eigen Values	81.10	87.00	89.56	90.83	93.98	95.00
2001						
Eigenvalue	824.01	100.1	24.96	9.55	2.64	.95
Percent of Eigen Values	85.63	10.40	2.59	0.99	0.27	0.09
Accumulative of Eigen Values	85.63	86.03	88.63	91.62	94.90	95.10
2013						
Eigenvalue	720.02	76.45	20.86	5.43	1.80	.80
Percent of Eigen	80.60	8.40	2.57	0.81	0.20	0.05

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Values						
Accumulative of Eigen Values	80.60	86.45	89.00	91.71	93.95	95.56

Derived from Table 3 and formula (8), the linear formulas for computing EVI is created as follows:

$$EVI_{1991} = 0.91 * A_1 + 0.06 * A_2 + 0.03 * A_3 + 0.003 * A_4 + 0.002 * A_5 + 0.0001 * A_6$$

$$EVI_{2001} = 0.85 * A_1 + 0.10 * A_2 + 0.03 * A_3 + 0.01 * A_4 + 0.003 * A_5 + 0.0009 * A_6$$

$$EVI_{2003} = 0.89 * A_1 + 0.08 * A_2 + 0.03 * A_3 + 0.008 * A_4 + 0.002 * A_5 + 0.0005 * A_6$$

In the formula, EVI is environmental vulnerability index, *A*1–*A*6 are six principal components sorted out from five initial spatial variables in 1991. Similarly, *B*1–*B*6 are principal components in 2001 and *C*1–*C*6 are the ones in 2013. The cumulative contribution of the six components is 95% (1991a), 95.10% (2001b) and 95.56% (2013c), respectively. Each of them lays in 95%, which accord with the convention of choosing factors by PCA method with a high reliability. However, there is still an information loss of about 5% when the number of selected components reaches six, which shows that the initial factors have relatively independent function on evaluation.

k) Vulnerability gradation using cluster principle

The EVI obtained by integrated vulnerability index calculation was a continuous value. To quantify the environmental vulnerability, the value was classified using the cluster principle and four classes were identified: Slight, light, Medial and Heavy vulnerability (Table 4).

Table 4 : The result of environmental vulnerability classification in the upper reaches of Minjiang River-valley

Evaluation level	Number	EVI	Feature description
Slight vulnerability	I	> 1.5	Relatively stable ecosystem and anti-interference ability, healthy dense vegetation and low altitude
Light vulnerability	II	1.5 - 2	Relatively unstable ecosystem and poor anti anti-interference ability complex vegetation distribution
Medial vulnerability	III	2 - 2.5	Unstable ecosystem, medial human interference, dominated by alpine shrub grass
Heavy vulnerability	IV	2.5 <	Extremely unstable ecosystem, high socio-economic activities, degraded forest

l) Vulnerability change trend

The change trend of environmental vulnerability was analyzed based on two approaches. First is qualitative approach, in that vulnerability values were divided qualitatively into grades: 1.Slight, 2.light, 3.Medial and 4.Heavy vulnerability. The analysis of vulnerability change trends for different years based on the grades of vulnerability was based on the area and area percent, occupied by each vulnerability grade. Secondly a quantitative approach in that the application of the weighted are sum of vulnerability values. The value obtained by calculating the total integrated environmental vulnerability index (EVSI) for each year using the function given by Li et al. 2005 and Brus, et al. 2013 as shown in eq. 6.

$$EVSI = \sum_{i=1}^{n} P_i \ X \ \frac{A_i}{S_j} \qquad (6)$$

In this formula, *n* is the number of valuation grade, EVSI*j* the EVSI in unit *j*, *Ai* the occupied area of grade *i* in analysis unit *j*, *Sj* the area of analysis unit *j*, and *Pi* is the graded value of grade *i*.

In general, the whole change trend can be worked out from change of EVSI value. This paper analyses the change trend through comparing the EVSI value of each period and the distribution of each level.

III. Results

a) Overall Changes

Agriculture and forested land makes up the largest percent of the study area with 35%, 40%, area in 1991 and vice versa in 2013 (Table 5). Forest makes up the largest land-cover, and occurs predominantly in the more upland areas with greater relief. Forest area decrease (222.53 Km^2) slightly during the first half of the study period but then increase (35.78 Km^2) during the second half of the study. Water makes up less than 15% of the upland landscape for all years of the study. Table 5 provides the areas of each class. The total area of the study area was 2000 km^2. From 1991 to 2001, there has been a net decrease of forest is 11.13 percent. But in 2001 to 2013, 6.71 percent forest area was added. Pasture and agriculture was added 4.44 and 5.17 percent respectively from 1991 to 2001 but both area reduce (7.08 and 3.23 respectively) from 2001 to 2013. These changes show governmental protection of forest

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area in between 2001 to 2013. Table 5 shows that no change in number of settlements from 1991 to 2001 but for next decay settlements and water body area were increased.

Table 5 : Land cover areas (km^2) change for 1991, 2001 and 2013

	1991		2001			
Class	**Area**	**%**	**Area**	**%**	**Area Diff.**	**% Diff.**
Water	209.85	10.49	243.77	12.19	33.92	1.7
Forest	804.02	40.2	581.49	29.07	-222.53	-11.13
Settlement	29.87	1.49	26.42	1.32	-3.45	-0.17
Pasture	213.03	10.65	301.75	15.09	88.72	4.44
Agriculture	743.23	37.16	846.57	42.33	103.34	5.17
Total	**2000**	100	**2000**	100		

	2001		2013			
Class	**Area**	**%**	**Area**	**%**	**Area Diff.**	**% Diff.**
Water	243.77	12.19	298.85	14.94	55.08	2.75
Forest	581.49	29.07	715.61	35.78	134.12	6.71
Settlement	26.42	1.32	43.55	2.18	17.13	0.86
Pasture	301.75	15.09	160.09	8	-141.66	-7.08
Agriculture	846.57	42.33	781.9	39.09	-64.67	-3.23
Total	**2000**	100	**2000**	100		

Regarding the management, the analysis of vegetation characteristics shows that in Jesnilk areas, stands are in better condition, with bigger trees showing larger basal area and larger crowns, showing evidence of little exploitation. The low wood exploitation is also unfavorable to the activation of vegetative regeneration for holm oak stands, which may in the long term endanger its sustainability. Conversely, the coppice resource dominates, trees are degraded and the abundance of holm oak coppices emphasizes the intensity of wood exploitation. When tree cover is maintained, it is often due to bushy stands, resulting from the degradation of previous tree clusters. During field visit and key note interviews we find that, tourism and socioeconomic activities are responsible for these land cover disturbance.

b) Types of Change

Change trajectories between the years 1991, 2001, and 2013 were compared on a pixel-by-pixel basis to examine possible land-cover disturbance (Tables 6). Thirty three percent of the landscape remained in the same land-cover class from 1991, 2001 to 2013. Two-date changes (1991–2001 and 2001–2013) show 950 km^2 forest and 3000 km^2 agriculture area was stable in last two decades. 140 km^2 agriculture, 20 km^2 forest and 18 km^2 pasture area encroached by settlements from 2001 to 2013. Stable forest cover mostly was located in high elevation areas of the mountain, especially in Jesenilk, Bruntal, Sumperk and Rymarov.

Table 6 : Types of changes between 1999 and 2013 for areas analysed

Cross table 1991-2001						
CLASS	WATER	FOREST	SETTLEMENT	PASTURE	AGRICULTUR	**Total**
Water	235.38	148.87	0.47	20.04	19.8	**424.56**
Forest	266.97	974.07	8.02	331.45	202.03	**1782.53**
Settlements	0.35	31.94	5.66	39.84	66.12	**143.92**
Pasture	1.53	77.09	2.12	135.31	259.78	**475.84**
Agriculture	12.38	72.37	168.32	333.33	3404.05	**3990.44**
Total	**516.62**	**1304.33**	**184.58**	**859.97**	**3951.78**	**6817.29**
Cross table 2001-2013						
CLASS	WATER	FOREST	SETTLEMENT	PASTURE	AGRICULTUR	**Total**
Water	318.72	161.83	4.6	15.68	19.68	**520.51**
Forest	179.63	988.09	20.39	50.45	57.76	**1296.32**
Settlements	0.12	12.49	11.79	5.54	156.41	**186.35**
Pasture	2.36	462.99	18.74	120.7	262.02	**866.81**
Agriculture	3.3	237.62	140.5	322.02	3239.15	**3942.59**
Total	**504.12**	**1863.03**	**196.02**	**514.38**	**3735.02**	**6812.57**

However, it may not absolutely represent the real land cover disturbance because of the difficulty of modelling the factors influencing this disturbance and the magnitude of human reaction capacity. On the other hand, the pressure exerted on forest depends on the socio-economic and tourist context and may change in the future, according to the disturbance that these societies are experiencing. Indeed, the rapid opening up of the study area due to tourism since the 1980s, the development of commercial agriculture and the national and international development initiatives—electrification in 2002, the introduction of the gas stove, the emergence of the cell phone in 2005, foreign aid offered by different NGOs—have widely contributed to accelerating the land disturbance of practices, as well as creating new production systems likely to partially reduce the pressure exerted on the forest and agriculture. One example of these tendencies is the slight decline of pastoralism, which reduces the cutting of leaf fodder during the cold season.

c) Impact of Tourism

Table 7 summarizes the changes in land cover extent by proximity for all 3 tourism facilities. From 1991 to 2001 forest area was reduce in 0 - 5, 5 - 10 and 10 to 15 km^2 distance in all three tourist site. But it's increase from 2001 to 2013. In Olomouc there is negligible forest area from 0 to 15 km^2 so total area of forest removal is very less. In the village of Rymarov, removal of forest area is more than double of Olomouc. As Jesenilk is very high dense forest area so here removal of forest area was very high. In Jesnilk from 0 - 5, removal of forest is 16.31%, 5 - 10 km is 12.82% and from 10 to 15 km removal of forest is 8.55% area from 1991 to 2001. It could be concluded from this that tourism villages do have an impact on the forest; however, there is considerable geographical variation as shown in table 8. In Olomouc and Rymarov agriculture area was decrease but pasture area was increased from 1991 to 2001 for all 0 to 15 km^2 distance. Both areas were decrease from 2001 to 2013 for all 0 to 15 km^2 distance. For Jesenilk,

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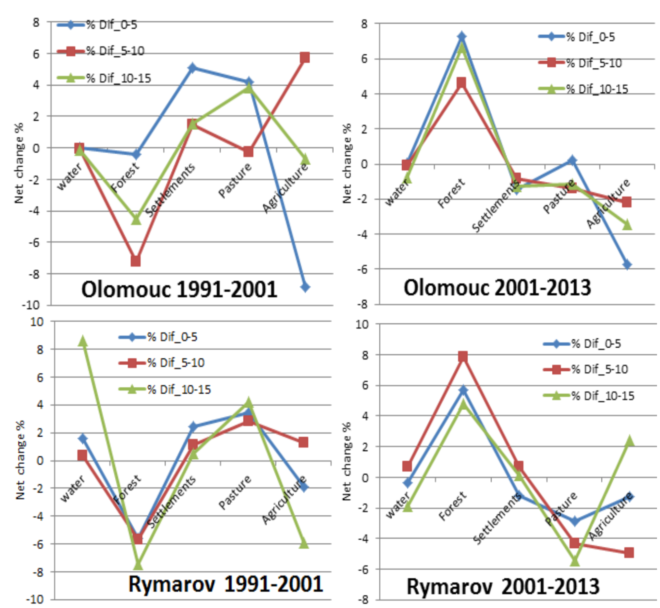
pasture and agriculture both have similar behaviour like Rymarov.

Table 7 : Net land cover change from 0 to 15 km^2 area summary table

Olomouc	0 to 5Km	1991		2001				2013		
Class	Area	%	Area	%	Area Diff.	% Diff.	Area	%	Area Diff.	% Diff.
water	0.34	0.4	0.34	0.4	-0.01	0	0.36	0.43	0.023	0.03
Forest	5.25	6.14	4.78	5.72	-0.46	-0.42	10.92	12.98	6.136	7.26
Settlements	4.35	5.1	8.50	10.17	4.15	5.07	7.02	8.35	-1.478	-1.48
Pasture	2.74	3.2	6.19	7.41	3.46	4.21	6.43	7.64	0.236	0.24
Agriculture	72.75	85.16	63.80	76.31	-8.95	-8.85	59.37	70.6	-4.43	-5.71
Total	85.43	100	83.61	100			84.10	100		
	5 to 10Km									
water	1.70	0.71	2.27	0.95	0.57	0.24	2.05	0.84	-0.22	-0.11
Forest	15.00	6.24	11.21	4.68	-3.79	-1.56	22.60	9.26	11.39	4.59
Settlements	6.82	2.84	10.57	4.41	3.75	1.57	8.65	3.55	-1.92	-0.86
Pasture	8.37	3.48	17.99	7.50	9.62	4.02	14.90	6.11	-3.09	-1.40
Agriculture	208.44	86.73	197.67	82.46	-10.77	-4.27	195.77	80.24	-1.9	-2.22
Total	240.33	100.00	239.71	100.00			243.97	100.00		
	10 to 15Km									
water	8.15	2.07	7.83	1.96	-0.32	-0.11	4.64	1.19	-3.19	-0.77
Forest	50.38	12.77	32.92	8.23	-17.46	-4.53	58.07	14.87	25.15	6.63
Settlements	11.37	2.88	17.66	4.42	6.29	1.54	12.17	3.12	-5.49	-1.30
Pasture	22.25	5.64	37.78	9.45	15.53	3.81	32.49	8.32	-5.29	-1.13
Agriculture	302.50	76.65	303.58	75.94	1.08	-0.71	283.21	72.51	-20.37	-3.43
Total	394.65	100.00	399.77	100.00			390.58	100.00		
Rymarov	0 to 5Km	1991		2001				2013		
Water	2.59	3.13	3.84	4.72	1.25	1.59	3.56	4.34	-0.28	-0.38
Forest	14.88	17.94	10.05	12.35	-4.84	-5.59	14.79	18.03	4.75	5.68
Settlementa	0.98	1.18	2.92	3.58	1.94	2.40	1.98	2.42	-0.93	-1.16
Pasture	4.37	5.27	7.12	8.74	2.75	3.47	4.83	5.89	-2.29	-2.85
Agriculture	60.12	72.48	57.46	70.61	-2.66	-1.87	56.88	69.32	-0.58	-1.29
Total	82.94	100	81.38	100			82.05	100		
	5 to 10Km									
Water	11.77	4.89	25.99	10.88	14.22	5.99	27.56	11.59	1.57	0.71
Forest	92.97	38.62	63.77	26.69	-29.20	-11.93	82.17	34.55	18.40	7.86
Settlementa	3.31	1.37	3.02	1.26	-0.29	-0.11	4.67	1.96	1.65	0.70
Pasture	22.97	9.54	28.12	11.77	5.15	2.23	17.67	7.43	-10.45	-4.34
Agriculture	109.74	45.58	118.03	49.40	8.29	3.82	105.76	44.47	-12.27	-4.93
Total	240.76	100.00	238.93	100.00			237.83	100.00		
	10 to 15Km									
Class	Area	%	Area	%	Area Diff.	% Diff.	Area	%	Area Diff.	% Diff.
Water	27.65	7.01	58.54	15.66	30.89	8.65	55.55	13.75	-2.99	-1.91
Forest	140.70	35.66	105.49	28.22	-35.21	-7.44	133.45	33.03	27.96	4.81
Settlementa	5.33	1.35	6.93	1.85	1.60	0.50	7.88	1.95	0.95	0.10
Pasture	31.96	8.10	46.00	12.31	14.04	4.21	27.84	6.89	-18.16	-5.41
Agriculture	188.95	47.89	156.87	41.96	-32.08	-5.92	179.33	44.38	22.46	2.42
Total	394.59	100.00	373.83	100.00			404.05	100.00		
Jesenik	0 to 5Km	1991		2001				2013		
Water	9.81	11.87	27.437	28.31	17.63	16.44	12.34	15.29	-15.09	-13.02
Forest	31.25	37.82	20.851	21.51	-10.40	-16.31	27.73	34.35	6.88	12.84
Settlementa	1.51	1.83	1.555	1.6	0.04	-0.23	2.48	3.08	0.93	1.48
Pasture	9.74	11.79	11.345	11.7	1.61	-0.09	8.48	10.5	-2.87	-1.29
Agriculture	30.32	36.7	35.74	36.87	5.42	0.17	29.69	36.78	-6.05	-0.09
Total	82.63	100	96.93	100			80.73	100		
	5 to 10Km									
Water	35.25	14.54	31.53	13.86	-3.72	-0.68	57.59	24.01	26.06	10.15
Forest	122.84	50.68	86.11	37.86	-36.73	-12.82	104.04	43.37	17.93	5.51
Settlementa	1.42	0.59	1.20	0.53	-0.22	-0.06	3.71	1.55	2.51	1.02
Pasture	26.98	11.13	37.76	16.60	10.78	5.47	19.97	8.32	-17.79	-8.28
Agriculture	55.91	23.07	70.85	31.15	14.94	8.08	54.57	22.75	-16.28	-8.40
Total	242.40	100.00	227.45	100.00			239.88	100.00		
	10 to 15Km									
Water	40.97	11.55	51.49	14.64	10.52	3.09	78.76	22.14	27.27	7.50
Forest	157.95	44.54	126.54	35.98	-31.41	-8.55	143.81	40.43	17.27	4.45
Settlementa	2.75	0.78	3.77	1.07	1.02	0.30	6.04	1.70	2.27	0.63
Pasture	36.69	10.35	51.78	14.72	15.09	4.38	23.48	6.60	-28.30	-8.12
Agriculture	116.29	32.79	118.09	33.58	1.80	0.79	103.62	29.13	-14.47	-4.45
Total	354.65	100.00	351.67	100.00			355.71	100.00		

The analysis of overall disturbance in Jesnilk area through remote sensing appears that many areas mapped as "stable" also experienced a strong exploitation of vegetation which may have led to qualitative land cover disturbance. More generally, the various canopy cover mapped using remote sensing may show very different morphology, which means that the changes in terms of area and percentage cover revealed by remote sensing analysis may neglect, at least locally, the qualitative disturbance of the vegetation.

Fig. 8 shows the proportional change in forest with increasing distance from the three tourist site. These graphs provide trend lines, which show both positive and negative relationships between land cover change (Forest, Agriculture, Settlements, Water body, Pasture) and distance from villages. A positive trend shows that with less distance from the city/villages there is more removal of forest, agriculture (relative to the forest, agriculture area available), which is what you would expect based on Von Thunen's model of resource use (increasing resource use with decreasing distance to markets). In Olomouc from 1991 to 2001 water was stable, forest, agriculture was go in negative direction and settlement, pasture in positive direction for all three distance (0 – 15 km^2). In 2001 to 2013 forest protected and increase in positive direction. Other classes was stable or in negative direction. In Rymarov forest and agriculture was go in negative direction but rest classes was grow in positive direction from 1991 to 2001. In next decay forest was grow in positive direction but rest classes was stable or over all in negative direction. Jesnilk results are also very much similar to Olomouc and Rymarov (fig. 8). This is showing forest protection from 2001 to 2013. Bruntal, Sumperk, Jeseník, Rymarov, Zabreh, Unicov, Litovel, and Prostejov are in an area of forest and pasture development and located at the northern part of the study area. Hranice, Opava, Krnov, Stemberk, Olomouc,Vitkov, Mohelnice and Prerov are in an area of agriculture oriented and located in south part of study area.



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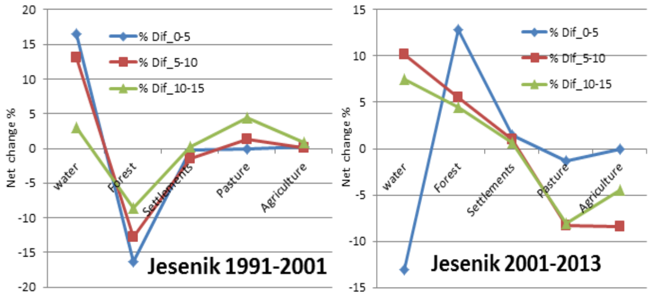

Fig. 8 : Net changes in land cover area around individual tourism facilities

Fig. 8 also displays the separate trends in forest change in relation to distance for each of the three analyzed places. Olomouc is located in the south part of study area and is a relatively large town with plenty of visitors and through traffic from trekkers, tourists, which explains the high level of forest removal. The trend line has a positive relationship indicating decreasing forest removal at greater distance from the settlement. Jesenilk also shows the same positive relationship and a high proportion of forest removal. Rymarov is in an area with little agriculture, suggesting that tourism and socioeconomic activities could be the main reason for forest harvesting. There has also been a road development in this area allowing tourists to reach Jesnilk much faster than in the past. The new road could also make it easier to export logs from this region.

d) Land Classification Change

In the image classification agriculture land makes up the largest percent of the Olomouc region with 37%, 42%, and 39% respectively for 1991, 2001, and 2013 (Fig. 9). Forest makes up the next largest land-cover, and occurs predominantly in the more upland areas with greater relief. Forest area decrease dramatically during the first half of the study period from 40% to 29% but then rigid to 35% during the second half of the study. Other classes make up around 25% of the all over the study area for last three decades.

Figure 9 illustrates the land cover classification results of the study area. This comprehensive analysis of land cover provides both the timing and nature of land cover changes. To simplify for illustration purposes, we categorized three major categories of land cover classes: forest, agriculture and others (settlement, water body and pasture). For example, we can easily derive information since past 30 years. The largest loss of forest was from forest to develop and the largest gain of forest was from barren to forest in the study area. It can also provide new kinds of information about what kind of land cover change occurred on a yearly basis for the entire scene.

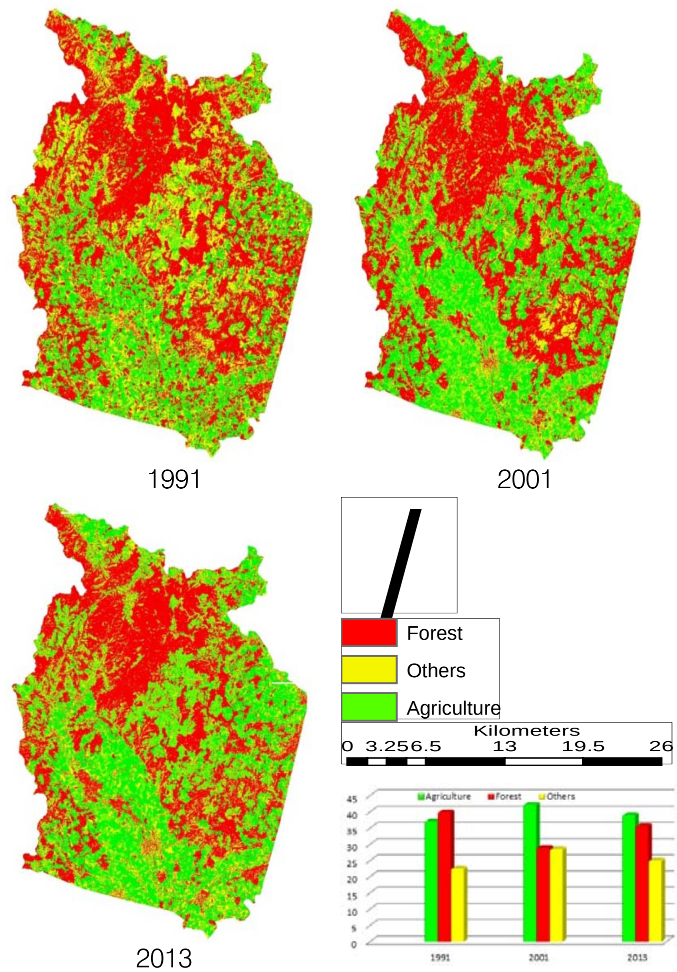

Fig. 9 : Land cover classification for the Olomouc region for 1991, 2001, and 2013

The change that occurred at these pixels was obvious when viewed from the perspective of the entire time series. This approach allows the identification of the timing of each change, as well as the kind of change. When the time series has been built for a pixel and analyzed for change, it is possible to use the estimated time series models between the changes to identify the land cover class for the pixel at different time periods. For the pixel located at first year, the estimated model preceding the change in 1991 can be used to classify the land cover for the entire time prior to the change. Similarly the estimated method subsequent to the change can be used to identify what land cover came after the change in 1991. The shape of the time series method can be very helpful in land cover classification which is evident in the time series graphs at the bottom, as initially pixels located in year 1991 and 2013 were conifer forest and pixel located in 2001 was a hardwood forest, and they are readily distinguishable by the difference in the amplitude of their time series.

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Table 8 : Results of land use/land cover classification for 1991, 2001 and 2013 images showing area of each category and class percentage

Class	1991	%	2001	%	2013	%
Agricultur	743.23	37.16	846.57	42.32	781.9	39.09
Forest	804.02	40.02	581.49	29.07	715.61	35.78
Others	452.48	22.62	571.94	28.59	502.49	25.12
Total	2000		2000		2000	

e) Change Detection

Figure 9 shows the land cover classifications produced for 1991, 2001 and 2013 from Landsat images, and figure 10 shows the areas of forest addition and removal. Table 8 provides the areas of each class. The total area of the study area was 2000 km^2. From figure 9, it is clear that most of the forest is in the northern part of the study area, which has higher elevation and higher rainfall. This area has larger trees suitable for timber production and is closer to major urban areas, such as Bruntál, Šumperk, Jeseník, Rýmařov. In this area there has also been forest added but this was less than what has been removed. In the flat southern region, figure 10 shows that more forest has been removed than added, but the extent of this change was small compared to the changes in the north. The spatial analysis in relation to socio-economic activities confirms this.

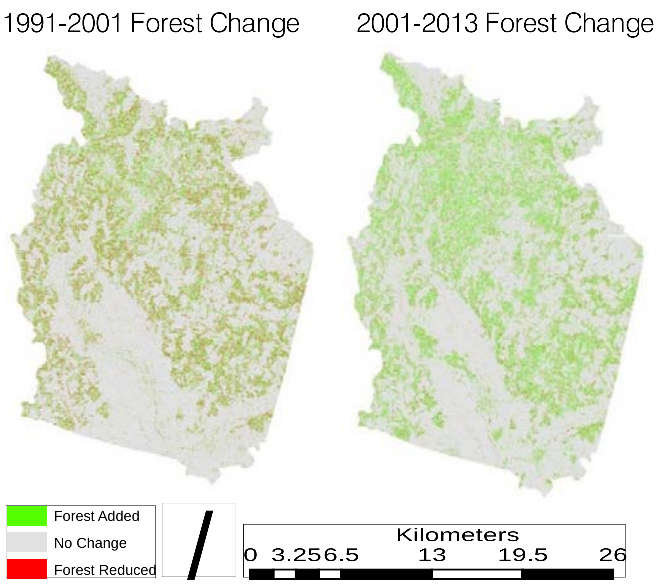

Fig.10 : Increase and decrease in forest cover

Change trajectories between the years 1991, 2001, and 2013 were compared on a pixel-by-pixel basis to examine possible land-cover disturbance (Tables 9). Thirty three percent of the landscape remained in the same land-cover class from 1991 to 2013. Two-date changes (1991–2001 and 2001–2013) show that, 2300 km^2 forest and 1500 km^2 agriculture area was stable in last two decades. 140 km^2 agriculture, 20 km^2 forest and 18 km^2 pasture area was encroached by settlements from 2001 to 2013. In 2001, 260 km^2 other classes and 480 km^2 agriculture area added in forest area. 313 km^2 others and 127 km^2 agriculture areas were removed from forest area from 1991 to 2001. 118 km^2 agriculture and 245 km^2 other class area added in forest class. Stable forest cover area was mostly located in high elevation area of the mountain, especially in Jesenilk, Bruntal, Sumperk and Rymarov.

Table 9 : Types of changes between 1999 and 2013 for areas analysed

1991-2001	Forest	Others	Agriculture	Total
Forest	2340	313	127	2780
Others	262	427	437	1126
Agricultur	480	901	1525	2906
Total	3082	1641	2089	6812
2001-2013	Forest	Others	Agriculture	Total
Forest	2348	277	467	3092
Others	245	477	902	1624
Agricultur	118	479	1495	2092
Total	2711	1233	2864	6808

This study employed the post-classification change detection technique, which was efficient in detecting the nature, rate and location of changes, and has been successfully used by a number of researchers in the study of natural resources [97]. An overlay procedure using the GIS was adopted in order to obtain the spatial changes in land cover during two intervals: 1991–2001 and 2001–2013. Application of this technique resulted in a two-way cross-matrix, describing the main types of change in the study area. Cross tabulation analysis on a pixel-by-pixel basis facilitated the determination of the quantity of conversions from a particular land cover class to other land use categories and their corresponding area over the period evaluated. A new thematic layer containing different combinations of ''from–to'' change classes was also produced for each of the two three-class maps (Table 9).

Using the Landsat datasets, we calculated producer accuracy for all potential change pixels at three decade time steps. In the study area, within-class and between-years reveal different characteristics of change. Figure 10 shows examples of within-class and between-years changes for 1991-2001 and 2001-2013. The within-class distances appear to highlight the contrast between forest and non-forest areas in a given year. The between-year changes are noisier, but highlight locations with large differences between two years including newly changed areas and agricultural areas that were inherently more variable.

f) Analysis Based on Trajectories

This three decade trajectories analysis was focus on forest, agriculture and different factors drive changes in the region. Two-date changes (1991–2001 and 2001–2013) show stable non-forest (agriculture and

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others) areas cover over 38% landscape while stable forest cover (F–F) drops from 54% (Table 10). In the study area old permanent agriculture regrowth and regrowth with new clearing class was 1.07% of the total area. Forest regrowth with new clearing and old permanent forest regrowth area was around 4% of the total area. Old permanent agriculture clearing area was approximately 2% of the total area. The 3-date change trajectories allow us to determine a single pixel's trajectory over time with more details (Table 10).

In the study many small fields were cleared and then were reforested (O–F–F), while many other small areas had O–F–O trajectories. Our field observations demonstrated that these were smallholder fields of shifting agriculture that were growing maize, pineapples, or other cash crops that were probably used in restaurants in Olomouc region. There was not any recent agriculture regrowth (O–O–A) and recent forest regrowth (O–O–F) class in the study area. But due to some specific location requirement old agriculture with regrowth (A–O–A) and old permanent agriculture clearing (A–O–O) was present (Fig. 11).

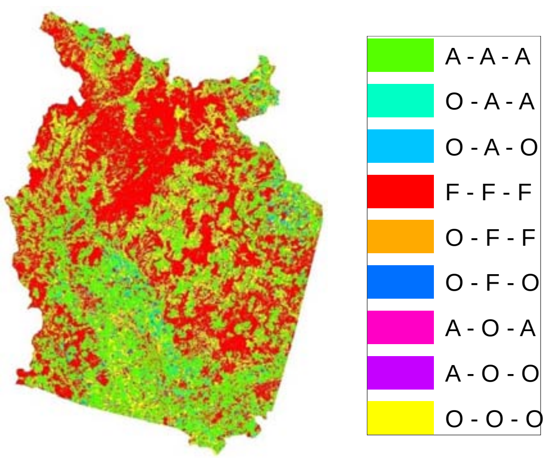

Fig. 11 : Land-cover classification trajectories for 1991–2001–2013 in the Olomouc. ''F'' refers to forest, "A" agriculture and ''O'' to other classes (pasture, settlements, water body)

After change trajectory calculation, distribution map of all the trajectories in the study area from 1991 to 2013 were generated. In the map, green, red and yellow pixels stand for "no change", while others stand for all kinds of "change". However, some trajectories would never happen and some others may take much small parts in all the trajectories so that they can be omitted. Through majority analysis with a 5×5 mask, the scattered trajectories with small count numbers in the whole area were assigned the value of neighbors in majority. It suggests that these changes were extensively induced by organized human activities, which coincides with the local practical situation. The study area suffers serious soil losses, which has brought great damage to the local residents. In order to conserve soil, the government has called on the local people to take measures to better the ecological environments.

Table 10 : Land-cover change trajectories in Olomouc and their descriptions 1991, 2001, 2013

	Change trajectory			Description	Area (km^2)	%
	1991	2001	2013	LULC change classes		
1	Agriculture	Agriculture	Agriculture	Stable primary or secondary agriculture	333.79	16.69
2	Other	Agriculture	Agriculture	Old and permanent agriculture regrowth	11.57	0.58
3	Other	Agriculture	Other	Agriculture regrowth with new clearing	9.88	0.49
4	Forest	Forest	Forest	Stable primary	1086.57	54.33

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6	Other	Forest	Other	Forest regrowth with new clearing	61.66	3.08
7	Agriculture	Other	Agriculture	Old agriculture clearing with regrowth	8.32	0.42
8	Agriculture	Other	Other	Old and permanent agriculture clearing	38.76	1.94
9	Other	Other	Other	Stable primary or secondary others	439.64	21.98
10	Other	Other	Agriculture	Recent agriculture regrowth	-	-
11	Other	Other	Forest	Recent forest regrowth	-	-

During the first and second periods, the main trajectories were dominated by deforestation transitions that led to the decline of old growth forests and the increase of arboreous shrub land as a result of logging practices. A remarkable finding was, however, that the transition from old growth forest to arboreous shrub land changed from highly systematic in the first period to highly random in the second, similar to the majority of the transitions affecting native forest cover between 1991 and 2001. This finding suggests that the same type of transition (deforestation in this case) can be caused by either permanent or sudden forces that take place in the landscape. In the study area, the period of random changes (and coincidentally of a large amount of swap change) coincides with the beginning of the globalization process, characterized by trade liberalization policies and structural adjustment reforms which opened up the economy to international trade, favored international investments, and reduced the role of the state in favor of market mechanisms to drive development [98]. The arrival of salmon and mussel farming and the transnational processing industries shows us how the globalization process manifested itself in the study area. During the 1991 and 2001's, rural migration rates and urban population increased, thus expanding the demand for firewood, the main product extracted from native forests in northern part. Added to this increased logging, the "woodchips exporting boom" (early 1990's to mid-2000's), led to abrupt deforestation, as indicated by the direct change from old growth and secondary forest to shrub lands through clear cutting.

g) Correlation in vulnerability index and exposer index for all land cover classes

VI was calculated based on the results of SI and AI (Eq. 2). The values of VI and EI in five land cover classes are presented in Fig. 12. The result demonstrates that vulnerability of land cover classes tends to increase with the increase of Exposure Index, although this correlation does not follow a linear trend. Settlement is the most vulnerable one in five land cover classes. Explanations for the curve are: (1) water class follows relatively slow process of change, and still maintain stability. (2) Land use is changed rapidly in settlements, forest and agriculture, leading to rapid socio-economic transformation. The traditional agricultural system is collapsing, but emerging system on industry and commerce is trying to establish. These changes make the system vulnerable. In other words, these land-cover classes lost too much and gain too little from development. (3) Agriculture area encroached by other classes for commercial and urban residential and that`s why exploited most. Economic development and land use type are both relatively stable. No change or stable areas have much time to adjust in these changes and show stronger adaptive capacity.

Table 11 : Land use/cover area in three decade

	1991		2001		2013	
Class	**Area**	**%**	**Area**	**%**	**Area**	**%**
Water	209.85	10.49	243.77	12.19	298.85	14.94
Forest	804.02	40.2	581.49	29.07	715.61	35.78
Settlement	29.87	1.49	26.42	1.32	43.55	2.18
Pasture	213.03	10.65	301.75	15.09	160.09	8
Agriculture	743.23	37.16	846.57	42.33	781.9	39.09
Total	**2000**	100	**2000**	100	**2000**	100

Comparing of EI and VI for last three decades, water have lowest vulnerability index and settlements have highest vulnerability index due to high socio-economic activities (Fig. 12). Agriculture has highest exposer index and second highest vulnerability, which

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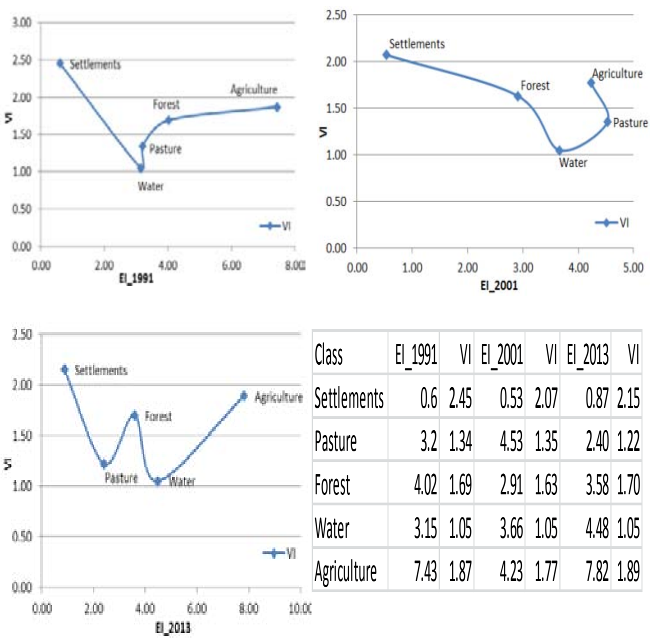
show its high rate of production and conversion. From 1991 to 2001 exposer intensity was reduced due to utilization of pasture area. Forest area have very less variation in vulnerability from 1991 to 2013 but its exposer was high from 1991 to 2001 and then stable due to governmental protection from 2001 to 2013. Water class is stable but from 2001 to 2013, its exposer was little bit high due to urbanization and industrialization. Pasture area have always second lowest vulnerability and low exposer rate but it was highest exposed in 2001 because it was used in place of agriculture land (Fig. 12).



Class	EI_1991	VI	EI_2001	VI	EI_2013	VI
Settlements	0.6	2.45	0.53	2.07	0.87	2.15
Pasture	3.2	1.34	4.53	1.35	2.40	1.22
Forest	4.02	1.69	2.91	1.63	3.58	1.70
Water	3.15	1.05	3.66	1.05	4.48	1.05
Agriculture	7.43	1.87	4.23	1.77	7.82	1.89

Fig. 12 : Correlation of Vulnerability Index (VI) and Exposure Index (EI)

Figure 13 shows all land cover class change gradient of development. From a temporal perspective, all land cover classes in Olomouc was transformed into developed area in different time frame because of the higher exposer intensity in agriculture area. In 1991 all classes were less developed in compare of 2013. Then these all classes underwent the transformation process respectively in the 1991, 2001 and 2013, which included three stages: land acquisition for construction, industrial estate development and improvement of urbanization or settlements. This process started in settlements in 1991 and later in other classes. Spatial gradient of vulnerability five land cover classes in 2013 can be considered as representing temporal gradient of one land cover class in five stages. Therefore, the results of vulnerability analysis over area helped us to know how vulnerability of an area land use change process. Undeveloped or less developed area was vulnerable within the land use change process. However, with resilience in difficult situations, it was adaptive and less vulnerable after its turning into developed area.

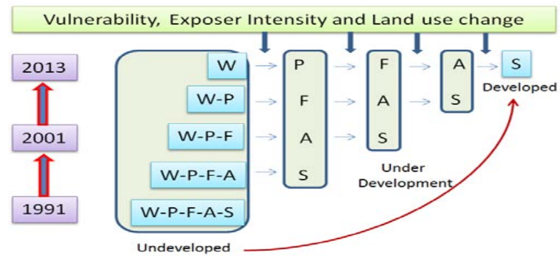


Fig. 13 : Transformation of five land cover classes over past 3 decades. S = Settlements, A = Agriculture, F = Forest, P = Pasture, W = Water

Generally, the curve of VI–EI is an inverted-U shape, which means VI will raise at first and drop later with the growth of EI. Besides, we cannot conclude every land cover class would develop through the path from rural stage to urban stage. In this case, the land use intensity of water did not change significantly during 1991–2013, the EI and VI of water was the least. If the land use will not evolve from agriculture to industrial and finally to urbanization in this area, the VI might decrease, considering the AI will improve with the development while the SI will remain stable. Furthermore the five stages are definitely typical ones, because they represent four types of driving forces for land use change, which are agricultural, governmental, industrial, and commercial forces (Fig. 13). Agricultural force is the weakest one with the limit of productivity. Governmental and industrial forces always get entangled and are the most powerful forces to change the land use intensity. It is a weak pressure on land use intensity that land use type changes from industrial use to commercial use or residential use. These findings suggest that the more powerful driving force, the more pressure on land use intensity and the more the impact on natural resources. However, if the land covers classes own a strong adaptive capacity; their vulnerability can be trailed off [99].

Table 11 presents characteristic of environmental vulnerability level and EVI. Stability is the main parameter for environmental vulnerability levels. The calculated values of EVSI of the study area for each year and percentage area of each vulnerability levels are presented in Table 12. Change trends show that EVSI decrease continuously from 2.11 to 2.01 from the year of 1991 to 2013. Results show that: (a) during 1991 and 2001, slight and heavy vulnerability levels had decreased by 33.83% to 27.16% and 11.20% to 0.85% respectively. Where light and medial vulnerability increased 31.95% to 39.20% and 23.02% to 32.79% respectively. (b) During 2001 to 2013, slight and heavy vulnerability increased by 27.16% to 32.04% and 0.85% to 4.55% respectively. However, in the same period light and moderate vulnerability were decrease from 39.20% to 39.15% and 32.79% to 24.26% respectively. Medial environmental vulnerability was shown in entire three decade period.

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Table 12 : Computed results from formula 3 and percentage area of each vulnerability level

Vulnerability	1991			2001			2013		
	Area	%	EVSI	Area	%	EVSI	Area	%	EVSI
Slight	676.69	33.83		543.15	27.16		640.86	32.04	
Light	638.96	31.95		784.07	39.20		782.96	39.15	
Medial	460.37	23.02	**2.11**	655.75	32.79	**2.07**	485.26	24.26	**2.01**
Heavy	223.98	11.20		17.03	0.85		90.92	4.55	
Total	**2000.00**	**100.00**		**2000.00**	**100.00**		**2000.00**	**100.00**	

h) Vulnerability Grade

Vulnerability evaluation showed in figure 14 and 15 for the year 1991, 2001 and 2013. The general environmental vulnerability trend shown in table 12 that the situation in 2013 with an EVSI 2.01 is better than 2001 with an 2.07 and latter is better than 1991 with an 2.11. The high value of EVSI means more serious situation. It show that the light vulnerable zone lies within average-value range with the largest area proportion accounting for 31.95%, the medial vulnerable zone account for 23.02%, the slight vulnerable zone account for 33.83%, and the heavy vulnerable zone accounts for 11.20%. The profile of index shows an asymmetry normal distribution and the center of profile lean to "medial" level in 1991, shown in Fig.1 4. In 2001 slight, light, medial and heavy vulnerability was 27.16%, 39.20%, 32.79% and 0.85% respectively. And in 2013 slight, light, medial and heavy vulnerability was 32.04%, 39.15%, 24.26% and 4.55% respectively.

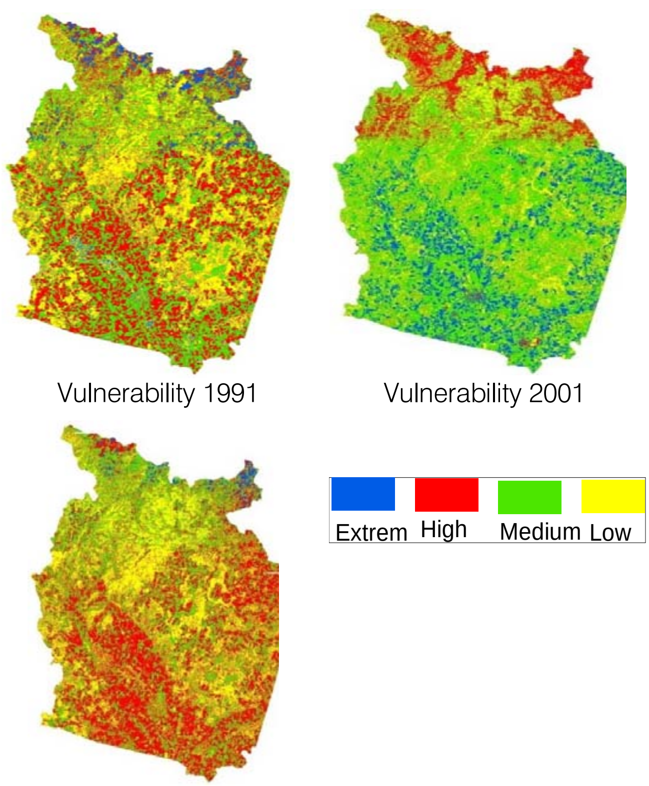

Fig. 14 : Environmental vulnerability maps of the study area

Landscape stability of the study area was observed to be very dynamic. The area is under the influence of different land use activities namely agriculture, infrastructure development, mining and industry. Based on the influences of these activities, the size of the area characterized by each degree of vulnerability in each year has also been changing in a floating pattern. There is neither continuous increase nor decrease of a particular vulnerability grades. Through the visual interpretation of fig. 14 above, the heavy vulnerability grade seem to extend outwards all directions from the center.

i) Geographical Distribution of Vulnerability

Figure 15 shows that heavy environmental vulnerability was very high in 1991 but it was very less in 2001 due to protection of forest and then again little bit increase in 2013. Heavy vulnerability is present in areas, which is related to socio-economic activities. Slight and light environmental vulnerability is present in stable forest or low human impact areas. Percentage levels for slight and light increased, while it decreased for moderate and heavy levels as the altitude increased. Environmental vulnerability related to slope at low to moderate levels was found to be confined between 20° to 50°. However, heavy vulnerability level was recorded in a steepest slope situation. Slight and light vulnerability levels concentrated in north, north-east, north-west and west aspects. While medial and heavy vulnerability levels concentrated in south, southeast, south-west and west aspects. The maximum values of medial and heavy vulnerabilities were recorded in south-west and central part of study area.

The EVSI apparently presented distinct geographical distribution. The study area characterized by typical mountainous area showed landforms rising and falling violently. Mountain spread, slope direction and degree, and vertical changing climate cause great difference in natural resources and consequently on the human activities [100]. In lower altitude environmental vulnerability is high due to more socio-economic activities and human interferences such as regular constructions of roads and settlements, extensions of agriculture area and forest encroachment or degradation. But in high altitude vulnerability is low due to less socio-economic activities and human interferences as environmental conditions for human activities were not favorable. The greater environmental vulnerability threats at steep and very steep slopes resulted from serious soil erosion, low soil moisture, high landslide possibility and poor soil fertility problems. The overall study area environmental vulnerability is light with an around 40%, based on natural factors. The study area is characterized by typical middle-high mountainous area with landforms rising and falling violently. The highest elevation is 1500m. This mountain region have pumped storage hydro power plant. It has

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the largest reverse hydraulic turbine in Europe – 325 MW, it is the power plant with the highest gradient in the Czech Republic – 510.7m and has the highest installed output among the hydro power plants in the Czech Republic – 2*325 MW. It shows that the results strictly represent regional feature.

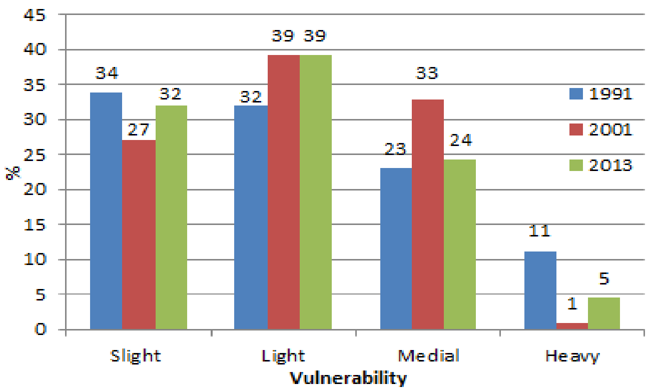

Fig. 15 : Environmental vulnerability maps of the study area

Last three decades environmental vulnerability trends are changes and basically based on forest damage or encroachments. Few other factors are also important such as landforms, water heat condition and soil types [101]. These factors directly related to socio-economic activities, resulting the increase pressure of human on land, which lead to rapid changes of land use. Thus, the coverage of land is cutting down, and soil erosion is intensified eventually, resulting in a further degradation of eco-environment.

IV. Discussion

At lower altitudes, a mixture of agriculture and forestry should be implemented. However, to meet the needs of the local population and tourist that would grow substantially in the next 5 to 10 years, a portion of the land must be used for grain production. Nevertheless, some of this land could be reused for forestry at some time in the future. The recommended reallocations were tested in a few experimental sites and more or less reflected the land use practice in reality. As in any assessment, though, accuracy of the final results was subject 1.0 the accuracy of the input data layers. Some data (e.g., land cover) had a definite boundary, whereas other variables *(e.g.,* climate and socio-economic) had a vague boundary. Therefore, the final results involved some uncertainty and should be treated with caution.

The irrational way of land use such as conversion from woodland to farmland has led to land degradation. However, through reallocation of land that has been excessively exploited to a new use (commensurate with its potential, this problem could be remedied. The recommended optimal allocation emphasized the ecological suitability for exploitation of natural resources and encouraged mixed farming with forestry, pasture and stockbreeding [102]. Naturally, switching from farming to forests would reduce grain output. However, improving farmland productivity through construction of irrigation facilities as well as converting the existing sloped farmland into terraced land to conserve soil and water could compensate these decreases.

Nevertheless, successful implementation of these recommendations relies on other related measures [103]. Those farmers disadvantaged by the reallocation should be compensated for their economic loss in the form of a government-sponsored grant. In this way farmers' livelihoods would not be negatively affected. Another means of achieving the reallocation was through cultivation of medicinal herbs. As a perennial vegetative cover these plants could prevent soil erosion. Finally, to reduce overpopulation, reallocation of some of the rural population should be encouraged. With these measures the recommended reallocation could ensure sustainable exploitation of land resources in the study area.

In this case study, our findings indicate that the rationality in forest use still remains unworkable due to the absence of alternatives that would reconcile the ecological resilience, the mitigation of the current degradation trends, and the population's needs for livelihood. More specifically, the failure of natural resources management seems also to rely on the impossible equation between growing population needs and the physically limited production capacity of the natural environment (soils, climate) leaving no place to intensification, except with substantial inputs from outside the system. Such a saturation of traditional systems, triggered mainly by the population growth, is widely occurring in many places throughout the world [104. The solution relies on a deep transformation of the traditional system, typically changing from self-sufficiency to a higher level of connection with the external economy (people working in cities, multiplication of income sources). This explains why some forests close to urban areas may be in bad condition than forests located in remote traditional areas. A comparable environmental breakpoint was reached in the Czech in 19th century, with a very strong degradation of mountains areas triggered by tourist and population growth, and was overcome during the 20th century with the transition from a self-sufficient production to a wider opening to the national economy.

This work provides an empirical assessment of land cover change dynamics in Olomouc region. The results show that forest cover change involves a series of complex trajectories, some of which are cyclical and reversible, while others are more linear and permanent. These diverse trajectories are consistent with a highly

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dynamic landscape dominated by forms of small-holder land use that reflect heterogeneous livelihood strategies. In-depth analysis of the transition matrices allowed us to separate systematic from random transitions, which revealed unexpected dynamics. Usually, in rural landscapes dominated by peasant farming systems, forest cover loss is attributed to shifting cultivation. Our results, however, show that native forests have been systematically replaced by a range of other covers and land uses over time, and that agricultural expansion is just one of the direct causes of forest decline.

In the last period (2001-2013), most forest cover transitions became systematic again, driven by new forces that led to different cycles of old growth forest decline. The most systematic transition and relevant in terms of magnitude, was the change of old growth to secondary forest at an average annual rate. This very recent forest degradation relates mostly to peasant agricultural systems and can be associated to an increasing firewood demand from an expanding population in urban areas outside of the cities/villages [105, 106].

The above land use change trajectories and trends indicate significantly increasing pressure on available land resources in the study area, leading to the cultivation of increasingly marginal areas, which again leads to dramatic soil fertility decline. It is imperative that these trends are taken into consideration when developing strategies for agricultural development in Olomouc. However, it may not absolutely represent the real land cover disturbance because of the difficulty of modelling the factors influencing this disturbance and the magnitude of human reaction capacity. On the other hand, the pressure exerted on forest depends on the socio-economic and tourist context and may change in the future, according to the disturbance that these societies were experienced. Land use/cover changes were mainly caused by human activities and natural forces [107, 108].

Overall, the results reflect the conflicting interactions between physical and human systems in the study area. In this respect, a key question to address is how to generate the incentives that move individuals from conflicting relations with their natural system, toward more sustainable landscape transitions and trajectories without the regulatory presence of the government (e.g. a ban on logging). Worldwide, land is private property and its usufruct is an important right for the landowner, which implies its free use and also determines its value [109, 110]. The forest dynamics described in this study to systematic economic forces such as firewood and industrial timber demand. If these landowners continue to degrade their forest resources at the rates observed between 1991, 2001 and 2013, by 2020 few and small patches of old growth forest can be expected to remain [111, 112].

V. Conclusions

This research provides evidence that the impact of tourism on land cover in the Jesenik mountain tourist region. Forest area decrease closer to city and its increase after 10 km distance of the city. Tourism facilities have closer proximity and associated with a decrease in forest extent. However this research cannot say that all land cover disturbance are due to only tourism but there are some other factors such as agriculture expansions, timber harvesting, wind and snow damage could also responsible for land cover disturbance. It appears that due to market demand forest harvesting, agriculture, pasture, water body and settlement area is increasing. Climate and elevation is also effect on their extensions. Population growth and increasing of socio-economic activities are also responsible for the land cover disturbance.

In this research work, land cover change trajectories for three different dates from 1991 to 2013 were extracted from satellite imageries by object oriented classification methods. Classification results were calibrated with ground truth trajectories. These results are useful to spatio-temporal variability of landscape pattern and their change trajectories with natural factors. Analysis based on these landscape trajectories demonstrates that major parts of land use/cover changes have been caused by human activities, most of which, under the direction of local government, have mainly led to virtuous change in the study area. This study was carried out on small study area with three major land cover classes. The significant body of data containing accurate spatial and thematic detail that was yielded by the analysis sheds considerable light on recent land cover and its dynamics. So in the later research, more influential factors would be taken into the analysis, including some human geographical factors and economic geographic factors, such as transport, social economy and so on.

Our results have important policy implications, for developed and developing countries that are undergoing rapid urbanization and industrialization. This conversion increases the vulnerability and exposer. Urbanization has negative impacts, particularly as a cause of environmental pollution derived by intensive energy consumption and material flows, and leading to dramatic changes in land use, loss of biodiversity, habitat fragmentation and a decline in ecosystem services which is the main cause of high vulnerability and exposer index. This case study articulated the effects of land use change and offered a vulnerability analysis framework for sustainability. The measurement of vulnerability and exposer can be appropriate and useful to identify vulnerable people, region or sectors at local scales under strict conditions. Our comparison of vulnerability and exposer index in different land cover classes that are undergoing similar transformation

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process but with a clear time lag may shed some lights to temporal trend of vulnerability and expose within a single land cover class that follows similar transformation trajectory. Further studies in different areas are required before any general conclusions can be made. Nevertheless, the results have strong policy implications, which suggest the need for tailor-made policy responses to enhance adaptive capacity of land cover class that are exposed to rapid land use change, and ensure the development associated with the land use change can benefit the local community as well.

This research show environmental vulnerability in a mountain area and evaluates the situation with the support of remote sensing and GIS. SPCA method was used for weights and membership of all factors. It finds that over all study area environmental vulnerability is light level and its distribution is vertical and horizontal nature. As EVSI reduced from 1991 to 2013 so it`s assume that vulnerability is reducing due to governmental policies and protection. The main cause of environmental vulnerability is socio-economic activities. The results indicate it is urgent that, besides the improvement and reinforcement of compensation mechanism construction, the work of eco-environmental recovering and rebuilding should be carried out according to regionalization. Results also indicate that RS, GIS and SPCA approach are good in mountain region for environmental vulnerability evaluation. They also facilitated the derivation and application of the numeric environmental vulnerability evaluation. These findings provide quantitative basis and support for forest policy, management issues and institutional analyses in planning and management of the mountain regions.

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References Références Referencias

1. Czech Business Authority (2010) Annual Report 2010, at http://www.businessinfo.cz/files/archiv/dokumenty/cr_regions_olomouc.pdf
2. Czech Tourist Authority (2011) Annual Report 2011, at http://czech.kiwano.net/pdf/to02.pdf
3. Boori, M.S., & Amaro, V.E. (2011), Natural and eco-environmental vulnerability assessment through multi-temporal satellite data sets in Apodi valley region, Northeast Brazil. *Journal of Geography and Regional Planning (JGRP), ISSN 2070-1845.* Vol. 4(4): 216 – 230.
4. Boori, M.S., & Amaro, V.E. (2011), A remote sensing and GIS based approach for climate change and adaptation due to sea-level rise and hazards in Apodi-Mossoro estuary, Northeast Brazil. *International Journal of Plant, Animal and Environmental Sciences (IJPAES), ISSN: 0976-4550.* Vol. 1(1): 14–25.
5. Dong, Y., Forster, B., Ticehurst, C. (1997). Radar backscatter analysis for urban environments. International Journal of Remote Sensing, 18(6), 1351–1364.
6. Adriaenssens, V., De Baets, B., et al., (2004). Fuzzy rule-based models for decision support in ecosystem management. Sci. Total Environ. 319, 1–12.
7. Alphan, H. (2003). Land use change and urbanization in Adana, Turkey. Land Degradation and Development, 14(6), 575–586.
8. Boori, M.S., Vozenilek, V. (2014), Land use/cover, vulnerability index and exposer intensity. Journal of Environments. Vol. 1(1): 01 – 07.
9. Boori, M.S., Vozenilek, V. (2014), Remote sensing and GIS for Socio-hydrological vulnerability. *Journal of Geology and Geosciences (JGG), ISSN 2329-6755.* Vol. 3(3): 01 – 04, *Doi:10.4172/2329-6755.1000e115*
10. Andrade, M.M.N.d., Szlafsztein, C.F., Souza-Filho, P.W.M., Araujo, A.d.R. (2010), A socioeconomic and natural vulnerability index for oil spills in an Amazonian harbor: a case study using GIS and remote sensing. Journal of Environmental Management 91, 1972–1980.
11. Antonio, G.S., Juan Alfonso, B., Jos´eManuel, N., (2003). Assessing landscape values: a proposal for a multidimensional conceptual model. Ecol. Model. 168, 319–341.
12. Marín, S. L., Nahuelhual, L., Echeverría, C. (2011). Projecting landscape changes in southern Chile: simulation of human and natural processes driving land transformation. Ecological Modelling,. doi:10.1016/j.ecolmodel.2011.04.026.
13. Messerli, B. & Ives, J.D. (1997), Mountains of the world: a global priority. New York: Parthenon.
14. Moran, E. F. (2005), Human–environment interactions in forest ecosystems: an introduction. In E. F. Moran, & E. Ostrom (Eds.), Seeing the forest and the trees: Human–environment interactions in forest ecosystems (pp. 3–21). Cambridge, MA: MIT Press.
15. Antrop, M. (2005). Why landscape of the past are important for the future. Landscape Urban Plan. 70, 21–34.
16. Arrowsmith, C. & Inbakaran, R. (2002), Estimating environmental resiliency for the Grampians National Park, Victoria, Australia: a quantitative approach. Tour Manag 23: 295–309.
17. Bai, X.M., Chen, J., Shi, P. (2012), Landscape urbanization and economic growth in China

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Positive feedbacks and sustainability Dilemmas. Environmental Science & Technology 46, 132–139.
18. Lynn, N.A. & Brown, R.D. (2003), Effects of recreational use impacts on hiking experiences in natural areas. Landsc Urban Plan 64:77–87.
19. Mather, A. S. (1986), Land use. London, UK: Longman Group.
20. Boori, M.S., Vozenilek, V., Burian, J. (2014), Land-cover disturbances due to tourism. Proceedings of the Fifth International Conference on Innovations in Bio-Inspired Computing and Applications IBICA 2014. Springer International Publishing, Pages 63-72.
21. Bolstad, P. V., & Lillesand, T. D. (1991). Rapid Maximum Likelihood classification. Photogrammetric Engineering & Remote Sensing, 57, 67–74.
22. Bontemps, S., Bogaert, P., Titeux, N., Defourny, P. (2008). An object-based change detection method accounting for temporal dependences in time series with medium to coarse spatial resolution. Remote Sensing of Environment 112 (6), 3181–3191.
23. Boori, M.S., & Ferraro, R.R. (2013), Microwave polarization and gradient ratio (MPGR) for global land surface phenology. *Journal of Geology and Geosciences (JGG), ISSN 2329-6755*. Vol. 2(2): 01 – 10, *Doi:10.4172/2329-6755.1000114*
24. Irwin, E.G. & J. Geoghegan. (2001). Theory, data and methods: Developing spatially explicit economic models of land use change. Agriculture, Ecosystems & Environment 85: 7–23.
25. Jensen, J. R. (Ed.), (2005), Introductory digital image processing: A remote sensing perspective (3rd ed.). London, UK: Pearson Education.
26. Jensen, J. R., & Im, J. (2007). Remote sensing change detection in urban environments. In R. R. Jensen, J. D. Gatrell, & D. McLean (Eds.), Geo-spatial technologies in urban environments: Policy, practice and pixels (2nd ed.). (pp. 7–30) Heidelberg: Springer-Verlag.
27. Boori, M.S., & Ferraro, R.R. (2012), Northern Hemisphere snow variation with season and elevation using GIS and AMSR-E data. *Journal of Earth Science and Climate Change (JESCC), ISSN 2157-7617*. Vol. S12: 001, Special Issue 2012: 01 – 06, *Doi:10.4172/2157-7617.S12-001*
28. Burgi, M., Hersperger, A.M., Hall, M., Southgate, E.W.B., Schneeberger, N. (2007). Using the past to understand the present land use and land cover. In: Kienast, F., Wildi, O., Ghosh, S. (Eds.), A Changing World. Challenges for Landscape Research. Springer, Dordrecht, Netherlands, pp. 33–144.
29. Buckley, R.C.; Pickering, C.M.; Warnken, J. (2002), Environmental management for Alpine tourism and resorts in Australia. Tourism and development in mountain regions. Wallingford: CABI Publishing; 27–45.
30. Kangas, J., Store, R., Leskinen, P., et al., (2000). Improving the quality of landscape ecological forest planning by utilizing advanced decision-support tools. Forest Ecol. Manage. 132, 157–171.
31. Kasperson, J.X., Kasperson, R.E., Turner, I. I. B.L., (1995). Regions at Risk. United Nations University Press, Tokyo.
32. Lambin, E. F., & Geist, H. J. (2003), Regional differences in tropical deforestation. Environment, 45(6), 22–36.
33. Buntaine, M.T.; Mullen, R.B.; Lassoie, J.P. (2006), Human use and conservation planning in Alpine areas of Northwestern Yunnan, China. Environ Dev Sustain 9:305–24.
34. Chatterjea, K. (2007), Assessment and demarcation of trail degradation in a nature reserve, using GIS: case of Bukit Timah nature reserve. Land Degrad Dev 18:500–18.
35. Boori, M.S., & Ferraro, R.R. (2014), Global Land Cover classification based on microwave polarization and gradient ratio (MPGR). Geo-informatics for Intelligent Transportation (GIS Ostrava 2014) Technical University of Ostrava, Ostrava-Poruba, Czech Republic, January 27-29, 2014.
36. Coppin, P., Jonckheere, I., Nackaerts, K., Muys, B., Lambin, E. (2004). Digital change detection methods in ecosystem monitoring: a review. International Journal of Remote Sensing, 25(9), 1565–1596.
37. Enea, M., Salemi, G., (2001). Fuzzy approach to the environmental impact evaluation. Ecol. Model. 135, 131–147.
38. European Bank for Reconstruction and Development (EBRD) and the state of transition in central and eastern Europe (Resolution 1254 (2001)) stars.coe.int/ta/ta01/ERES1254.HTM
39. Eurostat, (2012). Farm structure survey. Structure of agricultural holdings 2007. Luxembourg: European Communities. Online source http://epp.eurostat.ec.europa.eu/portal/page/portal/agriculture/data/database (1.11.2012).
40. Evers, M.; Jonoski, A.; Maksimovic, C.; Lange, L.; Ochoa, S.; Cortés, J.; Almoradie, A.; Dinkneh, A. (2012). Enhancing stakeholders` role by collaborative modelling for urban flood risk reduction. Nat. Hazards Earth Syst. Sci., 12, 2821-2842, 2012.
41. Foley, J. A.; DeFries, R.; Asner, G.; Barford, C.; Bonan, G.; Carpenter, S. R.; et al. (2005), Global consequences of land use. Science, 309, 570–574.
42. Gaughan, A. E. (2006), Spatial and temporal land-cover transformation in the Angkor basin: A changing landscape in Cambodia, 1989–2005. Thesis, University of Florida, Gainesville.

© 2014 Global Journals Inc. (US)

43. Geneletti D. & Dawa D. (2009), Environmental impact assessment of mountain tourism in developing regions: A study in Ladakh, Indian Himalaya. Environmental Impact Assessment Review 29: 229–242.
44. Walker, R. (2004), Theorizing land-cover and land-use change: the case of tropical deforestation. International Regional Science Review, 27(3), 247–270.
45. Wright, S. J. (2005), Tropical forests in a changing environment. Trends in Ecology and Evolution, 20(10), 553–560.
46. Godde, M.P.; Price, M.F.; Zimmermann, F.M. (2000), Tourism and development in mountain regions: moving forward into the new Millennium. Tourism and development in mountain regions. Wallingford: CABI Publishing; p. 1-25.
47. Green, G. M.; Schweik, C. M.; Randolf, J. C. (2005), Retrieving land-cover change information from Landsat satellite images by minimizing other sources of reflectance variability. In E. F. Moran, & E. Ostrom (Eds.), Seeing the forest and the trees: Human–environment interactions in forest ecosystems (pp. 131–160). Cambridge, MA: MIT Press.
48. Hao, Y., Zhou, H.C.H., (2002). A grey assessment model of regional eco-environment quality and its application. Environ. Eng. 20 (4), 66–68.
49. Boori, M.S (2010), Coastal vulnerability, adaptation and risk assessment due to environmental change in Apodi-Mossoro estuary, Northeast Brazil. *International Journal of Geomatics and Geosciences (IJGGS)*, *ISSN 0976-4380.* Vol. 1(3): 620 – 638.
50. Hartter, J., Lucas, C., Gaughan, Andrea, E., Aranda, L. L. (2008). Detecting tropical dry forest succession in a shifting cultivation mosaic of the Yucata´n Peninsula, Mexico. Applied Geography, 28, 134 -149.
51. Hardin, P. J., Jackson, M. W., Otterstrom, S. M. (2007). Mapping, measuring, and modeling urban growth. In R. R. Jensen, J. D. Gatrell, & D. McLean (Eds.), Geo-spatial technologies in urban environments: Policy, practice and pixels (2nd ed.). (pp. 141–176) Heidelberg: Springer-Verlag.
52. Boori, M.S., Amaro, V.E., & Vital, H. (2010), Coastal ecological sensitivity and risk assessment: A case study of sea level change in Apodi River (Atlantic Ocean), Northeast Brazil. World Academy of Science, Engineering and Technology (WASET), International Science Index 47, International journal of Environmental, Earth Science and Engineering, ISSN 1307-6892. Vol. 4(11): 44-53.
53. Hathout, S. (2002). The use of GIS for monitoring and predicting urban growth in East and West St Paul, Winnipeg, Manitoba, Canada. Journal of Environmental Management, 66, 229–238.
54. Hecht, S. B., & Saatchi, S. S. (2007). Globalization and forest resurgence: changes in forest cover in El Salvador. BioScience, 57(8), 663-672.
55. Holland, J.; Burian, M.; and Dixey, L. (2003), Tourism in Poor Rural Areas.
56. IPCC Working Group II (2007), Fourth Assessment Report. Cambridge University Press, Cambridge.
57. Carmona, A., Nahuelhual, L., Echeverría, C., Báez, A. (2010). Linking farming systems to landscape change: an empirical and spatially explicit study in southern Chile. Agriculture, Ecosystems and Environment, 139, 40-50.
58. Nepal, S.K. & Chipeniuk, R. (2005), Mountain tourism: toward a conceptual framework. Tour Geogr 7:313–33.
59. Nevtipilova, V., Pastwa, J., Boori, M.S., Vozenilek, V. (2014), Testing artificial neural network (ANN) for spatial interpolation. *International Journal of Geology and Geosciences (JGG), ISSN 2329-6755*. Vol. 3(2): 01 – 09, *Doi:10.4172/2329-6755.1000145*
60. Chaplin, J. & brabyn, L. (2013), Using remote sensing and GIS to investigate the impacts of tourism on forest cover in the Annapurna Conservation Area, Nepal. Applied Geography 43: 159-168.
61. Jensen, J. R., Hodgson, M. E., Tullis, J. A., Raber, G. T. (2004). Remote sensing of impervious surfaces and building infrastructure. In R. R. Jensen, J. D. Gatrell, & D. McLean (Eds.), Geospatial technologies in urban environments: Policy, practice and pixels (pp. 5–20). Heidelberg: Springer.
62. Boori, M.S., Amaro, V.E., & Targino, A. (2012), Coastal risk assessment and adaptation of the impact of sea-level rise, climate change and hazards: A RS and GIS based approach in Apodi-Mossoro estuary, Northeast Brazil. *International Journal of Geomatics and Geosciences (IJGGS), ISSN 0976-4380*. Vol. 2(3): 815 – 832.
63. Johnson, R. D., & Kasischke, E. S. (1998). Change vector analysis: a technique for the multi-temporal monitoring of land cover and condition. International Journal of Remote Sensing, 19, 411–426.
64. Lankao, P.R., 2010. Water in Mexico City: what will climate change bring to its history of water-related hazards and vulnerabilities? Environmental and Urbanization 22, 157–178.
65. Li, A., A. Wang, S. Liang & W. Zhou. (2005). Ecoenvironmental vulnerability evaluation in mountainous region using RS and GIS: A case study in the upper reaches of Minjiang River, China. Ecological Modelling 192: 175-187.
66. Boori, M.S., & Amaro, V.E. (2011), A remote sensing approach for vulnerability and environmental change in Apodi valley region, Northeast Brazil. World Academy of Science, Engineering and Technology (WASET), International Science Index

© 2014 Global Journals Inc. (US)

50, International journal of Environmental, Earth Science and Engineering, ISSN 1307-6892. Vol. 5(2): 01-11.
67. Lindner, M., Maroschek, M., Netherer, S., Kremer, A. (2010), Climate change impacts, adaptive capacity, and vulnerability of European forest ecosystem. Forest Ecology and Management 259, 698–709.
68. Li, Q. (2004). Land Use/Cover Change Analysis in Pali Gad Watershed (Aglar Sub-Watershed) and Its Impact on Soil Erosion Processes – A Geospatial Approach. India Institute of Remote Sensing. Dehradun, India.
69. Townshend, J. R. G., & Justice, C. O. (1995). Spatial variability of images and the monitoring of changes in the normalized difference vegetation index. International Journal of Remote Sensing, 16, 2187–2195.
70. Liu, J. (1996), Macro-Scale Survey and Dynamic Study of Natural Resources and Environment of China by Remote Sensing. Press of Science and Technology of China, Beijing.
71. Li, X., & Yeh, A. G. O. (1998). Principal component analysis of stacked multi-temporal images for the monitoring of rapid urban expansion in the Pearl River Delta. International Journal of Remote Sensing, 19, 1501–1518.
72. Boori, M.S., Amaro, V.E., & Vital, H. (2010), Coastal ecological sensitivity and risk assessment: A case study of sea level change in Apodi River (Atlantic Ocean), Northeast Brazil. *International Journal of Environmental and Earth Sciences, ISSN 2010-4030.* Vol. 1(3): 127 - 136.
73. Ministry of Regional Development (2013), Tourism in the Czech Republic, Prague: Ministry of Regional Development.
74. Boori, M.S. (2011), Avaliação de impacto ambiental e gestão dos recursos natuarias no estuário Apodi Mossoró, nordeste do Brasil. Library thesis from Federal University of Rio Grande do Norte, Brazil.
75. Brouwer, F. M. (2001). The relation between agriculture, land use and policy in Europe. In Kaleidoscopic view on social scientific global change research in the Netherlands (pp. 8e10).
76. Brus, J., Boori, M.S., Vozenilek, V. (2013). Detection and visualizations of ecotones – important landscape pattern under uncertainty. *Journal of Earth Science and Climate Change (JESCC), ISSN 2157-7617.* Vol. 4(3): 01 – 04, *Doi:10.4172/2169-0316.1000e108*
77. Nicholls, R.J., Wong, P.P., Burkett, V., Woodroffe, C.D., Hay, J. (2008), Climate change and coastal vulnerability assessment: scenarios for integrated assessment. Sustainability Science 3, 89–102.
78. Nelson, R. F. (1983). Detecting forest canopy changes due to insect activity using Landsat MSS. Photogrammetric Engineering & Remote Sensing, 49, 1303–1314.
79. Niamir, M. (1990), Traditional woodland management techniques of African pastoralists. Unasylva 160, 49–58.
80. Ridd, M. K., & Liu, J. J. (1998). A comparison of four algorithms for change detection in an urban environment. Remote Sensing of Environment, 63, 95–100.
81. Boori, M.S., & Amaro, V.E. (2010), Detecting and understanding drivers of natural and eco-environmental vulnerability due to hydro geophysical parameters, ecosystem and land use change through multispectral satellite data sets in Apodi estuarine, Northeast Brazil. *International Journal of Environmental Sciences (IJES), ISSN 0976-4402.* Vol. 1(4): 543–557.
82. Rindfuss, R. R., Walsh, S. J., Turner, B. L., II, Fox, J., & Mishra, V. (2004), Developing a science of land change: challenges and methodological issues. Proceedings of the National Academy of Sciences of the United States of America, 10(3), 13976–13981.
83. Saaty, T.L., Vargas, L.G. (1991), Prediction, Projection and Forecasting. Kluwer Academic Publishers, Dordrecht.
84. Semwal, R.L.; Nautiyal, S.; Sen, K.K.; Rana, U.; Maikhuri, R.K.; Rao, K.S.; Saxena, K.G.; (2004), Patterns and ecological implications of agricultural land-use changes: a case study from central Himalaya, India. Agric. Ecosyst. Environ. 102, 81–92.
85. Serra, P., Pons, X., & Saurı´, D. (2008). Land-cover and land-use change in a Mediterranean landscape: a spatial analysis of driving forces integrating biophysical and human factors. Applied Geography, 28, 189–209.
86. Zhao, J., Zhu, Y., Shao, G., Ness, D., 2008. Coping with an urbanizing world: interdisciplinary research towards sustainability. International Journal of Sustainable Development and World Ecology 15, 284–287.
87. Zhou, Q., Li, B., Kurban, A. (2008b). Spatial pattern analysis of land cover change trajectories in Tarim Basin, northwest China. International Journal of Remote Sensing 29 (19), 5495–5509.
88. Shah, J.; Nagpal, T.; Brandon, C.J. (1997), Urban air quality management strategy in Asia, a guidebook and a series of city reports. Washington, DC: The World Bank; p. 1-188.
89. Singh, R.B. & Mishra, D.K. (2004), Green tourism in mountain regions — reducing vulnerability and promoting people and place centric development in the Himalayas. JMt Sci 1:57–64.
90. Skalo_s, J., & Engstová, B. (2010). Methodology for mapping non-forest wood elements using historic cadastral maps and aerial photographs as a basis for management. Journal of Environmental Management, 91, 831e843.

© 2014 Global Journals Inc. (US)

91. Boori, M.S., & Amaro, V.E. (2010), Land use change detection for environmental management: using multi-temporal, satellite data in Apodi Valley of northeastern Brazil. *Applied GIS International Journal, ISSN 1832-5505.* Vol. 6(2): 1-15.
92. Sklenicka, P., Lhota, T., Cecetka, J. (2002). Soil porosity along a gradient from forest edge to field. Bodenkultur, 53, 191e197.
93. Sklenicka, P., & Salek, M. (2008). Ownership and soil quality as sources of agricultural land fragmentation in highly fragmented ownership patterns. Landscape Ecology, 23, 299-311.
94. Parinet, B., Lhote, A., Legube, B., (2004). Principal component analysis: an appropriate tool for water quality evaluation and management—application to a tropical lake system. Ecol. Model. 178, 295–311.
95. Toll, D. L., Royal, J., Davis, J. B. (1980). Urban areas update procedures using Landsat data. In Proceedings of American Society of Photogrammetry. Falls Church, VA: American Society of Photogrammetry.
96. Start, D. (2001), Livelihood Insecurity and Social Protection: A Re-emerging Issue in Rural Development, Development Policy Review, 19 (4), London: Blackwell Publishing
97. Stevens, S. (2003), Tourism and deforestation in the Mt Everest region of Nepal. Geogr J 169:255–77.
98. Voženílek, V., Morkesová, P., & Vondráková, A. (2014), Cognitive aspects of map symbology in the world school atlases. Procedia - Social and Behavioral Sciences, Volume 112, Pages 1121-1136
99. Boori, M.S., Amaro, V.E., Linhares, P., Targino, A. (2010). Eco-environmental Vulnerability analysis by the remote sensing satellite data sets in Apodi Valley Region, Northeast Brazil. University of Coimbra, Portugal. ISBN 978–989–96810–0-2.
100. Voženílek, V., Michalík, J., Vondráková, A., & Brychtová, A. (2014), Mapping and visualisation of activities in special education. Procedia - Social and Behavioral Sciences, Volume 112, Pages 1106-1120
101. Wang, C., Jamison, B.E., Spicci, A.A. (2010). Trajectory-based warm season grassland mapping in Missouri prairies with multi-temporal ASTER imagery. Remote Sensing of Environment 114 (3), 531–539.
102. Wotling, G., Bouvier, Ch., Danloux, J., et al., (2000). Regionalization of extreme precipitation distribution using the principal components of the topographical environment. J. Hydrol. 233, 86–101.
103. Zhang, B. P., Yao, Y. H., Cheng, W. M., Zhou, C. H., Lu, Z., Chen, X. D. (2002). Human-induced changes to biodiversity and alpine pastureland in the Bayanbulak Region of the East Tianshan Mountains. Mountain Research and Development, 22, 1–7.
104. Zuo, W.; Zhou, H. Z.; Zhu, X. H.; Wang, Q.; Wang, W. J. & Wu, X. Q. (2005), Integrated evaluation of ecological security at different scales using remote sensing: A case study of Zhongxian County, the Three Gorges area, China. *Pedosphere.* 15(4): 456-464.
105. Boori, M.S., Vozenilek, V. (2014), Land use/cover, vulnerability index and exposer intensity. *Journal of Environments*. Vol. 1(1): 01 – 07.
106. Sinclair, R. (1967), Von Thünen and urban sprawl. Annals of the Association of American Geographers, 57, 72-87.
107. Singh, A. (1989). Digital change detection techniques using remotely sensed data. International Journal of Remote Sensing, 10(6), 989–1003.
108. Boori, M.S., Vozenilek, V. (2014), Remote sensing and GIS for Socio-hydrological vulnerability. *Journal of Geology and Geosciences (JGG), ISSN 2329-6755*. Vol. 3(3): 01 – 04, *Doi:10.4172/2329-6755.1000e115*
109. Boori, M.S., Vozenilek, V., Burian, J. (2014), Land-cover disturbances due to tourism. Proceedings of the Fifth International Conference on Innovations in Bio-Inspired Computing and Applications IBICA 2014. Springer International Publishing, Pages 63-72.
110. Bao, H. J.; Wu, Y. Z.; Wu, C. F.; Xu, B. G. (2005), Planning and design for eco sustainable farmland consolidation. *Pedosphem.* 15(3): 327-333.
111. Blodget, H., Taylor, P., Roark, J. (1991). Shoreline changes along the Rosetta-Nile Promontory: monitoring with satellite observations. Marine Geology, 99, 67–77.
112. Boori, M.S., Vozenilek, V. (2014), NASA EOS Aqua Satellite AMSR-E data for snow variation. *Journal of Geology and Geosciences (JGG), ISSN 2329-6755*. Vol. 3(4): 01 – 06. *Doi:*10.4172/2329-6755.1000e116

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