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D5.2: Report on the use of phenology related measures and indicators for selected sites at varying spatial scales

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Author: Andrej Halabuk

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D5.2: Report on the use of phenology related measures and indicators for selected sites at varying spatial scales

Multitemporal analysis of NDVI for grassland mapping and classification

Author: Andrej Halabuk

Institute of Landscape Ecology SAS

1. Introduction

Since the first temporal composite data of NDVI from AVHRR has become available in early 80-ies, a massive utilization of these data series emerged. This lead to the development of novel approaches for analysing time series of satellite data with high temporal resolution for land cover mapping and assessment. Within this deliverable, we have briefly reviewed the main approaches available and through case studies assessed their performance for grassland mapping and monitoring. Hence, we considered studies that used data from sensors with high temporal resolution, namely: AVHRR, SPOT VEGETATION, MODIS and MERIS. Grassland ecosystems were selected as land cover class with special interest within the EBONE team as these ecosystems along with their importance as an agricultural landscape, also bear high biodiversity values and there is still lack of precise information of their spatial extent and status at pan European scale. The importance of precise grassland monitoring is proven by their incorporation as a special class in the recently established land monitoring component of the GMES where specific approaches are being developed in order get more precise information on specific features such as grasslands, wetlands, forests. First synthesized results of utilization of multitemporal AVHRR NDVI data for grassland vegetation assessment were reported from semiarid Africa in the special issue of Intern. Journal of Remote Sensing in 1986 proving that coarse data (8 km spatial resolution) with high temporal resolution could be used for grassland vegetation monitoring at regional scale. This issue discussed the first time series based approaches for detecting the different phenologies of grassland vegetation types by satellite data, their interrelation to regional climatic conditions, estimating of biomass, detecting droughts, etc. Since that time, and even more after the Terra and Aqua satellites have been launched, a wide range of possible applications have emerged in grassland remote sensing that could be broadly classified into three groups:

1. grassland mapping
2. grassland type classification and monitoring
3. grassland change analysis

Grassland mapping includes those applications when there was no or poor knowledge about grassland occurrence. These are mainly relevant at broader scale and grassland mapping actually occurred within the global and regional land cover mapping initiative using multitemporal analyses. Grassland type classification and monitoring includes a broad variety of studies which location of particular grasslands was known, focus on multitemporal analyses to increase the knowledge on grassland status e.g. increasing thematic detail of grassland types, biomass estimation, stress detection, fire risk, etc. Grassland change analysis involve those studies that utilize longer time series in order to assess changes in grassland occurrence and status, e.g. overgrowing, drying, change of Land management practice, and studies of trend and seasonal change, phenology shifts and prediction of future grassland change including climate change studies. In this deliverable we were mainly focused on the first two categories: grassland mapping and grassland type classification and monitoring.

1.1. Multitemporal analysis of NDVI Time series

Multitemporal approaches comprise a broad group of techniques that explore and analyse dynamic changes of the land surface. In particular, seasonal change and long-term change of vegetation greenness are mainly studied using time series of vegetation indexes such as EVI or NDVI. NDVI time-series belong to the most widespread and commonly used to characterize seasonality, inter-seasonal variability, phenology, overall productivity, biomass, etc. (see Pettorelli et al., 2005 for review). Since coherent time series of NDVI at global scale have been available, specific methods have been developed using information of

distinct seasonality or phenology of land cover classes for land cover classification and mapping (Reed et al., 1994; DeFries et al., 1995). These approaches would use multi-date NDVI images that reflect main seasonal differences in a specific region (Wessels et al. 2004); various multitemporal metrics (DeFries et al., 1998; Sedano et al., 2005; Samson et al., 1993; Paruelo et al., 2001); phenometrics (Reed et al., 1994); or time series analysis of whole annual NDVI series (Evans and Geerken, 2006; Jakubauskas et al., 2001; Hall-Bayer et al., 2003). All variety of image classification methods using supervised, unsupervised or multitemporal segmentation (here later referred as “multitemporal classification”) were used to produce a full coverage land cover map (Mucher et al., 2000); classify specific ecosystems (Hill et al., 1999; Paruelo et al., 2001); or to extract phenology-based information of sample sites (Paruelo et al., 1998; Fontana et al., 2008). Different methods for pre-processing the noisy raw time series data have also emerged, and have been thoroughly tested and validated across the different biomes and scale (Hill and McDermid, 2009). In our case studies we tested different approaches using mainly MODIS 16 day NDVI and 8 day surface reflectance composite data with 250m spatial resolution, which are of the most commonly used products for multitemporal land cover mapping at regional scale.

1.2. Grassland mapping

Grassland mapping and detection is mainly incorporated in land cover classification initiatives at global, national and regional scales where grasslands are represented as 1 or more land cover classes. Grasslands in different classification legends are defined quite consistent usually as the land cover class with prevailing open herbaceous or grassy vegetation with less than 10% tree cover. Coarse spatial resolution satellite data with global coverage stimulated the development of many large scale land cover mapping products that use information of specific temporal behaviour of the land cover classes for their classification. The main global land cover maps that exist (Discover, Vega200, UmD, Globcover, Modis GLC) proved variable validation statements for grasslands however validation of global products is tricky and validation statements cannot be reasonably compared with regional studies. It is obvious, that despite of the extremely valuable contribution to global studies, these global coarse resolution products fail to capture land cover and land use variability at finer scales (national and regional) especially in heterogeneous landscape where mixed pixels are prevalent. As a result coarse resolution maps have to use complex mosaic classes in their classification system. For example, Mucher et al. (2000) stated that almost 27 % of Europe occurred in complex vegetation mosaics of the IGBP Discover product. These complex classes can include grassland ecosystems and thus contribute to underestimation and uncertainty in grassland distribution. Sedano et al. (2005) by using 250m MODIS product demonstrated that the 1 km MODIS GLC product does not capture the spatial land cover variability of the study area, providing a very broad classification in which most of the region is covered by only two classes (savannah and woody savannah). These two classes account for 59.33% and 36.1%, respectively of the study area, misrepresenting the heterogeneous distribution pattern of the land over and land use types in the study area. This clearly showed that the small-scale agriculture, dominating the region, could not be separate at 1 km spatial resolution. In addition, due to their similar phenology and structure, grasslands and agriculture crops are difficult to separate at 1 km resolution. Although we did not carry out that quantitative validation of the global grassland products at regional scale, Fig. 1 illustrate that both the distribution and coverage of grasslands differ a lot in our study area and global products will probably not be suitable for grassland monitoring in Europe.

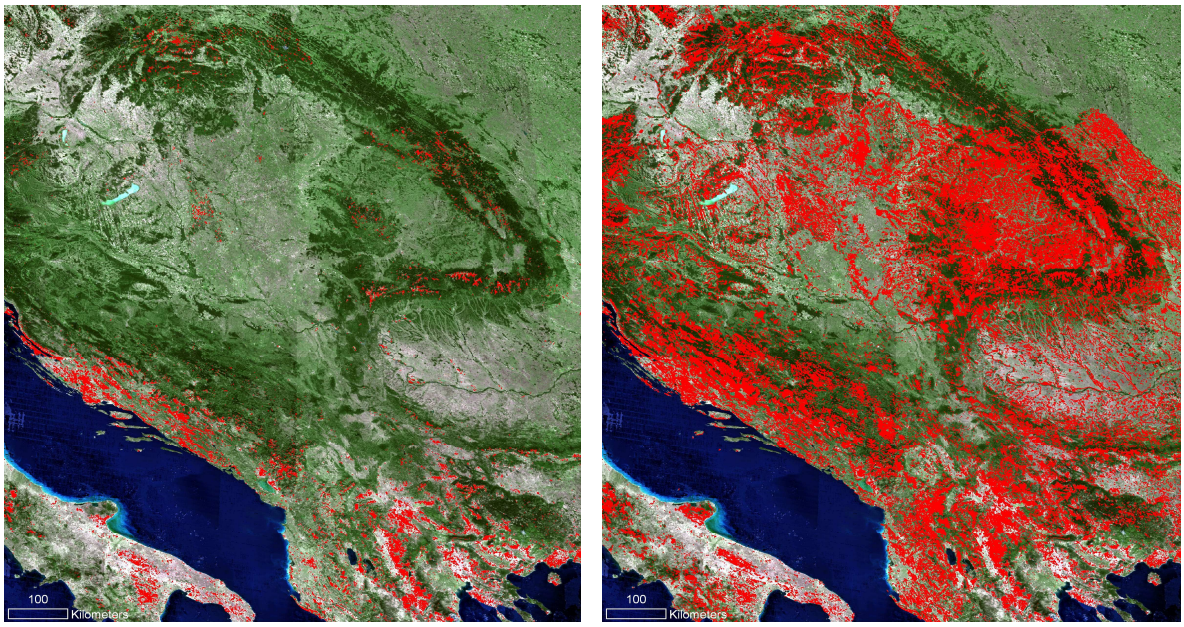

Fig 1: Comparison of distribution grassland land cover class in MODIS GLLC product (left) and CLC class 231 product (right)

At continental scale there were also many initiatives using coarse resolution sensors for multitemporal classifications (see Franklin and Wulder, 2002 for overview). For example Stone et al., (1994) used a multistep combined approach where seasonality was also used to map the land cover in South America. They achieved a good accuracy for the grassland classes ranging from 81% (savannah/grassland) to 87.5 % (mountain grasslands). However due to the small area of flooded grassland in the validation sample these grasslands only achieved 36% accuracy. Giri and Jenkins (2005) used a multi-date classification of MODIS surface reflectance product at 500 m resolution to produce a land cover map for greater Mesoamerica and reported a grassland producer's accuracy of 60 %; a user's accuracy of 65 % and a substantial misclassification with shrub lands. In Europe, the Pelcom initiative (Mucher et al., 2000) delivered a land cover map with grassland user's accuracy of 42% and producer's accuracy of 36 % using a heterogeneous validation data set and 53% and 52% using homogenous validation data set. At regional scale, regionally specific approaches can benefit from specific knowledge on drivers and effects that determine the distinct seasonal profile of different land covers. Mucher et al., (2000) succeed in mapping grassland at national scale in the Netherlands by exploiting these distinct seasonal features between grassland, arable land, forest and water: In early spring, there is a significant difference in spectral reflectance between grassland and arable land because most arable land is still bare. Exceptions are areas covered with winter wheat, which will be confused with grassland. However, as winter wheat is harvested around the end of July, wheat can be separated from grassland using data acquired after July. Similarly Moody et al. (2001) described regional specific distinct temporal profiles of NDVI for main vegetation types (including grasslands) and the use of the Fourier terms (amplitudes and phases of a series of harmonics) derived from the NDVI time series of single year for the distinction of the main vegetation types in southern California. The mean NDVI, or 0th-order harmonic, indicated overall productivity, allowing the differentiation of unproductive, moderately productive, and highly productive sites. The amplitude of the he first harmonic indicated the variability of productivity over the year as expressed in a single annual pulse of net primary production. This summarized the relative dominance of evergreen vs. deciduous or annual habit. The phase of the first harmonic summarized the timing of green-up relative to the timing of winter and spring rains. This differentiated rapidly responding annual grasslands from slowly responding evergreen life-forms, and irrigated agriculture. The second harmonic indicated the strength and timing of any biannual signal. This provided information on secondary vegetation types, such as sub

canopy grasses beneath evergreen woodlands or mixtures of annual grasslands and irrigated agriculture. The authors reported an overall 77% producer's and 46% user's accuracy with high levels of misclassification of the woody and open shrub savannah. Jakubauskas et al. (2001) used similar approach in cropland dominated landscape in south-western Kansas in the High Plains. The authors reported the best classification accuracy for grasses (72 producer's, 66% user's accuracy) and the weak accuracy for wheat. The small patches were the worst classified demonstrating how mapping is often confounded by the spatial resolution of the fields being smaller than the resolution of the scanner. Sedano et al. (2005) used multitemporal analysis of MODIS 250m for a rapid, operable and low-cost land cover mapping product protocol developed for natural resources and biodiversity. The monitoring concluded that complementary to existed global land cover product their regional specific approach based on knowledge of specific phenology responses of main vegetation types can effectively map and monitor regional ecosystems. Using different multitemporal spectral indexes and 250m multitemporal NDVI they were able to capture grasslands at around 85% accuracy. Huang and Siegert (2006) optimized a land cover classification of North China to detect areas at risk of desertification. By exploiting the seasonal information from the 1km NDVI time series product of Spot VGT they increased the thematic detail of the grasslands class by subcategorizing it into – "sparse", "dense" and "mixed with agriculture", achieving producer's accuracy of 66 %, 91 %, 86 % and user's accuracy of 89 %, 75 % and 79 % respectively. The authors proved that different vegetation types and land use practices show distinct temporal shape of the NDVI. Geerken et al. (2009) developed shape based classification system for Middle East study area matching pre-defined class specific temporal profiles of NDVI with the temporal response of respective pixels. The authors defined 32 classes in the total with inclusion of many mixed and mosaic classes such as "dense bushes and grass", "shrubs, grasslands, low productive", "shrubs, grass, scattered fields", "sparse grasslands" with high values of accuracy in all mapped classes. However, when there is no a-priori knowledge on the temporal behaviour of specific grasslands (e.g. drivers and effects that affect temporal NDVI profiles) or when grassland seasonality varies a lot in space and between years, the mapping accuracy of grasslands is greatly reduced even at regional scale. For example Gao et al. (2009) using object-oriented multitemporal classification for Mexico achieved disappointing grassland mapping results (22 % user's accuracy and 59 % producer's accuracy), the main misclassification being with temperate forests. Similarly, Matsuoka et al. (2004) struggled to sufficiently discriminate agricultural fields from grasslands in the Yellow river basin which they attributed towards the lack of distinction between the multitemporal metrics of grasslands and single cropped agricultural fields. Mucher et al. (2000) using a classification approach, that was very successful in The Netherlands (80% accuracy for grasslands), do not obtain satisfactory results in Eastern Spain which was explained mainly by a variable eco-climate and a heterogeneous landscape. Ratana et al. (2005) showed that the MODIS seasonal - temporal VI profiles are highly useful in mapping converted pasture in a highly complex and diverse cerrado landscape, however grassland and shrub cerrado formations were difficult to separate using their seasonal profile. To conclude, grasslands can be relatively successfully mapped in cases when they represent relatively large compact homogenous areas of similar grassland types or when a regional adaptive approach benefits from a-priori knowledge of the distinct seasonality of the respective mapped land cover classes. Taking into account all the above mentioned issues, we tested different approaches (including data pre-processing, classification strategies, training and validation data set) in order to assessed the added value of multitemporal analysis of MODIS 250m NDVI time series for mapping grasslands in heterogeneous landscape in Slovakia.

1.3. Grassland classification and monitoring

Grassland classification aims to bring more precise knowledge on grasslands in terms of types or condition when the location of grasslands is already known. Grasslands with similar physiognomy may have different temporal pattern of NDVI affected by a broad range of natural or human driven factors. Multitemporal analysis of NDVI time series iteratively explores the main determinants of seasonality and uses this information for the subsequent classification of grasslands to determine their vegetation type, status and functioning. Grassland classification may include both full coverage classification of grassland areas or exploration and classification of main grassland types of sampled areas. For example Aragon and Oesterheld (2008) used a combined approach using information of spatial arrangement (from single date HR Landsat TM image) and information on functional properties (NDVI dynamics derived from multitemporal MODIS 250m NDVI series) to map grassland vegetation communities in Argentinean flooded Pampa grasslands. The authors successfully classified 5 grassland vegetation types with an overall accuracy of 76% and documented that grassland vegetation communities significantly differ in their seasonal and interseasonal pattern of NDVI. Wen et al. (2008) identified 6 main grassland types in Tibet using time series analysis of MODIS NDVI profile with estimated accuracy ranges from 21 % (high cold meadow steppe) to 68 % (high cold typical steppe). Hill et al. (1999) classified a pastoral landscape in eastern Australia resulted into 8 broad categories: sown perennial pastures, sown perennial pastures with woodland, sown annual pastures, mixed pasture and cropping, native pastures, native pastures with woodland, degraded or revegetated areas and forest. Boles et al., (2004) distinguished 4 main types of grasslands in one of the world's largest grassland region of temperate East Asia: typical steppe, meadow/meadow steppe, meadow steppe/typical steppe, shrubland/grassland. Although they do not report a validation statement of each grassland type, the aggregated grassland class was mapped with an estimated 60 % user's and 46 % producer's accuracy. Paruelo et al. (1995, 1998) characterized seasonal patterns of the NDVI in 49 grasslands in North America with low human impact and derived indicative metrics of NDVI curve in order to describe climatic controls on grassland structure and functioning. Later Paruelo et al. (2001) used NDVI dynamics as a descriptor of ecosystem functioning and widely applied this approach for mapping and classifying ecosystem functional types. They used three measures calculated from the seasonal curve of NDVI: annual integral of NDVI as an estimate of primary production, relative annual range of NDVI and date of maximum NDVI both of which were used to capture the seasonality of primary production. There are many applications that using NDVI time series for grassland assessment. Perhaps the most widely used approach represents the analyses of the NDVI temporal profiles (and derived surrogates) to explore climate-grasslands relationships. This represents a long time effort to detect climate driven threats on grassland ecosystems. These grassland phenology studies include trend and seasonal change detection as a tool for climate change impact assessments (Tao et al., 2008). Land use change impacts on the NDVI profile can also be analyzed at regional scale (Paruelo, 2001) and indicators derived for direct or indirect biodiversity assessment (Coops et al., 2009; John et al., 2008; Huang et al., 2009). In our case study we explored the use of temporal NDVI profiles of grasslands to characterise grassland structure and functioning including their specific phenology, management, hydrology, and overgrowing.

2. Case study 1 - Grassland mapping

In our mapping case study we attempt to map the grassland land cover class in Slovakia by exploiting differences in the seasonal NDVI dynamics. The main objective was to test whether the grassland land cover class (as defined in CLC classification system) can be discriminated from other land cover classes, especially arable lands and forests by their specific seasonal NDVI profile. As mentioned above, temporal information based on seasonal profile of vegetation greenness (indicated by NDVI) has been used for rapid large scale land cover mapping. However the coarse spatial resolution of satellite data with high temporal resolution is considered as the main limitation for mapping of grasslands within the heterogeneous landscape. In this case study we tested the possibilities of multitemporal classification for full coverage mapping of grasslands and aimed to identify the main limitations of this approach for mapping of grasslands at regional scale in highly heterogeneous landscapes such as Slovakia.

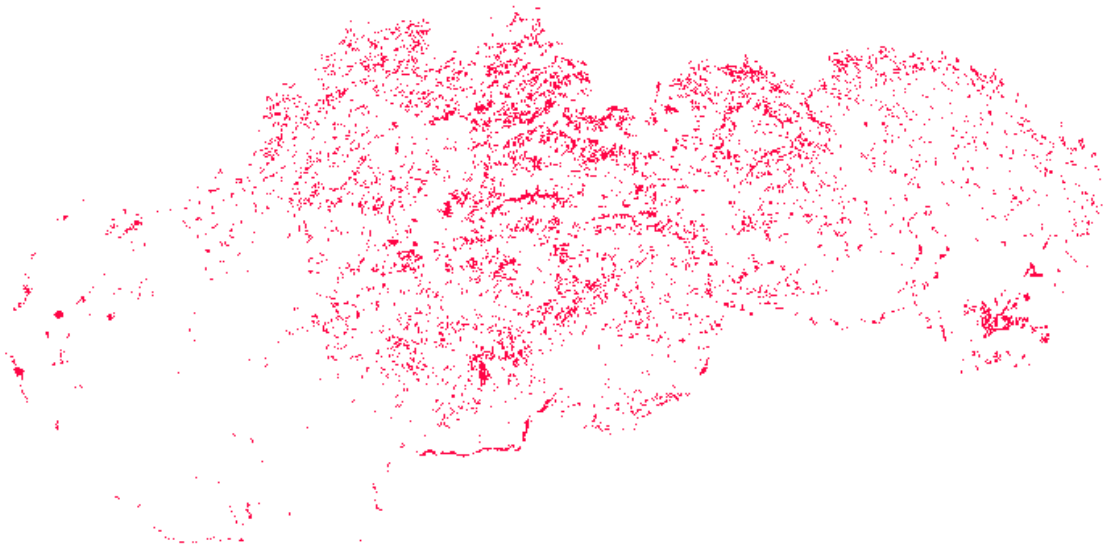

Fig.2.: Grassland distribution in Slovakia (CLC2000, class231 – pastures)

2.1. Study site

Grasslands in Slovakia are formed mainly as small scattered patches with diverse spatial arrangement (Fig. 2). From the agricultural statistics the total coverage of grasslands (excluded natural alpine grasslands) is estimated to be 690 000 ha which represents approx. 15% of the Slovakia and 30% of the agricultural landscape. CLC grassland class 231 clearly underestimates the total coverage of grasslands, perhaps because of the minimal CLC mapping unit (25 ha) and aggregated classes (242 and 243). Grassland vegetation types vary broadly based on the nutrition, geology substrate, hydrology and elevation. Land use represents an important driver of grasslands including grazing with different intensities on pastures, cutting on meadows or both (spring cutting and autumn pasturing). A substantial proportion of grasslands have been abandoned and overgrown after the changes in socioeconomically condition in early 90-ties. Recently, agro environmental subsidies have introduced special management in the most valuable semi natural grasslands in Slovakia.

2.2. Data and processing

We used MOD13Q1 (250m 16 day NDVI) and MOD09Q1 (250m 8 day surface reflectance) downloaded from Land Processes distributed active archived centre (LPDAAC) for the area covered by the Modis grid tile h19v4 (Fig. 12). Usefulness index and quality assurance layer of MOD09A1 were used to minimize negative effects of clouds, cloud shadows, aerosols, sun-sensor geometries and snow. Missing data were later interpolated and smoothed using Savitsky – Golay filter incorporated in the TimeSat software (Eklundh and Jonson, 2004) in order to produce complete NDVI time series from 2001 to 2010. Those areas for which two subsequent 16 day observation were missing were masked and omitted from later analyses. In our mapping case study we used annual time series of NDVI for 2009. In order to explore the effect of temporal resolution (16 day vs. 8 day composite series) and time period using for classification (whole annual series vs. vegetation growth period) we carried out the following analyses:

1. Principal component analysis (PCA) of the whole annual 16d NDVI series
2. PCA of the vegetation growth period (22nd March - 1st November) of the 8d NDVI
3. Fourier analysis (TFA) of the whole annual 16d NDVI series
4. TFA of the whole annual 8d NDVI series

Results from these analyses e.g. PCA component scores, amplitudes and phases of Fourier transform were later explored and used for the image classification. Two basic approaches for the image classification were used. The first approach was a maximum-likehood supervised classification which was applied to map 5 broad CLC classes:

Deciduous forests (CLC 311)
Arable land (CLC 21*)
Water areas (51*)
Grasslands (231)
Urban areas (1**)

We used the Corine land cover map from 2006 to learn the classification procedure (i.e. signature development). In order to minimize the number of mixed pixels (in multi-temporal space) within the CLC grassland polygons we first carried out a multitemporal segmentation using 4PCA components (Fig. 3).

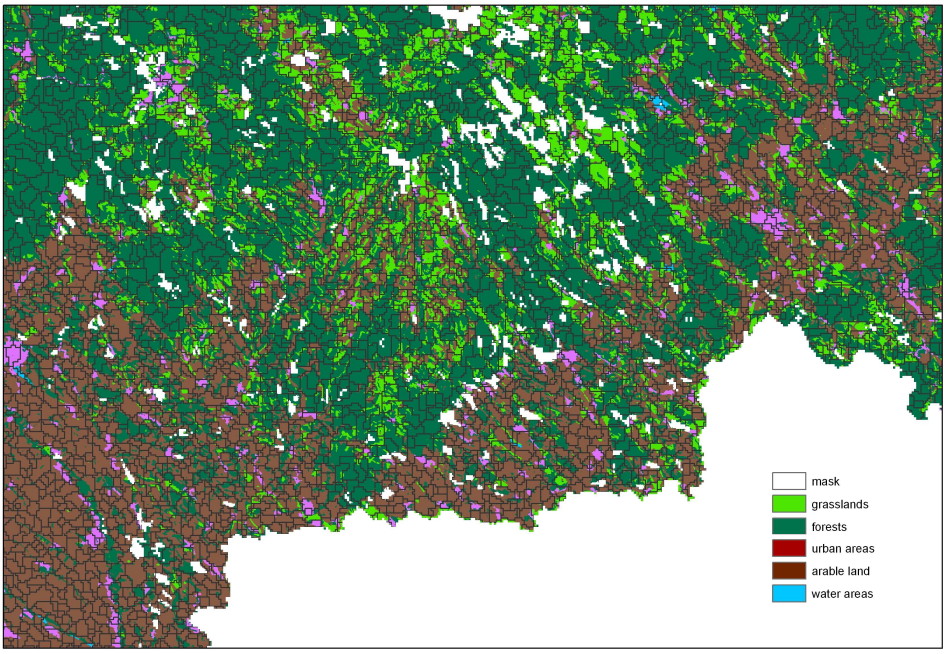

Fig. 3: Multitemporal segments for signature development

The second approach was an unsupervised classification approach. Here we used an ISODATA algorithm to produce multi-temporarily distinctive clusters. We set the maximum number of classes to 15 based on an expert judgement (i.e. based on the exploration of PCA components and Fourier terms) with the expectation of classifying the following classes:

- winter crops (wheat, oil rape)
- annual crops (barley)
- annual crops (corn, sunflower)
- deciduous forests
- shrubs
- coniferous forests
- cut grasslands
- uncut grasslands
- intensive grasslands
- overgrown grasslands
- alpine meadows
- water areas
- urban areas
- bare lands
- occasionally flooded areas

The class assigning of the resulting clusters was based on expert judgement by evaluating temporal profiles of the cluster centres and by iterative validation of clusters with reference temporal profiles. Two kinds of data were used for the validation. The first set represented randomly selected grasslands identified through the Slovakian land parcel information system and resampled to match the MODIS resolution using a simple majority rule (totally 80000 pixels). This validation sample set was considered to be heterogeneous. The second validation sample set was a subset of the first set representing only the pure homogenous grasslands. These were identified through a thorough inspection of Google Earth. Totally 3758 homogenous grassland pixels were selected for the validation (Fig. 4). Here we need to point out that these validation dataset represent only grasslands in agricultural land (excludes natural grasslands or pastures in forest landscape). A simple cross validation was used to estimate classification accuracies. Producer's accuracy describes how many of actual grasslands have been mapped. User's accuracy describes how many of mapped grasslands are actual grasslands. Users accuracy however was difficult to estimate as we did not have a reliable knowledge on the extent and distribution of grasslands and we did not have a "true zero" validation data set. Therefore we reported two Users accuracies. The first uses CLC class 231 and 321 as the mask for "real" grassland distribution and the second uses CLC 231, 321 and 243, 242 as the mask.

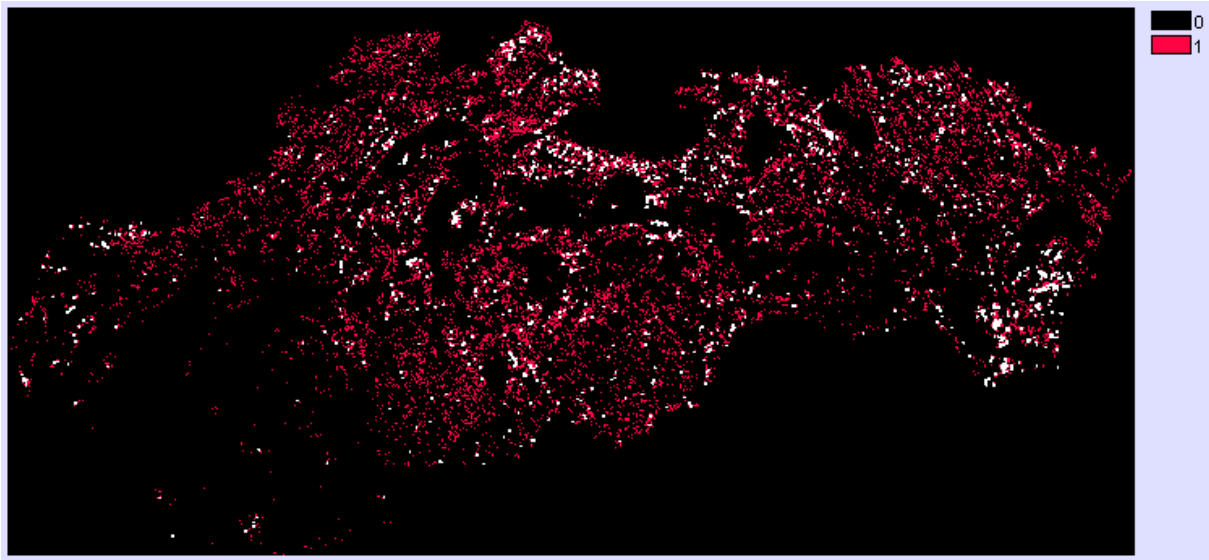

Fig. 4: Grassland validation sites (red – all; white – homogenous pixels)

2.3. Results

PCA of 16 day NDVI composite of the whole 2009 period

4 PCA components were extracted that explain almost 80 % of the seasonal variation of the data. The first component mainly characterises the start of the season (spring green up) and start of the senescence period in autumn. In the Slovak case, this component is related to deciduous forests, shrubs and grasslands as these massively green up during April and May and remain relatively green until October compared to agricultural areas (Fig. 5).

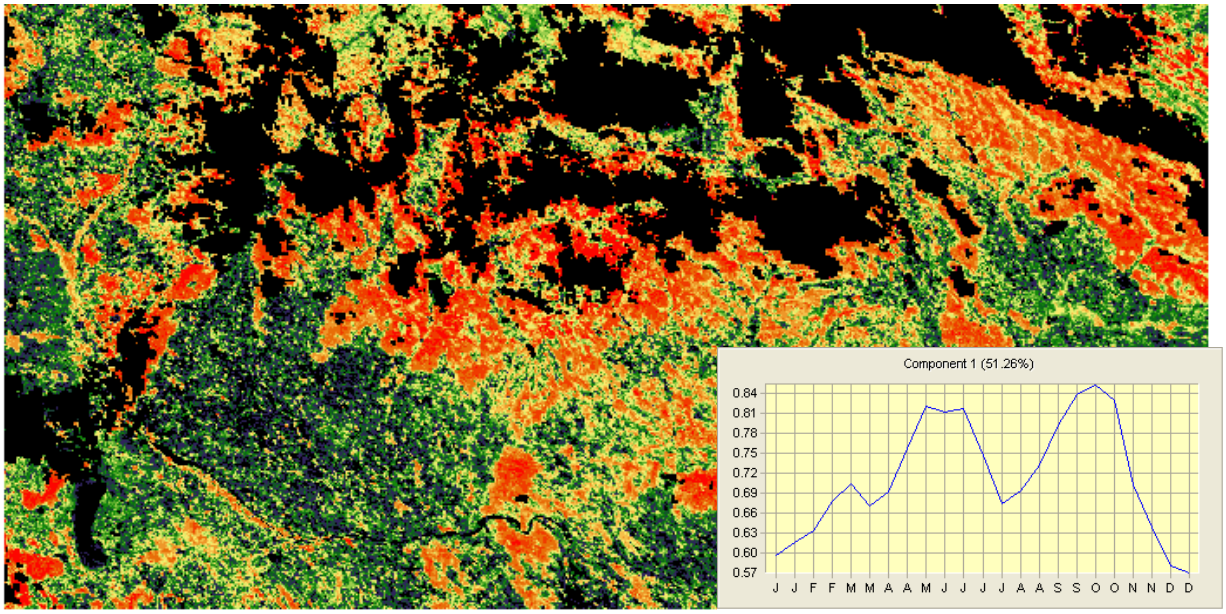

Fig. 5: PC1 scores derived from PCA of the whole period (red – high, blue – low, black – mask)

The second component characterises the variation within the peak vegetation season e.g. July, August and explains mainly the annual crops (as barley, corn, and sunflower) and part of the intensive grasslands (Fig. 6).

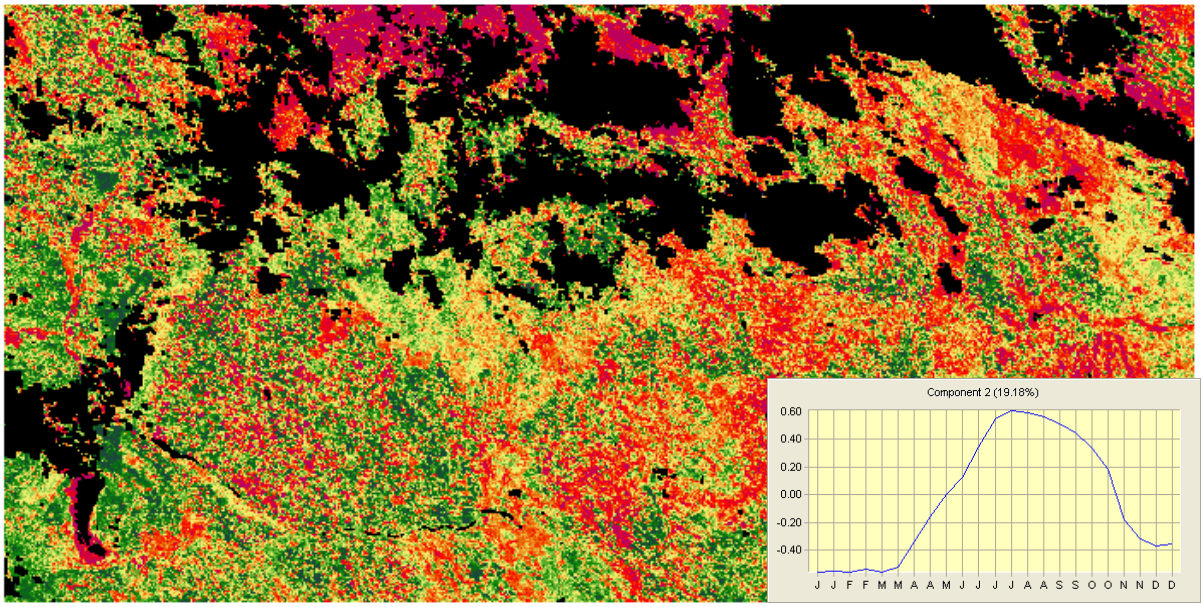

Fig. 6: PC2 scores derived from PCA of the whole period (red – high, blue – low, black – mask)

The 3rd component explains mainly winter crops (wheat, oil rape) because they are relatively green in winter and the arable land is usually ploughed up and left bare the next autumn and winter (Fig. 7).

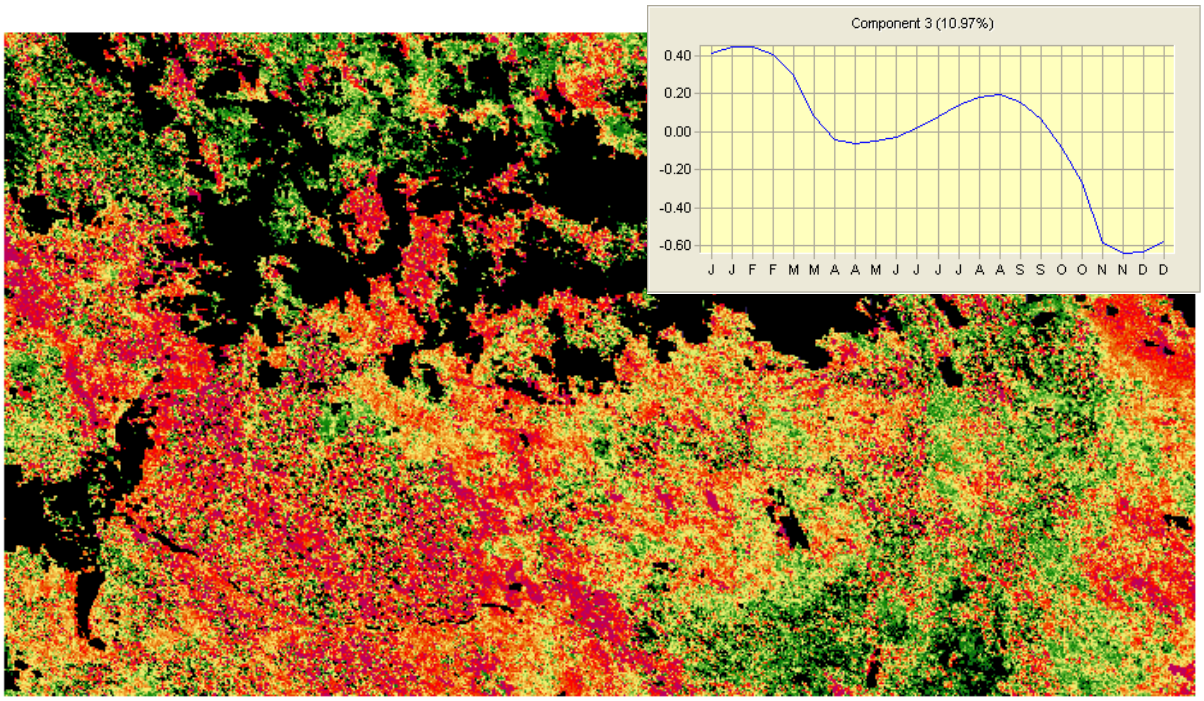

Fig. 7: PC3 scores derived from PCA of the whole period (red – high, blue – low, black – mask)

The fourth component probably represents a specific example of those annual crops (e.g. sunflower and corn) where crop residuals from the previous season have been left on the land and are ploughed up in April (Fig. 8).

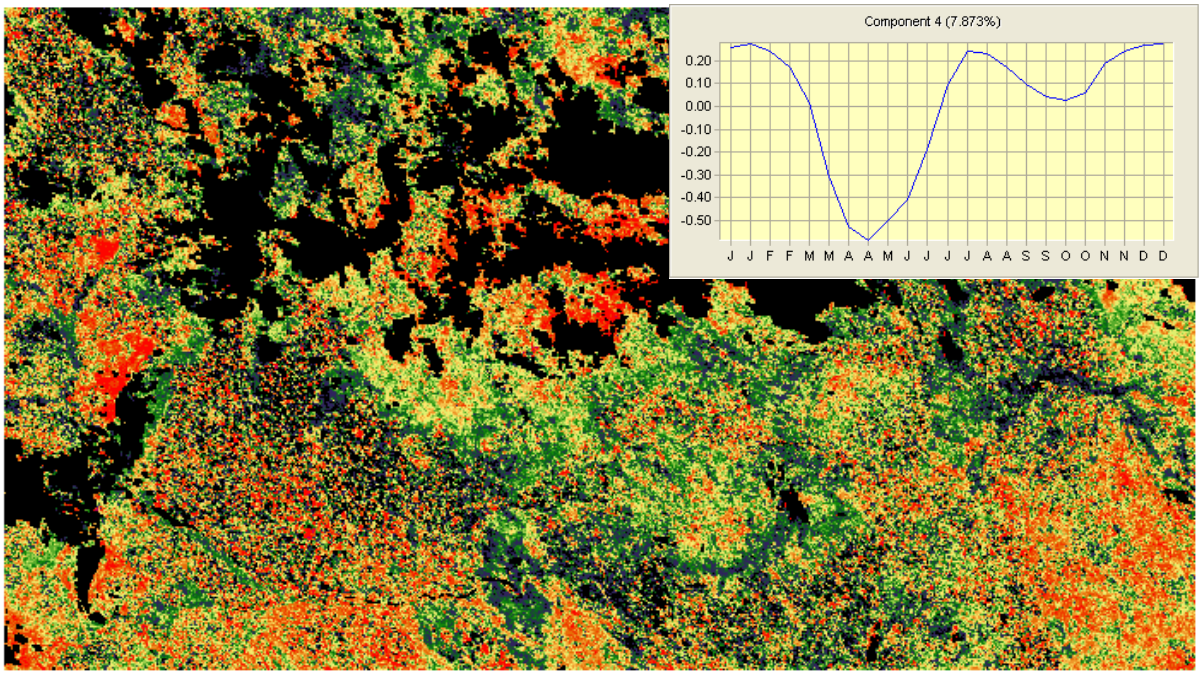

Fig. 8: PC4 scores derived from PCA of the whole period (red – high, blue – low, black – mask)

PCA of 8 day NDVI composite during vegetation season period 2009

Six components were extracted which explain 89% of the total variance. The first 4 components represent same vegetation types as described by components derived for the 16 day full year time series. However, two additional components that represent higher sub-seasonal variability were extracted. Component 5 probably reflects a one cut management practice and component 6 two cut management practices in agricultural landscape which could also represent cutting meadows (Fig. 9).

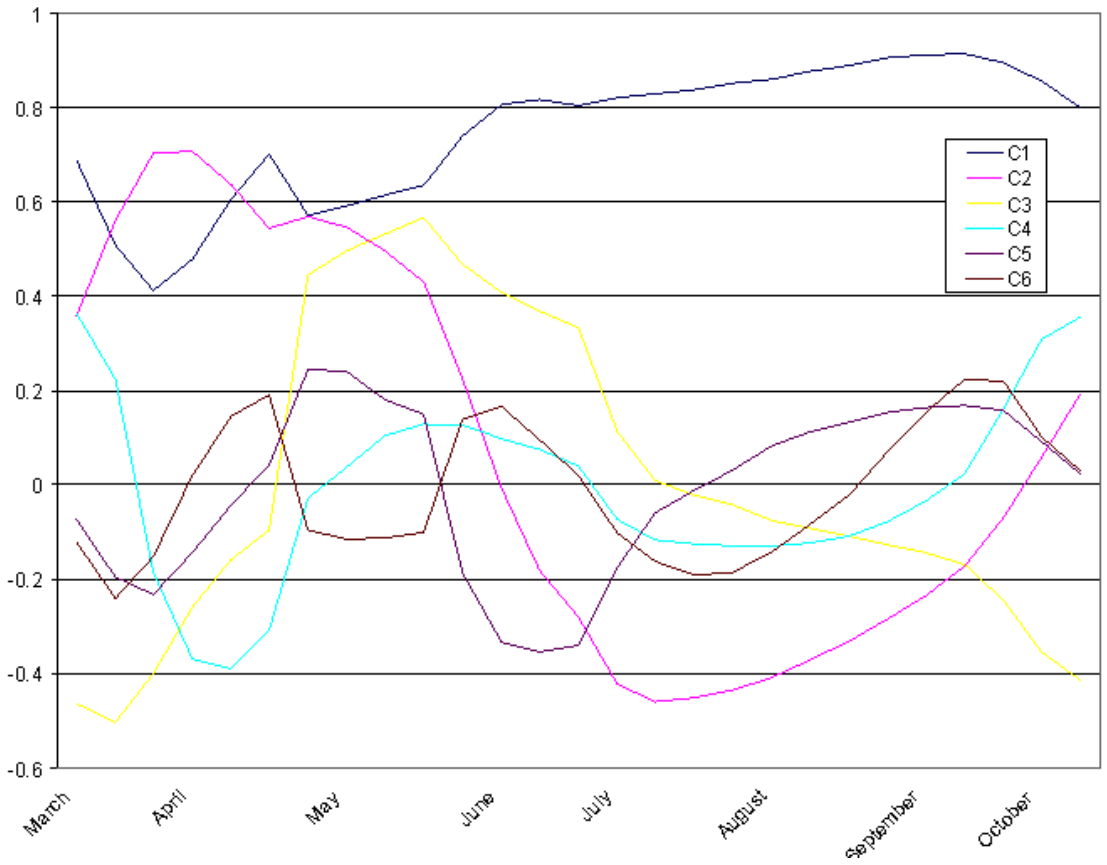

Fig. 9: Loadings of PC derived from 8 day NDVI composite during the vegetation growth period (March – October)

Temporal Fourier Analysis

Three harmonics were extracted with associated phases in order to reasonably interpret and label the classification clusters. Preliminary tests revealed that higher order Fourier terms may introduce more noise in classification results. Here first harmonic represents the annual amplitude of the NDVI curve being the highest in alpine meadows, deciduous forests and annual crops, and the lowest in coniferous forests, urban and water areas. Associated phase distinguishes winter and summer crops. The second amplitude reflects bimodal seasonality visible in agricultural crops and cut grasslands. The associated phase should reflect timing of cutting. We left the third harmonics because we believed this could reveal two-cut meadows, however this seems to be difficult to validate as for the many uncertainties depended mainly on quality of the data series and applied smoothing techniques.

Classification

Multitemporal signatures of forests, arable lands and grasslands (using 4 PCA components of the whole annual series of NDVI) indicate quite good sepearability although high variability was visible mainly for the arable land class. This is obvious because of different temporal response of individual agricultural crops. Cross tabulation of training samples with classified product indicates the main misclassification between grasslands and arable lands, however substantial disagreement was revealed between forests and grasslands (Tab. 1). Distribution of grasslands based on the supervised classification is shown on Figure 9. The results do not substantially differ when either PCA of 8 day vegetation growth period or Fourier terms were used for signature development.

Tab. 1: Error matrix of training sample (column) and classified results (rows)

	G	F	U	A	W	Total	ErrorC
G	345	44	65	54	0	508	0.32
F	32	196	27	17	0	272	0.27
U	16	0	59	29	0	104	0.43
A	12	12	38	413	19	494	0.16
W	11	55	2	3	75	146	0.48
Total	416	307	191	516	94	1524	
ErrorO	0.17	0.36	0.69	0.19	0.20		

Expert judgement of 15 clusters derived from unsupervised classification indicates using 6 PCA components of 8 day NDVI composite for vegetation growth performed the most reasonable results. The main source of bad classification results across the all analyses represents erroneous classification of grasslands as forests. Therefore the main visible criterion for the best analysis was the minimum erroneous classification of grasslands as deciduous forests. The full coverage map of the PCA based classification is illustrated on Fig. 10 and derived grassland distribution map on Fig. 11.

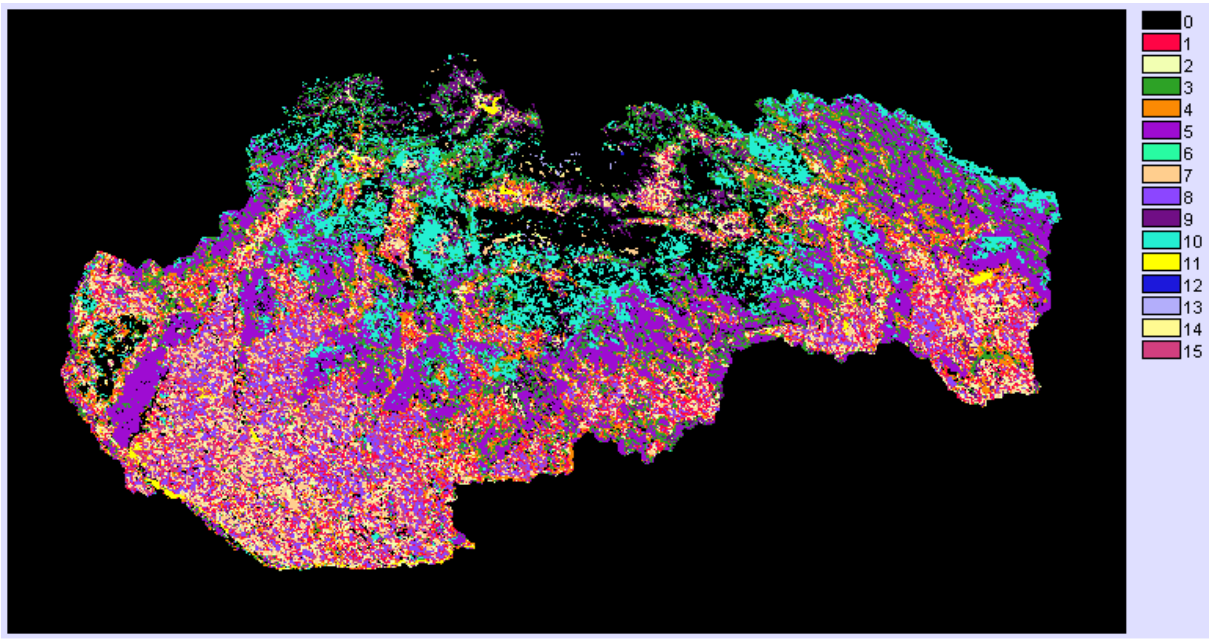

Fig. 10: Full coverage unsupervised product based on 6 PC of the vegetation growth period (Mar-Oct 2009)

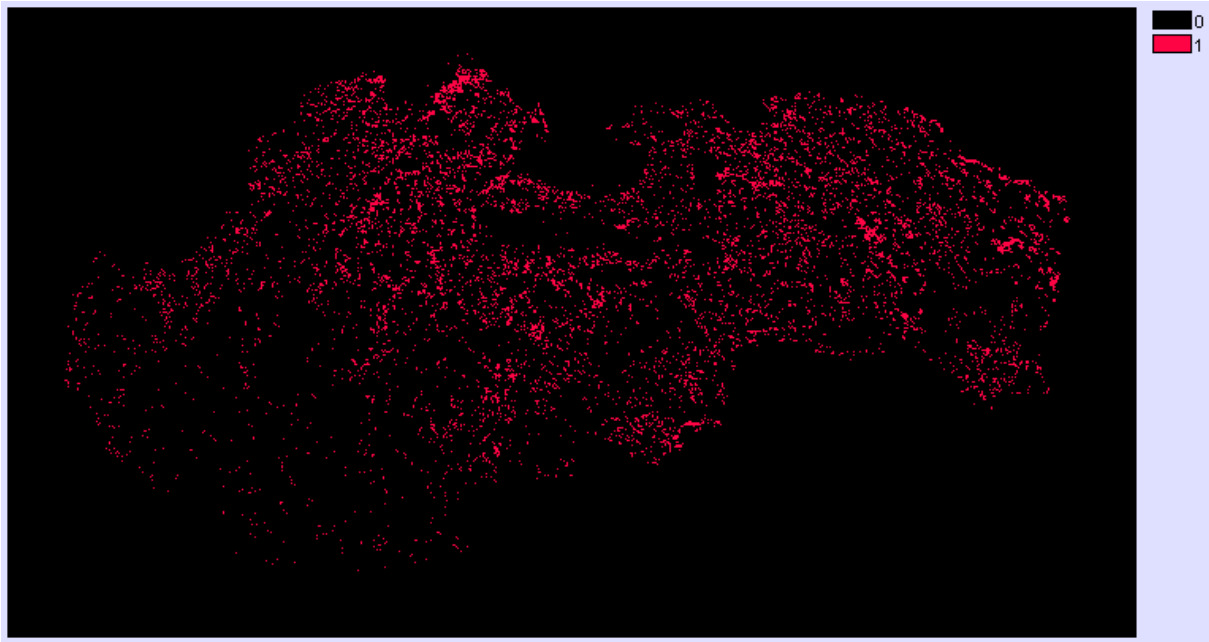

Fig. 11: Grassland distribution based on unsupervised approach using 6 PC of the vegetation growth period (Mar-Oct 2009)

Validation results of the all products are presented in Table 2. Based on the accuracy and reliability of the products and expert visual check of the full coverage map of clustering results (Fig. 10) we found that the PCA based approach using 8 day vegetation growth period outperformed the other tested approaches. Estimated users accuracies are fairly low across all the products. However, we need to comment here that our reference data is not necessarily correctly classified either and this needs to be considered in the interpretation of the users accuracies. In future studies we need to create true non-grass validation pixels evenly distributed across different land cover classes in order to provide more confident results on user's accuracy. Interesting findings were revealed in validation of CLC grassland product. Here, only a 38 % producer's accuracy was achieved which is relatively low number. This could be partly explained by minimal mapping unit of CLC approach, however as we used a majority rule for the spatial resampling of the validation data, we think that the validation pixels should be homogenous enough for detection in the CLC product. As for the total coverage area, unsupervised products clearly overestimate and CLC and supervised approach clearly underestimate the total coverage of grasslands.

Table 2: Total coverage and accuracy estimation of different analyses

Validation set		CLC	PCA based 8d	PCA based 16d	Fourier based	Supervised
Heterogenous	Area(ha)	223993	955100	922500	842500	433500
	Prod. acur.	38%	58%	51%	28%	16%
	Users acur.	58%	30%	30%	25%	38%
Homogenous	Prod. acur.	39%	68%	53%	38%	17%
	Users acur.	77.5	61%	60%	54%	53%

To conclude mapping of grassland land cover at regional scale in Slovakia based on solely multitemporal classification seems to be quite difficult not only because of the coarse resolution of MODIS data but, as it is later analyzed, also because of the fairly variable seasonal pattern of the Slovak grasslands. However we also documented that even the HR Landsat based CLC product in Slovak case is not very successful in grassland mapping.

3. Case study 2 - Grassland classification

Here assuming it is possible to first map the location and extent of grassland reliably, we explored the variability in the seasonal pattern of NDVI of grasslands across different study areas. We also explored possibilities of using temporal profiles of NDVI for extracting specific features of interests (e.g. cut management) or for phenology-based grassland type classification.

3.1. Study sites

Two grassland datasets were used to identify the location and extent of grasslands (Table 3).

Table 3: Data sets used for this case study

ID	Area	Grassland types	NDVI data applied	Temporal coverage	Source	Scale
1	Slovakia	All grasslands on agricultural land (excluding alpine meadows)	16 day; 8 day	2001-2010	National dataset – land parcel information system	National
2	Hungarian lowlands	N2000 grasslands	8 day	2006-2010	EEA database	Regional

Data set 1

We used homogenous pixel derived from Slovak national land parcel information system that mainly covered grasslands on agricultural land. Therefore natural grasslands (alpine meadows) and some pastures in forest landscape are not covered in this dataset. These sites were visually inspected on Google Earth. Totally 3758 pure pixels were included in this dataset (Fig. 12).

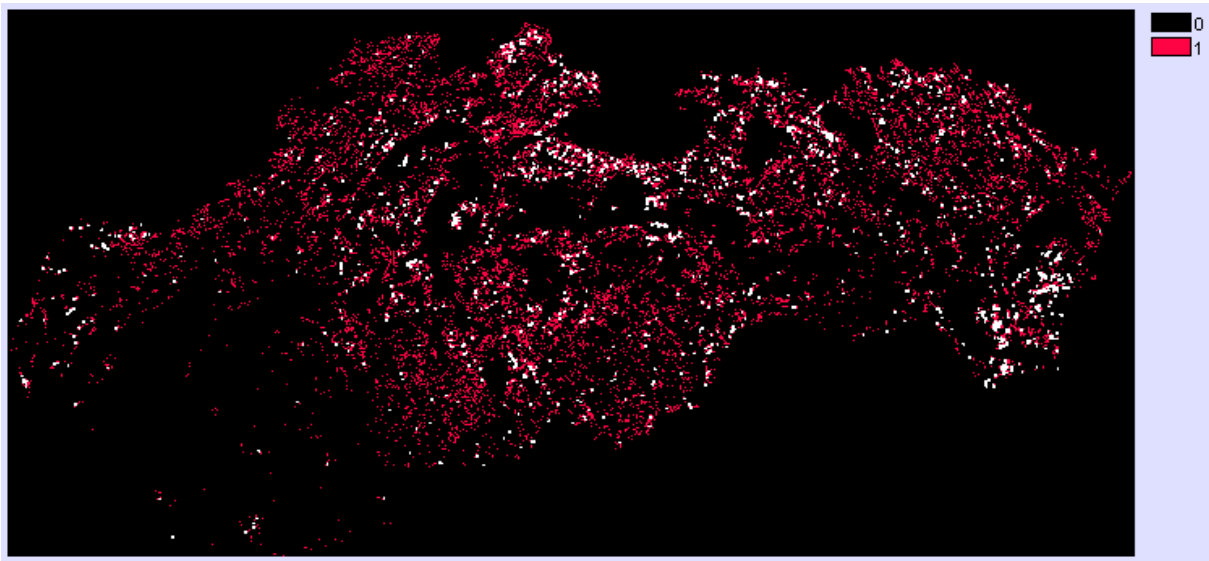

Fig. 12: Grasslands in Slovakia and 3750 selected homogenous pixels (white)

Data set 2

Natura 2000 grassland sites were extracted from EEA dataset. Only those Natura 2000 sites that contained 80 % majority of grassland habitats were included in data set. From there, 2800 pixels were randomly selected for the analysis (Fig. 13).

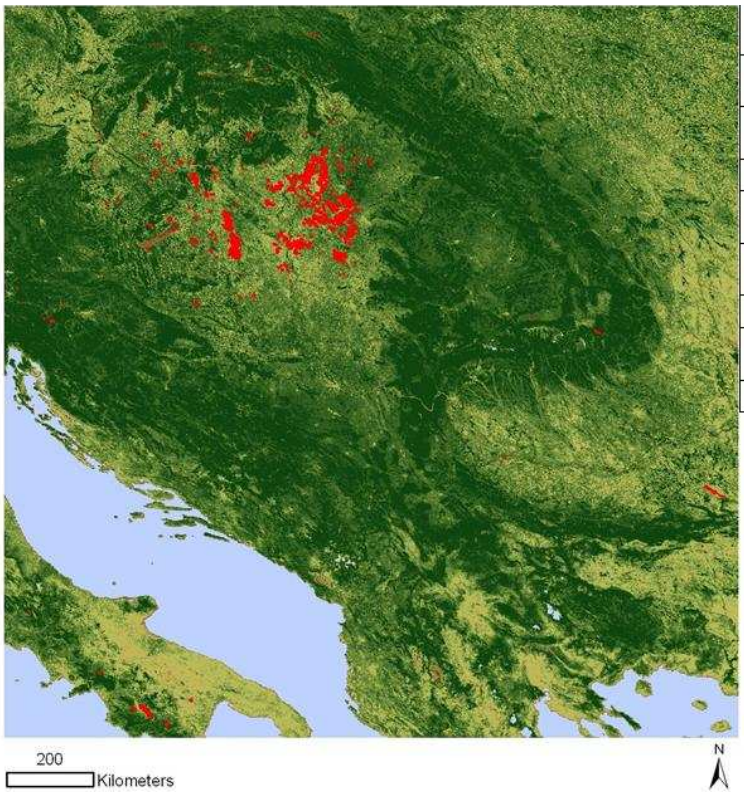

Fig.13: Hungrarian grasslands (data set 2)

3.2. NDVI data and processing

We used MOD13Q1 (16 day MVC NDVI with 250 m spatial resolution) and MOD09A1 (8 day surface reflectance at 250 m spatial resolution) downloaded from LP DAAC distribution centre for the area covered by Modis tile grid h19v4. Usefulness index and quality assurance layers of MOD09A1 were checked in order to minimize negative effects of clouds, cloud shadows, aerosols, sun-senzor geometries and snow. Missing data were interpolated and smoothed using Savitsky – Golay filter within the TimeSat software (Eklundh and Jonson, 2004) in order to get complete NDVI time series from 2001 to 2010. As a first step we used PCA of the 2009 annual series in order to explored main season-driven variability in grasslands. The extracted components were later used to produce a broad classification of grasslands based on their seasonality. Finally we used several specific multitemporal indexes (e.g. variability in peak season, spring negative anomaly, etc.) to test the potential for detecting grassland specific temporal features (e.g. cut management, flooding regime, etc).

3.3. Results

Using field observations and local expert knowledge we explored many NDVI time profiles that explained a wide variety of drivers of grassland status and functioning. Here we briefly described the following examples:

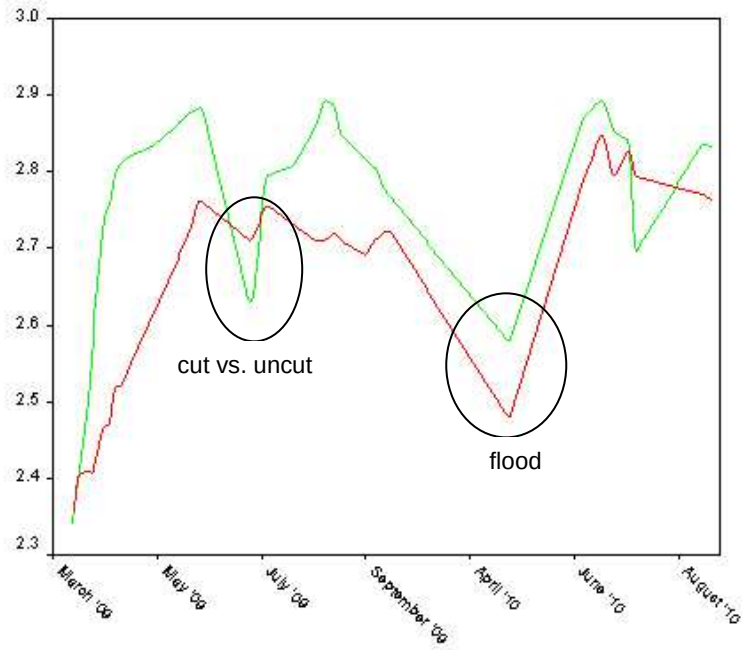

Fig. 14: Cut (green) vs. uncut (red) meadows, both flooded in spring 2010 (original scale of NDVI -1/+1 rescaled to 1/3)

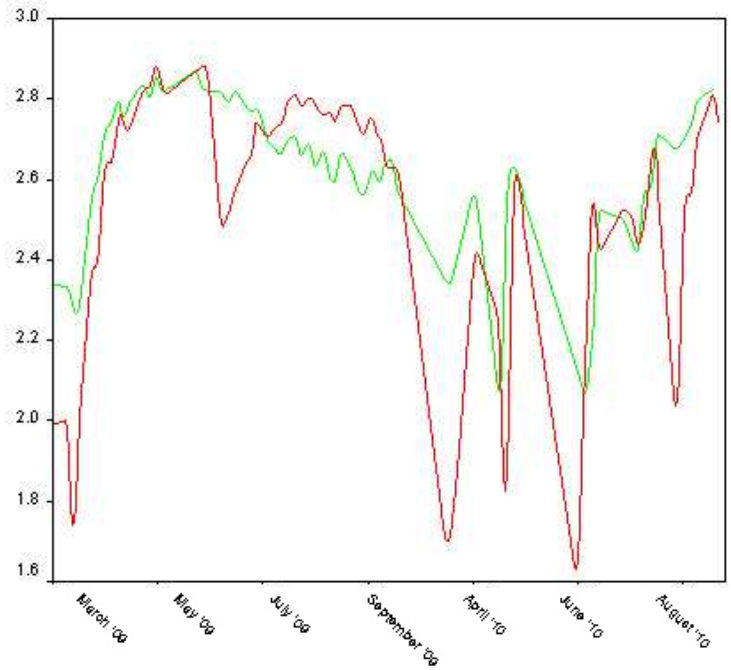

Fig. 15: Cut meadows (red) and pasture (green) both flooded several times at different rate during spring 2010 (original scale of NDVI -1/+1 rescaled to 1/3)

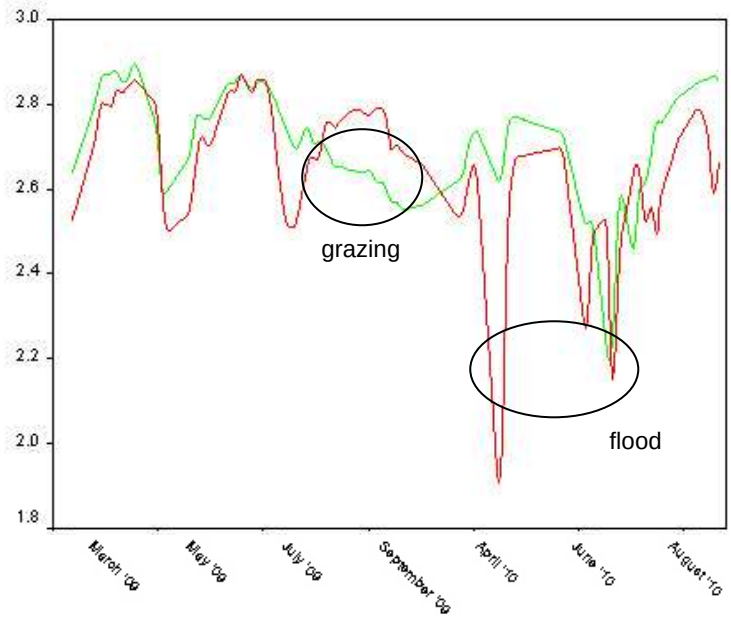

Fig. 16: Twice cut meadows with grazing in autumn (green), both sites flooded once (green) and two times (red) in 2010 (original scale of NDVI -1/+1 rescaled to 1/3)

The PCA of 16 day 2009 NDVI composite of Slovak grasslands (data set 1) extracted 5 components with a total explained variance of 91 % (Fig. 17). This demonstrates that the seasonal NDVI pattern of grasslands varies substantially. Factor loadings show that it is mainly the different timing of peak season, cutting and different greenness in spring and autumn determine seasonal variability in Slovak grasslands. Classification of these 5 components using k-means clustering resulted in 5 main types of grasslands with specific temporal profile of NDVI (Fig. 18).

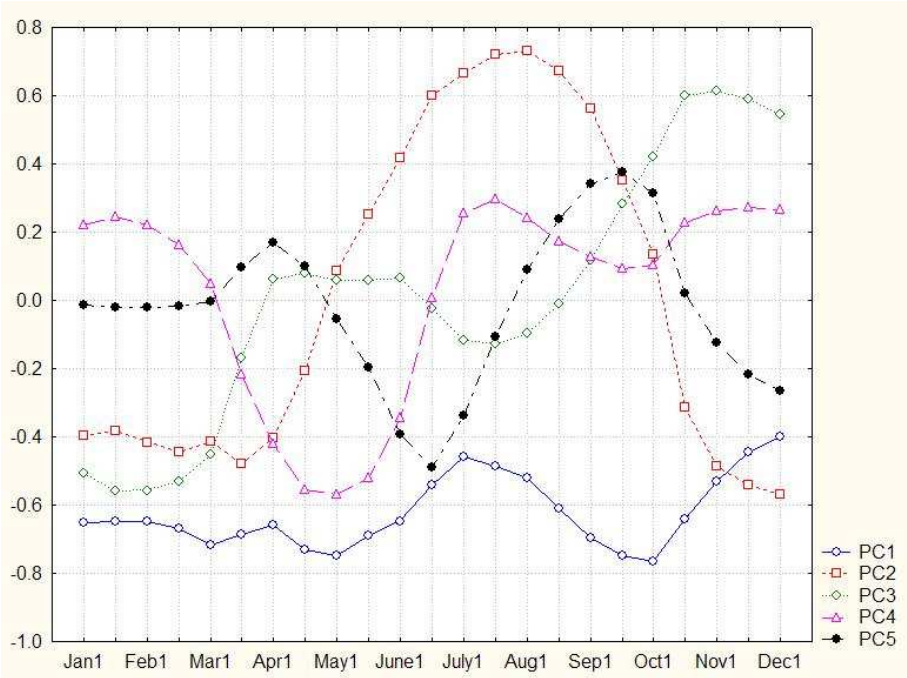

Fig. 17: Factor loadings resulted from PCA of 16 day 2009 NDVI composite of Slovak grasslands

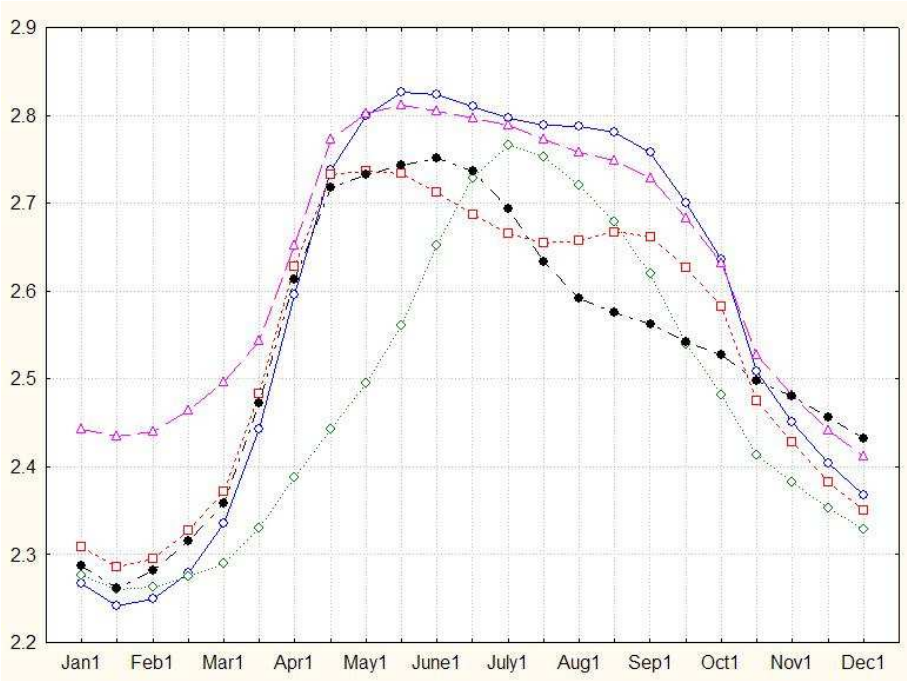

Fig. 18: Average temporal profile of NDVI of resulted clusters (16 day NDVI composite of 2009) (original scale of NDVI -1/+1 rescaled to 1/3)

It is visible that mainly productivity (blue and purple clusters), different management (red and black clusters) described main differences in managed grasslands. A special case represents green cluster that can be attributed to mountainous grasslands typical with shorter vegetation season and delayed vegetation peak.

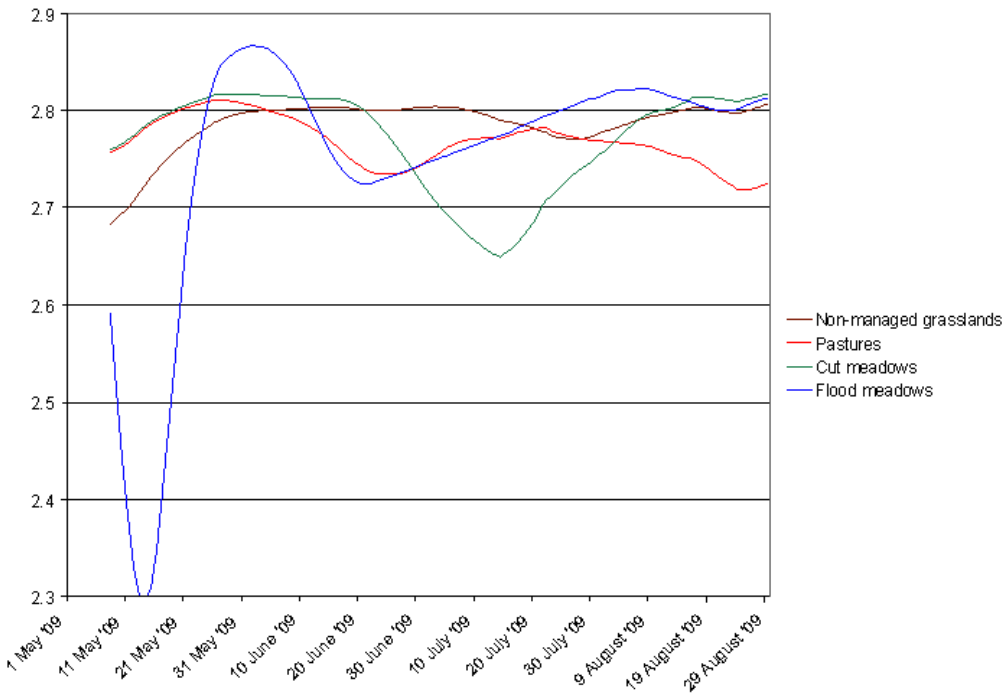

Fig. 19: Classification of grasslands using 8 day NDVI composite of vegetation growth period in 2009 (original scale of NDVI -1/+1 rescaled to 1/3)

When we used the same approach with increased temporal resolution (8day) of NDVI composite data from vegetation growth period (May-September) we obtained slightly different results (Fig. 19) with better distinction of flooded grasslands, pastures and cut grasslands. The same approach and data were used for classifying Hungarian grasslands in N2000 areas (Fig. 20). These grassland types exhibit distinct seasonal variability: wetland and salt marshes, cut meadows, pastures and non-managed natural grasslands.

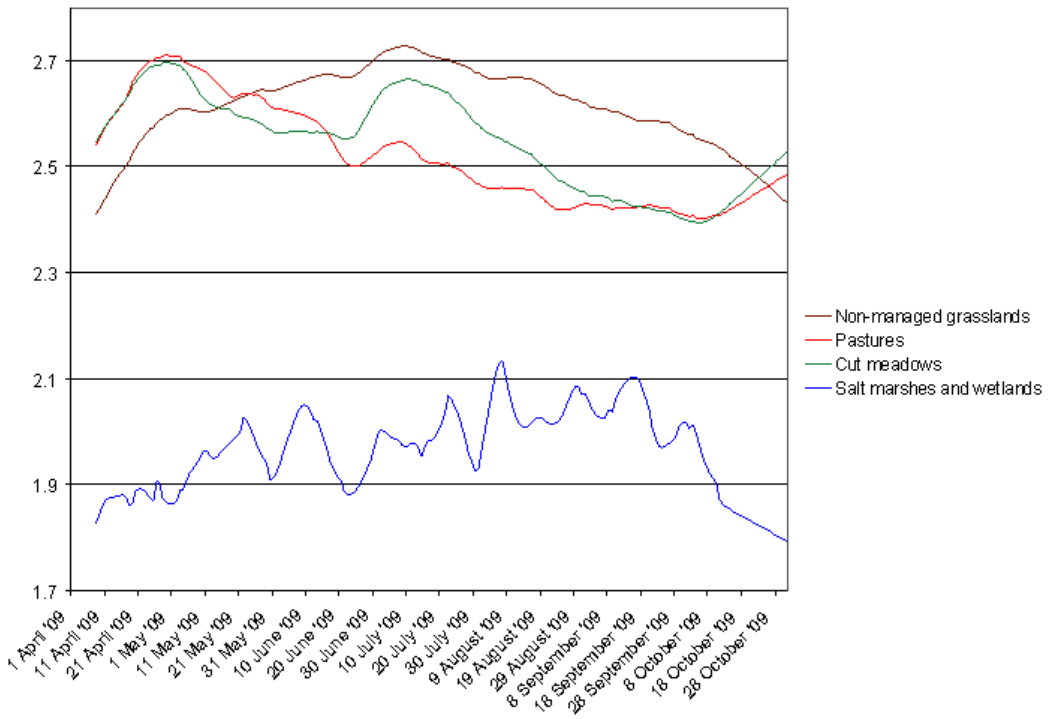

Fig. 20: Classification of Hungarian grasslands in Natura 2000 areas using 8 day NDVI composite of vegetation growth period in 2009 (original scale of NDVI -1/+1 rescaled to 1/3)

4. Discussion and conclusion

Grassland seasonal pattern of NDVI can vary substantially reflecting not only the differences in vegetation type but also land use, management practices or site hydrology. This fact mainly limits mapping of grassland as a single land cover class especially when above factors are evenly present across the study area. This was demonstrated in Slovakia by the supervised image classification where one “grassland signature” was confused with many forests, and arable crops. In fact, different land covers may have similar seasonal patterns of productivity (for example, some shrubs and the unmanaged grasslands); conversely, the same land-cover type may have different NDVI dynamics (for example, the intensive grasslands and extensive grasslands. On the other hand in unsupervised approach clusters with similar seasonality were merged together and misclassification was introduced by our attempt to attribute distinct seasonal information to respective land cover class. We demonstrated the limitation of using supervised approach for a full coverage classification at broader scale which required more effort in training compared to the relatively easy labelling of an unsupervised product.

It seems that PCA approach were more suitable for exploring distinctive characteristics of NDVI temporal profile across different land cover classes. Although Fourier harmonics revealed some specific features (e.g. alpine meadows) and better reflect phenology we got more noisy classification results leading to more difficult labelling of the clusters. However as PCA is fully data dependent, better stratification (e.g. forested, agricultural landscape) may

increase explanatory power of PCA. NDVI temporal profile of majority of grasslands in Slovakia was similar to that of deciduous forest which causing the main misclassifications. It seems that excluding of winter months for analysis and using of 8 day NDVI composite data within vegetation growth period also increased explanatory power of PCA. Wen et al. (2008) also reported that using of vegetation growth period was better than the whole year time series for multitemporal analysis of Tibetian grassland classification. In fact, analysis of the whole annual period can be negatively influenced with winter periods and noise in data that is not primarily connected to vegetation seasonality resulting in producing of unmeaning full classes (Mucher et al., 2000). To conclude, the first reason of our poor success in grassland mapping relates to classification problem of land cover.

Different approaches for classification legend of land cover may lead to diverse final products resulting in uncertainties of information about status and changes of the landscape. Harmonization of the different approaches is very difficult because of diverse user community across the many disciplines and applications e.g. biodiversity conservation, hydrology, nature resource management, climatology, etc.). At regional scale broadly used CLC product faced many criticisms for inconsistent approach for classification and researches call for harmonized approaches for the European land cover classification (Mucher et al., 2000). As for the biodiversity observation initiative within EBONE project, usefulness of land cover maps for biodiversity assessment and monitoring needs to be further evaluated what will be done in near future. Going back to the classification problem, grasslands appeared to be relatively consistent in different classification legends as grassland or pastures, sometimes with different proportion of trees, based mainly on the physiognomy of grasslands. However, grasslands can vary a lot reflecting land use (meadow, pasture), management practice (one cut, two-cut, improved, semi-natural), hydrology regime (seasonally flood meadows), degradation (sparsely vegetated, overgrazed), abandon (overgrown). All these information are crucial as the indicators of their biodiversity values. Therefore, in their simple merging in one grassland land cover class, a poor knowledge would be extracted for biodiversity assessment. Hence, we suggest incorporating also information on temporal behaviour and seasonality into the classification system in order to reflect functioning of grasslands as proposed by Paruelo et al. (2001). A new approach within the EBONE project has been fostered in order to make classification of land cover more suitable for consistent large scale habitat mapping and biodiversity assessment. Furthermore the classification approach would reflect current and future possibilities and limitation of remote sensing what gives this approach more chance to be applicable and operational. At the broader scale (European and Global), this process is not easy and many case studies need to be done across the scale in order to test its applicability. In this deliverable we reflect mainly regional and local scale which allows reasonable validation of the results. GHC are think to reflect several features of land surface (including phenology) what all should help to precisely define habitats for biodiversity assessment. Loveland et al. (2000) defines logic of land cover class definition based on their similar physiognomy and seasonality. Paruelo et al. (2001) using rather ecosystem function types than land cover classes and stated that these better reflect status and functioning of ecosystems allowing better detection of threats and trends. In fact, when landscape is monitored, (for example by using CLC1990 and CLC2000 products) the same area could be identified as 231 after 10 years stated for no negative trend in grassland change. However analysis of the landscape based on the ecosystem functioning (e.g. temporal pattern of productivity) could reveal gradual degradation of the area (e.g. abandonment followed by successive overgrowing of meadows). This information is crucial for biodiversity observation and can serve as early warning system for change detection.

The second limitation of the multitemporal image classification is coarse spatial resolution of the sensors. This is obvious mainly in diverse heterogeneous landscape what broadly demonstrated by many authors (Wessels et al. 2004).

Mucher et al. (2000) produced relatively accurate classification of grasslands in Netherland what could be caused by their large quasi homogenous status and extent across the landscape. On the other hand when grassland landscape is very diverse with patchy mosaic of small patches and with different land use and management practices, classification could

became very difficult. Here we need to add that this is also problem of the HR based approaches. For example, accuracy of HR resolution based CLC grassland product in Slovakia was estimated only to 38%. This is could be due to the fact that many grasslands are incorporated within aggregated classes which can underestimate their total coverage estimates. For example 242 category of CLC represents almost 30 % of Slovakia indicating that we have a really poor knowledge about the grassland distribution. Unlike HR physiognomy based classification it is difficult to classified aggregated classes by multitemporal approach although some successful examples exist (Geerken et al., 2009). We think that combined approach using HR satellite data for spatial arrangement with functional information derived from coarser satellite data could be a good approach for mapping diverse heterogeneous landscape. In our example we did not document a big difference in accuracies when we validated results with pure homogenous pixels, what suggests that both high seasonal grassland variability and coarse spatial resolution were proportionally responsible for low capability of multitemporal approach for grassland mapping in Slovakia. However a relative importance of spatial resolution vs. within grassland temporal variability as main limits of multitemporal approach for grassland mapping needs to be further explored by comparative studies in contrasting grassland landscapes (e.g. Hungary vs. Slovakia). To conclude full coverage grassland mapping together with other land cover classes by using only multitemporal approach seems to be difficult. Combined approach with HR sensors is suggested in heterogeneous landscape. Furthermore, in order to deliver reasonable product of grassland mapping designated for biodiversity observation system, grassland classification (based on the NDVI temporal profile) needs to be reasonably defined reflecting information with added value for biodiversity monitoring and assessment. This classification should be regionally specific considering eco climatic conditions and different grassland types and land use practices.

Explanatory analysis of NDVI temporal profiles across the different regions identified specific features of grasslands in temporal space. In our second case study we demonstrated that when some knowledge about grassland occurrence exists, classification based on temporal NDVI profile brings reasonable information on grassland functioning. In general, productivity (which relate to amplitude of NDVI curve) and seasonality (range or variance within season) represent main distinctive characteristics of grasslands. Productivity and seasonality derived from NDVI temporal curve are broadly used in ecosystem classification studies (Paruelo et al., 2001). NDVI composite data at finer temporal resolution (8 day) better distinguishes grasslands. In more detailed examples we documented that also specific timing of NDVI peak, rate of increase of NDVI in spring, bimodal shape of NDVI, or negative anomaly in spring can be used for distinguishing of pastures, mountainous meadows, intensive, extensive meadows, flooded meadows or salt marshes. However, more regional specific knowledge from grassland experts needs to be used in order to derive consistent grassland classification system for broad scale mapping and classification.

In our examples we tried to briefly demonstrate capabilities and limitations of multitemporal approaches for grassland mapping and classification. It seems that for the mapping of grasslands in heterogeneous landscape, specific approaches need to be further explored for increasing of mapping capabilities of multitemporal analyses. These approaches (including seasonal based classification of grasslands) need to be tested in near future across contrasted landscapes. Anyway, explanatory analysis and classification of grasslands using available sample data revealed that specific features of grasslands can be detected and reasonable classification made what proves that multitemporal analysis should represent a valuable tool mainly in the assessment and monitoring component of the proposed biodiversity observation system.

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