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Izvorni znanstveni članak

Super Resolution Mapping of Agricultural Parcel Boundaries based on Localized Partial Unmixing

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ABSTRACT. Operational mapping of crop/agricultural parcel boundaries is a challenging task. It should be efficient and inexpensive process resulting with data useful for wide range of purposes. Hard classification of medium resolution (>15 m, <30 m) remote sensing data could be a solution but the spatial resolution of the imagery is not sufficient for many applications. In this paper a method for soft classification of medium remote sensing data and super-resolution mapping of crop boundaries is presented. The method is developed based on localized partial unmixing with estimating both target and background end-member spectra. The output was subjected to pixel swapping as super resolution mapping technique. Testing is done on real Landsat ETM+ imagery. The method is evaluated quantitatively and the results show significant increase of accuracy when compared to mapping from original remote sensing data.

Keywords: agricultural parcel mapping, super resolution mapping, partial unmixing, linear unmixing, pixel swapping.

1. Introduction

Crop monitoring and mapping have become an important issue during the last few decades. Operational mapping of crop boundaries in most cases coincide with mapping of agricultural parcels (Olivier and Guido 2001) which represent very important data for many purposes, from land and environmental management to control of subsidies. For example, in the Integrated Administration and Control System (IACS) of the European Union, agricultural parcel is defined as "one piece of land cultivated by one farmer with a single crop group" (Commission Regulation (EC) No. 1122/2009) and is the most detailed type of reference parcel in the Land Parcel Information System (LPIS) which is used for the control of area

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based subsidies in agriculture. Mapping of agricultural parcels, in an operational way, has been, so far, mostly process of manual digitizing of aerial and/or satellite imagery or a product of hard classification (De Witt and Clevers 2004).

In those cases accuracy of mapping is highly dependent on spatial resolution of the used imagery. Therefore, expenses of high or very high resolution imagery and manual digitalization are often limiting factors in establishing operational and adequately accurate mapping of crops. On the other side, hard per-pixel classification of lower resolution imagery, where each pixel in the image is allocated to the class with which it has the greatest spectral similarity, produce crop boundary prediction with inadequate accuracy since crop boundary lines usually run through the pixels that have mixed class composition (Cracknell 1998, Foody et al. 2005).

The solution could be found in estimation of crop boundary line on sub-pixel level of medium spatial resolution (>15 m, <30 m) imagery. It can be achieved by sub-pixel (or super-resolution) mapping where finer resolution data are extracted from original imagery retrieving spatial location for target land cover class (crops in this case) among the original mixed pixels (Atkinson 1997, Mertens et al. 2006). To perform this, a soft classification is needed aiming to retrieve the abundance of the target land cover class in each original pixel. The accuracy of super resolution mapping therefore strongly depends on the accuracy of applied soft classification output which is the result of an unmixing method and training statistics that is used.

The main assumption is that the reflectance of a pixel is a linear combination of endmember reflectancies. The high-quality end-member selection is thus very important to produce accurate abundances of target land cover class in each pixel (e.g. Tompkins et al. 1997, Bateson et al. 2000). However, reflectance is likely to vary across space and time, even for a narrowly defined end-member (Lobell and Asner 2004). For example, reflectance properties of vegetation depend on tissue optical properties, canopy structure but also on ecosystem (Asner 1998). Thus, defining an end-member spectra with respect to the end-members' variability is a difficult task that is addressed by various research papers (e.g. Bateson et al. 2000).

In this study, the results of an investigation to apply super resolution mapping techniques based on a linear partial unmixing for crop boundary prediction are presented and discussed. A specific linear partial unmixing method was developed to suppress the problems of soft classification related to the complex nature of crops as a land cover class. Namely, to perform linear unmixing within a mixed pixel, knowledge of the crop been mapped and other participating land cover classes spectra are required. However, crops are usually not spectrally homogeneous even across a single parcel and land cover classes forming the surrounding are mostly of different origin and thus it is difficult to determine their spectra to be applied in general. The approach threats the issues and implies taking advantage of applying partial linear unmixing (Nielsen 1998) and using local training statistics rather than global as it was suggested by Muslim et al. (2006) and adjusts them to the complex nature of crops. Also, the accuracy assessment for the outcome of the method is presented.

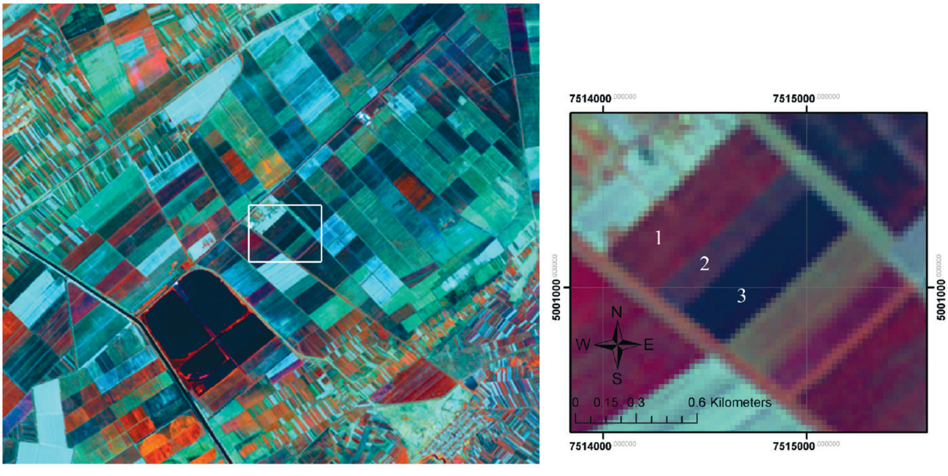
2. Method

The method consists of two consecutive segments: soft classification and sub-pixel mapping. While soft classification is performed to retrieve the abundance of the crop inside each mixed pixel the crop boundary is running through, sub-pixel mapping is aiming to allocate the crop fractions in the original pixels and consequently place the crop boundary line. As a soft classification method, a specially designed partial linear unmixing model is designed and pixel swapping algorithm is chosen to perform sub-pixel mapping.

2.1. Study Area and Image Data

The approach is experimentally tested on three agricultural parcels located in the Banat region, in the north-east of Serbia (21.18°E, 45.16°N). It is part of Vojvodina province which is the largest and most important agricultural area of Serbia. The landscape is characterized by large stretches of flat plains and highly fertile 'black soils'. The region mainly produces field crops, notably wheat, maize, sugar beet and livestock.

Six spectral bands (all except the thermal band), of the Landsat ETM+ image acquired on 28-07-2000 were used in the study. The data are extracted from IMAGE2000, EEA-JRC based on Landsat 7 ETM+ TESA 2000. It was orthorectified and resampled to 25 m pixel in the State Coordinate System of Serbia (Gauss-Krüger projection, datum Hermannskogel). To test the method, three neighbouring agricultural parcels with 29 ha, 13.5 ha and 26 ha were chosen, with unknown crops and phonological stages as it was considered irrelevant to the study (Fig. 1).



a) b)

Fig. 1. *a) Location of the study site (white rectangle), and b) three parcels mapped in the study.*

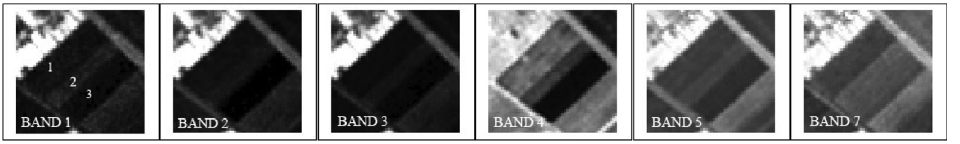


Fig. 2. *Six Landsat ETM+ spectral bands of the study area. Numbers on the first band assign the three crops being mapped in the study.*

2.2. Linear Unmixing

Soft classification is the first step in super resolution mapping. Assuming that only linear mixing occurred in the boundary pixels, linear unmixing model is chosen for performing soft classification. It allows estimation of the abundance of each class in pixels with mixed class membership (Nielsen 1998).

It is assumed that signal measured at each pixel consists of a linear combination of p end-members. End-member are considered as pre-determined classes with 100% abundance of one element and with no mixtures. The l-dimensional signal (where l represents number of spectral channels) for end-member i can be represented as a vector $\mathbf{m}_i = [m_1 \cdots m_{pl}]^T$, $i = 1, \ldots p$. Thus all end-members are represented by a matrix:

$$\mathbf{M} = [\mathbf{m}_1 \ldots \mathbf{m}_p] = \begin{bmatrix} m_{11} & \cdots & m_{p1} \\ \vdots & \ddots & \vdots \\ m_{1l} & \cdots & m_{pl} \end{bmatrix}, \tag{1}$$

with one column for each end-member. Finally, signal measured at each pixel $\mathbf{r}(x,y) = [r_1(x,y) \cdots r_l(x,y)]^T$ is a linear combination of the end-members $\mathbf{M}$; the abundances $\boldsymbol{\alpha}(x,y) = [\alpha_1(x,y) \cdots \alpha_p(x,y)]^T$ are the coefficients in the linear model:

$$r(x,y) = \mathbf{M}\boldsymbol{\alpha}(x,y) + \mathbf{n}(x,y), \tag{2}$$

where $\mathbf{n}(x,y) = [n_1(x,y) \cdots n_l(x,y)]^T$ is the residual or the noise. This is the linear mixture model.

To solve the system of equations involved, the sum of squared residuals $\mathbf{n}^T\mathbf{n}$, or more generally $\mathbf{n}^T \sum_n^{-1} \mathbf{n}$, is minimized where $\sum_n$ is the dispersion or co-variance matrix of the residuals. This is done by setting the partial derivative $\partial(n^T \sum_n^{-1} n) / \partial\alpha = 0$. The result is:

$$\boldsymbol{\alpha} = (\mathbf{M}^T \textstyle\sum_n^{-1} \mathbf{M})^{-1} \mathbf{M}^T \textstyle\sum_n^{-1} \mathbf{r}. \tag{3}$$

The estimator $\boldsymbol{\alpha}$ is central with dispersion $(\mathbf{M}^T \sum_n^{-1} \mathbf{M})^{-1}$. When $\sum_n = \sigma^2 \mathbf{I}$ where $\mathbf{I}$ is the $l \times l$ unit matrix and σ^2 is the variance of all residuals, $V\{n_i\} = \sigma^2$:

$$\boldsymbol{\alpha} = (\mathbf{M}^T\mathbf{M})^{-1}\mathbf{M}^T\mathbf{r}, \tag{4}$$

with dispersion $\sigma^2(\mathbf{M}^T\mathbf{M})^{-1}$.

2.3. Local Partial Unmixing with Known Target and Background Spectra

To perform a full linear unmixing described in the previous section, all end-members present in the scene should be known. This knowledge is often not available. Solution of the problem could be find in partial unmixing where only the presence of one or few desired (or target) spectra is estimated (Boardman et al. 1995, Nielsen 1998, Jacobsen et al. 1998).

Partial unmixing is built on the full linear mixture model in equation 2. The $\mathbf{M\alpha}$ term could be split into two terms, one which is the target end-member $\mathbf{d}$ with a corresponding abundance, and one which consists of the undesired or background end-members $\mathbf{U}$ with the corresponding vector $\boldsymbol{\gamma}$, of abundances:

$$\mathbf{r} = \mathbf{M}\alpha + \mathbf{n} = \mathbf{d}\boldsymbol{\alpha}_p + \mathbf{U}\boldsymbol{\gamma} + \mathbf{n}. \tag{5}$$

In this case, we consider the crop that has been mapped as the target end-member and surrounding, which could be mixture of a number of land cover classes (like asphalt, water, soil or another crop), as the background.

Partial unmixing methods usually don't require knowledge of background (undesired) end-member spectra but only of the target spectra. However, in this study, both target and background spectra were estimated and full linear unmixing applied in order to improve accuracy of the linear unmixing.

Since spectral variations of the target and the surroundings, even the small ones, could produce errors in soft classification if global training statistics is used (Muslim et al. 2006), local training statistics to estimate end-member spectra for linear unmixing model was applied. It means that crops are usually not spectrally homogeneous among the parcels they occupy and thus a unique end-member spectra representing the crop in linear unmixing model is not applicable for the entire parcel. It is exactly the same case with the surrounding land cover classes representing the background. Since the end-member spectra of each class in a pixel must be precisely known before carrying out the full linear unmixing method (Oki et al. 2004), it is assumed that on local level it is possible to estimate the target end background end-member spectra with sufficient accuracy as the spectral variations are sufficiently suppressed.

The problem is solved by designing a specific method where the mathematical models are performed on image sections cut by a kernel with the size of 3x3 pixels. The kernel moves across the border between the crop area and the surrounding area, thus covering both pixels with target (crop) spectra and pixels with background spectra, and makes a continual chain of the image sections (Fig. 3).

Rough border of the target crop area was extracted using a high-pass filter (Fig. 4) which detects the places where DN values are significantly changed, thus indicating change of land cover class. The filter was applied to all bands, but the near-infrared band gave the best result as the land cover classes of interest were the most spectrally distant there.

The 6-dimensional signals of all nine pixels in a 3x3 section are compared and the two of them that are found the most distant in the 6-dimensional feature space are considered to be the target and background end-member spectra and the other signals their linear mixtures. It could be considered sufficiently correct local

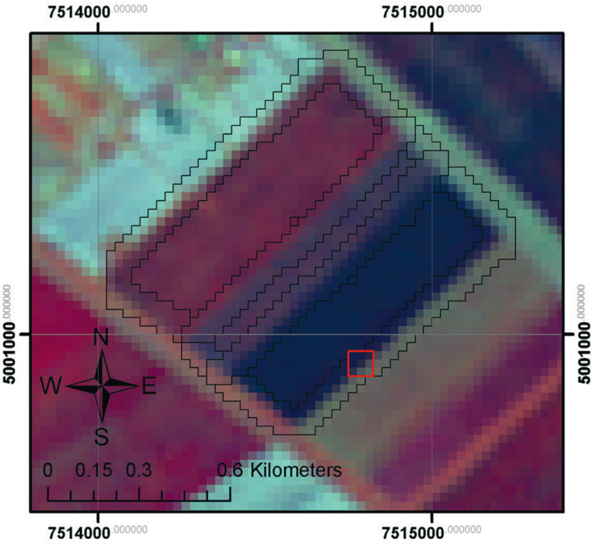


Fig. 3. *Chain of the local sections for localized unmixing along the border line between crop and surroundings. One section (an example) is presented as the red rectangle.*

Fig. 4. *Rough borders of the crops obtained by applying high-pass filter.*

estimation of target and background spectra with assumption that land cover classes making the surrounding of the target crop on such local level can be approximated by a single end-member spectra. Those end-member spectra are then applied in the linear unmixing model to retrieve the crop abundance values. Such calculations are performed on all of the sections.

There were 75 sections for the first crop, 67 for the second and 73 for the third. Statistics of the extracted values of target and background end-member spectra demonstrates the significant extents of local variations in target and especially in background spectra which additionally approves the method used (Table 1).

Table 1. *Variations of target and background end-member spectra for the three crops being mapped. Statistics are calculated with 74 input values for the first crop, 67 for the second and 73 for the third. Notice the significant variations in background spectra indicating the local variations of land cover classes that surround the crop.*

		Target				Background			
		Mean	**Maxi-mum**	**Mini-mum**	**Standard deviation**	**Mean**	**Maxi-mum**	**Mini-mum**	**Standard deviation**
CROP 1	Band 1	74	78	71	1.4	85	102	74	9.7
	Band 2	55	59	52	1.4	71	98	56	15.0
	Band 3	49	58	46	2.6	80	129	53	27.3
	Band 4	52	62	42	4.3	61	80	40	14.1
	Band 5	74	85	69	3.6	114	168	77	33.1
	Band 7	55	65	48	3.6	80	112	52	19.9
CROP 2	Band 1	74	80	71	2.0	78	89	74	3.4
	Band 2	53	59	47	3.6	60	76	55	5.5
	Band 3	49	60	43	4.5	60	88	52	9.2
	Band 4	40	60	23	13.8	47	74	38	9.8
	Band 5	70	85	62	5.9	86	135	75	15.9
	Band 7	57	69	48	5.6	66	93	56	9.4
CROP 3	Band 1	72	80	69	1.8	78	87	74	3.2
	Band 2	49	58	46	2.0	61	75	54	5.2
	Band 3	46	59	42	2.9	63	85	52	8.8
	Band 4	27	42	22	3.6	53	75	38	9.7
	Band 5	64	81	58	4.5	96	126	75	15.7
	Band 7	58	68	51	3.7	69	91	51	10.0

As the kernel moves smoothly across the crop border, sections overlap producing that most of the pixels took by the kernel will have not one, but two or more abundance values. The final value is the simple average.

The output of the linear unmixing was set to the range 0–100, to represent the percent of abundance of the crop in a given pixel (Fig. 5).

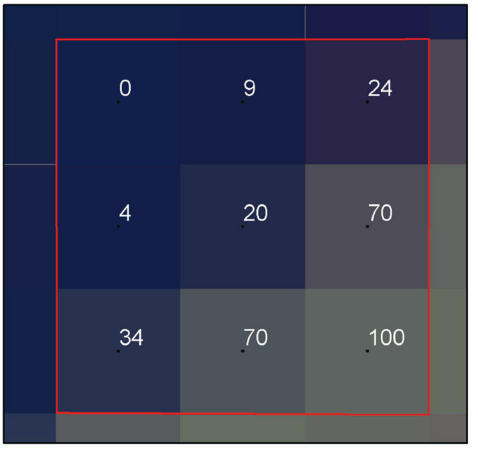


Fig. 5. *Abundance values obtained from the unmixing method for the example section.*

2.4. Pixel Swapping Algorithm

Soft classification performed resulted in percent of abundance of the target class in each original pixel. To indicate the location of sub-pixel components within each image pixel, the pixel swapping algorithm was applied (Atkinson 2005, Muslim et al. 2006). In this case, spatial resolution of the original image was 25 m and each pixel was divided on 16 sub-pixels, with pixel size of 6.25 m (Fig. 6). The final output of super resolution mapping is a binary map; for each sub-pixel, value 0 or 1 is allocated, assigning whether the sub-pixel belongs to the crop area or not (Fig. 7). It was automatically vectorized to generate the crop boundary line. The script written in Matlab for pixel swapping, made by the authors, was applied.

The algorithm is based on geostatistical method for classification of sub-pixels which take target values. For each sub-pixel the attractiveness A_i is calculated. The variable is a distance-weighted function of the target land cover class (crop in this case) percent in the neighbouring pixels:

$$A_i = \sum_{j=1}^{n} \lambda_{ij} z(u_j), \tag{6}$$

where n is number of neighbours, $z(u_j)$ is the value of percent of target land cover class at the jth pixel location and λ_{ij} is a distance-dependent weight predicted as:

$$\lambda_{ij} = \exp\left(\frac{-h_{ij}}{a}\right). \tag{7}$$

where h_{ij} is the distance between sub-pixel i for which attractiveness is calculated and neighbouring pixel on the location j, a is nonlinear parameter of the exponential model.

In this study, the inverse distance weighting function as a simplified version of above equation is used:

$$\lambda_{ij} = \frac{1}{h_{ij}}. \tag{8}$$

In each original pixel, number of sub-pixels belonging to the target class, k, is defined, in proportion to percent of the class in the original pixel. The k sub-pixels (within the original pixel) with the highest values of attractiveness are then assigned to belong to the target class.

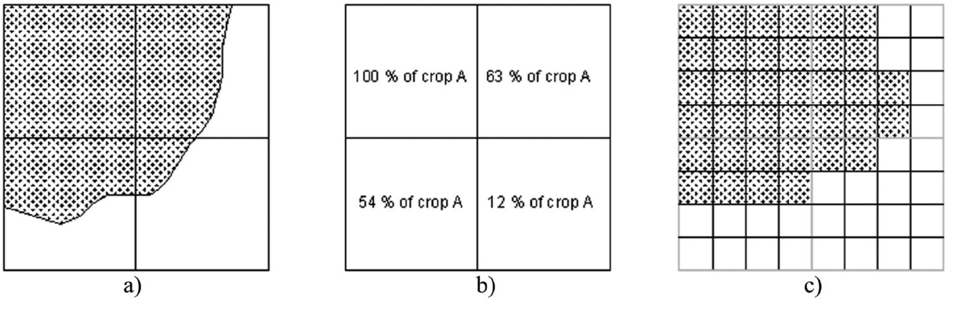


Fig. 6. *Illustration of pixel swapping method for grouping sub-pixels which belong to target class: a) Real spreading of target class over four original sized pixels, b) Percent of the target class in each of the four original sized pixels, c) Grouping of super resolution pixels that belong to target class.*

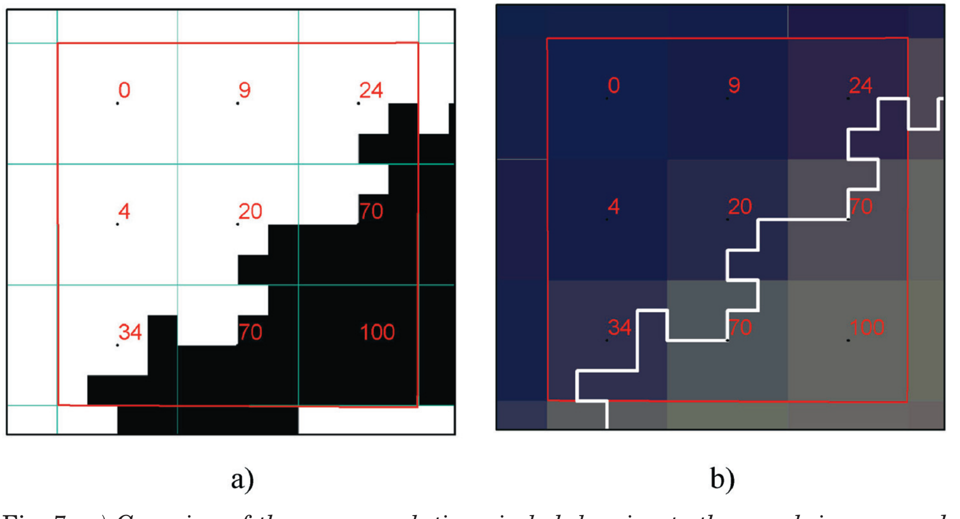


Fig. 7. *a) Grouping of the super resolution pixels belonging to the crop being mapped (white area) for the example 3x3 pixel section – numeric values in each pixel represent abundance of the crop, b) Boundary line of the crop being mapped (white line).*

3. Results, Verification and Discussion

The final results of the process are continual vector lines representing predicted crop boundaries for the three crops.

To verify the applied method, crop boundary lines resulted from super-resolution mapping were compared to reference boundary line digitized from 1 m spatial resolution orthophoto image (Fig. 8).

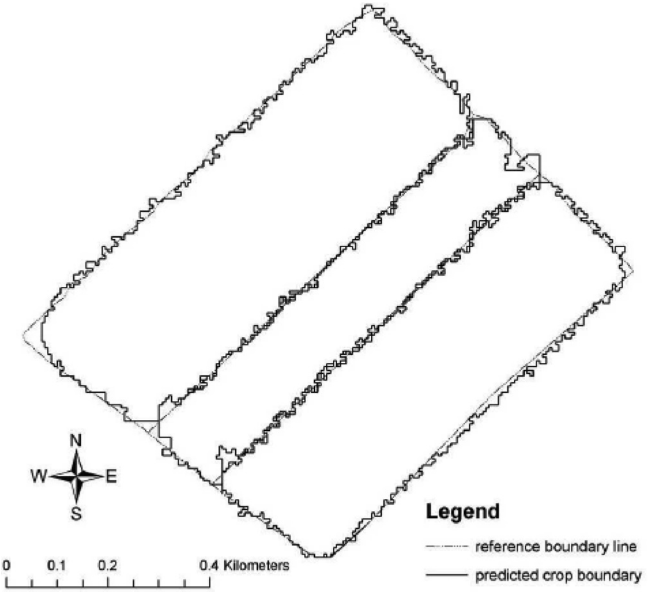


Fig. 8. *Crop boundary line generated from the supper resolution mapping compared with the reference line digitised from high resolution orthophoto.*

As the measure of the super resolution mapping accuracy, positional difference between generated and reference line was used:

$$e = \sqrt{\Delta X^2 + \Delta Y^2}, \tag{9}$$

where ΔX and ΔY represent positional differences in X and Y axis directions, respectively.

Positional shifts were calculated for 80 points, on every 5 m along the 400 m long segment of the mapped boundary lines.

Crop boundary line derived from the super resolution mapping has positional RMSE of 4.85 m and the other parameters which describe accuracy of the predicted crop boundary line are presented in Table 2.

The results of the super resolution mapping were compared to original remote sensing data. The new pixel size of 6.25 m compared to original resolution of 25 m

Table 2. *Accuracy parameters related to positional difference e between generated and reference line.*

Accuracy parameter	Formula	Result
Range (m)	$R = e_{max} - e_{min}$	11.57
Mean (m)	$\mu = \frac{\Sigma e}{N}$	4.85
Standard deviation (m)	$\sigma = \sqrt{\frac{\Sigma(e-\mu)^2}{N-1}}$	2.81

shows good visual improvement. Also, 4.85 m RMSE of the super resolution mapping means significant improvement of mapping accuracy if the super resolution method is applied.

However, resolution of satellite imagery used for the mapping could be a constraint for the described method in the cases when parcels are too narrow. The future research is thus needed aimed to estimate how accuracy of the method depends on parcel width and orientation in those boundary conditions. Furthermore, a smoothing of the parcel boundary lines would improve visual characteristics of the mapping result, however it would be interesting to analyse the impact of smoothing on geometric accuracy of parcel boundaries.

4. Conclusion

Precise agricultural mapping has become an important issue and one of the major applications in remote sensing. In this study, mapping of crop/agricultural parcel border was performed using localized partial unmixing and super resolution mapping from medium remote sensing imagery. The partial unmixing model was turned into full linear unmixing as both target and background end-member spectra were estimated. To increase the accuracy of end-member spectra estimation, and thus of the unmixing, localized approach was applied by cutting the original image into smaller sections.

The method was tested on real remote sensing data and the accuracy of the mapping was estimated. Relatively low positional RMS error of predicted crop boundary approved the ability of the method to perform very accurate super resolution mapping from inexpensive medium resolution remote sensing imagery in an efficient way. It could be a solution for many operational agricultural mapping projects like Land Parcel Information System (LPIS) and Control with Remote Sensing (CwRS). Although it is originally designed for crop mapping, application in mapping of other land cover features should be subject of further research.

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Kartiranje međa poljoprivrednih parcela super rezolucijom na temelju lokaliziranoga parcijalnog razdvajanja

SAŽETAK. Operativno kartiranje međa poljoprivrednih/žitnih parcela je izazovni zadatak. To bi trebao biti učinkovit i isplativ postupak koji bi rezultirao podacima korisnima za široku upotrebu. Gruba klasifikacija podataka daljinskog istraživanja srednje rezolucije (>15 m, <30 m) mogla bi biti rješenje, no prostorna rezolucija snimaka nije dovoljna za mnoge primjene. U ovom radu predstavljena je blaga klasifikacija podataka daljinskog istraživanja srednje rezolucije te kartiranja žitnih parcela super rezolucije. Metoda je razvijena na temelju lokaliziranoga parcijalnog razdvajanja procjenjujući spektar krajnjeg člana i cilja i pozadine. Rezultat je bio podvrgnut razmjeni piksela kao tehnike kartiranja super rezolucijom. Ispitivanje se provodi na stvarnim snimkama Landsat ETM+. Metoda je vrednovana kvantitativno, a rezultati pokazuju značajnu točnost u usporedbi s kartiranjem iz originalnih podataka daljinskog istraživanja.

Ključne riječi: *kartiranje poljoprivredne parcele, kartiranje super rezolucijom, parcijalno razdvajanje, linearno razdvajanje, razmjena piksela.*

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