SAR IMAGES AND ANCILLARY DATA IN CROP SPECIES INTERPRETATION

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ABSTRACT

A method for crop species interpretation was developed and tested. The idea of the method is to use multisource and multitemporal data, especially SAR images, and repeat the interpretation several times during the growing season as new images become available. A preliminary prediction about probable crop species is made using information on species grown in previous year. This prediction is based on knowledge of crop rotations and agricultural statistics of the area. The next data source to be included in the interpretation is a SPOT image from spring or previous autumn, which can be used to relatively accurately distinguish grasslands, spring crops and winter crops from each other. After this the interpretation is improved by using SAR images, which can be obtained throughout the growing season and in all kinds of weather conditions. The Dempster-Shafer theory of evidence is used to combine pieces of evidence from the various data sources. The method was tested in a study area situated near Seinäjoki in western Finland. An overall accuracy of 83% was reached when a SPOT image and four ERS-2 SAR images from 1996 and crop species information from 1995 were used as input data. Crop species information from 1996 was used for training and testing. When using the SAR images alone, the accuracy varied from 33% to 72%, depending on the number of images.

1. INTRODUCTION

To realize and plan the Common Agricultural Policy of the European Union, information on the areas of different crop species is needed. One method to collect this information is the use of satellite images. In this article the benefits of satellite SAR (Synthetic Aperture Radar) images in crop species identification are discussed.

The probability of cloudiness is rather high in Finland, thus hampering the use of optical satellite data in monitoring of agriculture. For the most accurate crop species interpretation, images from the important stages of crop development should be used. SAR images can also be obtained in night-time and through clouds, which makes selection of images easier. SAR is an active imaging instrument, which means that it sends pulses of microwave radiation and measures echoes from the target. For example ERS-1 AMI SAR uses microwave radiation of about 5 cm wavelength. Interpretation of crop species using SAR images is based on changes in backscatter. As the crops grow, the backscattering of the parcels gets weaker due to the absorption of the canopy. Furthermore, different crops tend to have different growing rhythms. Thus several SAR images registered at different times of the growing season are needed to obtain good results in the interpretation. (Schotten et al. 1995, ESA 1995)

In addition to SAR images, it would be useful to include other types of data in the interpretation. For example, knowledge of usual agricultural practice, such as rotation of crops, can provide valuable information for the interpretation if crop species grown in the previous year are known. Certain crops, e.g. turnip rape, peas and potatoes, are not usually grown in the same field in two successive years, and there are also other trends in rotation of crops. Another useful data source would be a SPOT satellite image registered late in the previous autumn or early in the spring. At these times of the year, grasslands, spring crops and winter crops can be distinguished from each other due to the different reflectance characteristics of these areas in the infrared channel of the sensor.

2. METHOD

The crop species interpretation method developed and tested is presented in Figure 1. The method is based on a knowledge-based approach, which provides flexible means of using different types of data, e.g. satellite images and map data, in the interpretation. A similar approach has been tested earlier at the Finnish Geodetic Institute for updating of topographic maps (Yu et al. 1996, Matikainen et al. 1997). The main source of data in the crop species interpretation is SAR images, but a SPOT image and information on crop species grown in previous year are also used. The SAR images are classified separately before the knowledge-based interpretation. The classification is based on temporal changes in radar backscatter, and results of this stage are then used together with the other data sources as input data for the knowledge-based interpretation. A rule-based interpretation program described in Soikkonen (1993) and Matikainen et al. (1997) was used to test the method.

3. STUDY AREA AND DATA

3.1 Study area

The method was tested in the Seinäjoki-site in western Finland, which is one of the 60 MARS (Monitoring Agriculture by Remote Sensing) Rapid Estimates sites in Europe. Crop species grown in the area in 1996 and crop species interpreted in the study are listed in Table 1.

Table 1. Crop species in the study area in 1996.

Crop species in 1996 according to MARS Rapid Estimates data	**Crop species in interpretation**
Barley (covered 47% of the arable land)	Barley
Oats (18%)	Oats
Turnip rape (3%)	Turnip rape
Rye (1%)	Rye
Perennial green fodder (16%)	Grassland
Fallow and green manure (14%)	Grassland
Permanent grassland -herbages (1%)	Grassland

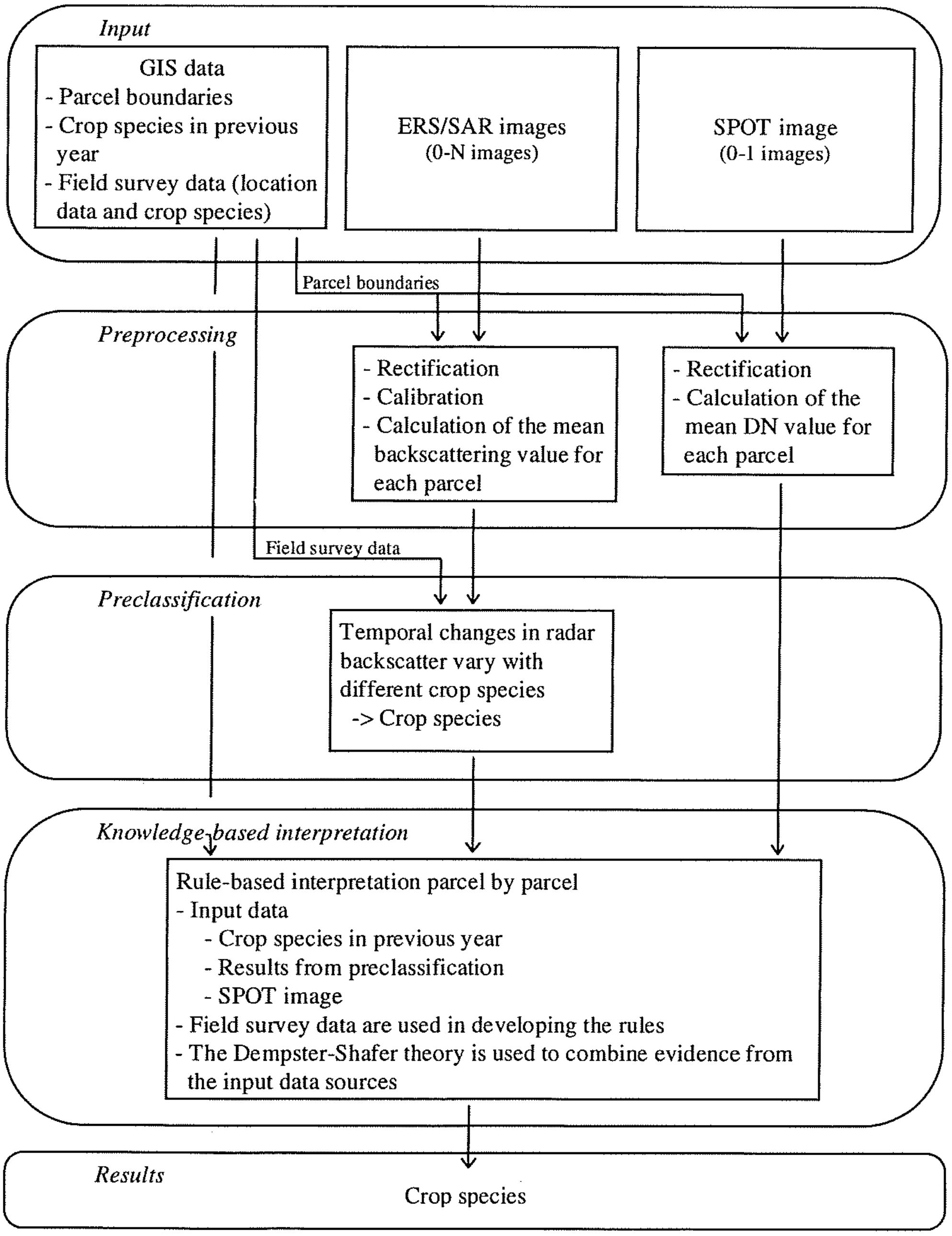

Figure 1. Method for crop species interpretation.

3.2 Satellite images

Four ERS-2 SAR images from descending orbits in summer 1996 (25 June, 30 July, 15 August, 19 September) and one SPOT image from 20 May 1996 were used in the study. All the images were rectified to the Finnish uniform coordinate system (YKJ) and resampled to 25-m pixel size. In rectification of the SAR images, PCI orthorectification software (PCI 1996) that uses digital elevation data and information on the satellite orbital parameters, e.g. imaging geometry, was used. The SPOT image was rectified using the PCI software and the normal geometric correction method based on polynomial transformation and resampling.

3.3 Parcel boundaries and crop species information

Parcel boundaries were digitized using aerial orthophotos and the Arc/Info software. The digitized data were then converted into 25-m raster data to be used in the rule-based interpretation. A problem in digitizing was the age of the orthophotos – some of them were more than 5 years old. According to visual evaluation, there were some differences between the digitized boundaries and boundaries visible in the SPOT image. Information on crop species in the parcels in 1995 and 1996 was collected from the Rapid Estimates data. Crop species from 1995 were used as one data source in the rule-based interpretation and crop species from 1996 as reference data instead of field survey data (Figure 1). 156 parcels were used as training parcels in SAR image classification and rule determination and 145 as test parcels in testing the accuracy of the results.

4. INTERPRETATION

4.1 Rule-based interpretation method based on the Dempster-Shafer theory of evidence

The interpretation program used in the study is capable of interpreting image pixels or segments by using rules and attributes derived for the pixels or segments from various data sources, e.g. satellite images, classification results and raster maps. In this study, the parcels digitized from the orthophotos were used instead of segments created by an image segmentation algorithm. Interpretation of one parcel is illustrated in Figure 2.

When interpreting a parcel, the rules give belief to various classes or sets of classes, depending on the values of the attributes for the current parcel. It is also possible to use initial belief values that are based on class probabilities calculated in a previous classification, e.g. Maximum Likelihood classification of SAR images, and are imported into the interpretation as an initial support file. All the belief values are combined by using the Dempster's rule of combination which is part of the Dempster-Shafer theory of evidence (Shafer 1976). The Dempster-Shafer theory of evidence is one of the numerical approaches that can be used to deal with uncertain information in various artificial intelligence systems. It has some advantages compared to other approaches, e.g. the Bayesian approach. One of these is that the theory is well suited to deal with evidence which may apply not only to single hypotheses but also to sets of hypotheses (Gordon and Shortliffe 1985). Another important advantage of the Dempster-Shafer theory is its ability to distinguish lack of belief from disbelief, which makes it possible to represent ignorance (Shafer 1976, p. 22). In the theory, a low degree of belief given to one hypothesis is not the same as a high degree of belief for the negation of the same hypothesis.

Perhaps the most difficult practical problem with the theory of evidence in applications such as multisource image classification is the lack of a direct computation method that would be used to derive the numerical belief values from the input data. A common approach in a knowledge-based system is to use belief values that are based on a human expert's judgement, but it is also possible to develop more objective statistical approaches (e.g. Peddle 1995, Gong 1996). In this study, belief values calculated from training data were used. Belief values obtained from the SAR image classification were assigned to classes by using an initial support file, while belief values from the other data sources were assigned through rules (Figure 2).

The Dempster-Shafer theory is often considered impractical due to the evidence-combination scheme which is computationally complex and has exponential time requirements (Gordon and Shortliffe 1985). In certain special cases, however, the computational complexity can be reduced. One of these is the situation where hypotheses form a hierarchy and each piece of evidence gives belief to only one hypothesis or complement of a hypothesis in the hierarchy (Gordon and Shortliffe 1985). The remaining belief (1–belief value) is given to θ, the set consisting of all the single hypotheses, and represents belief that cannot be assigned to any particular hypothesis. Shafer and

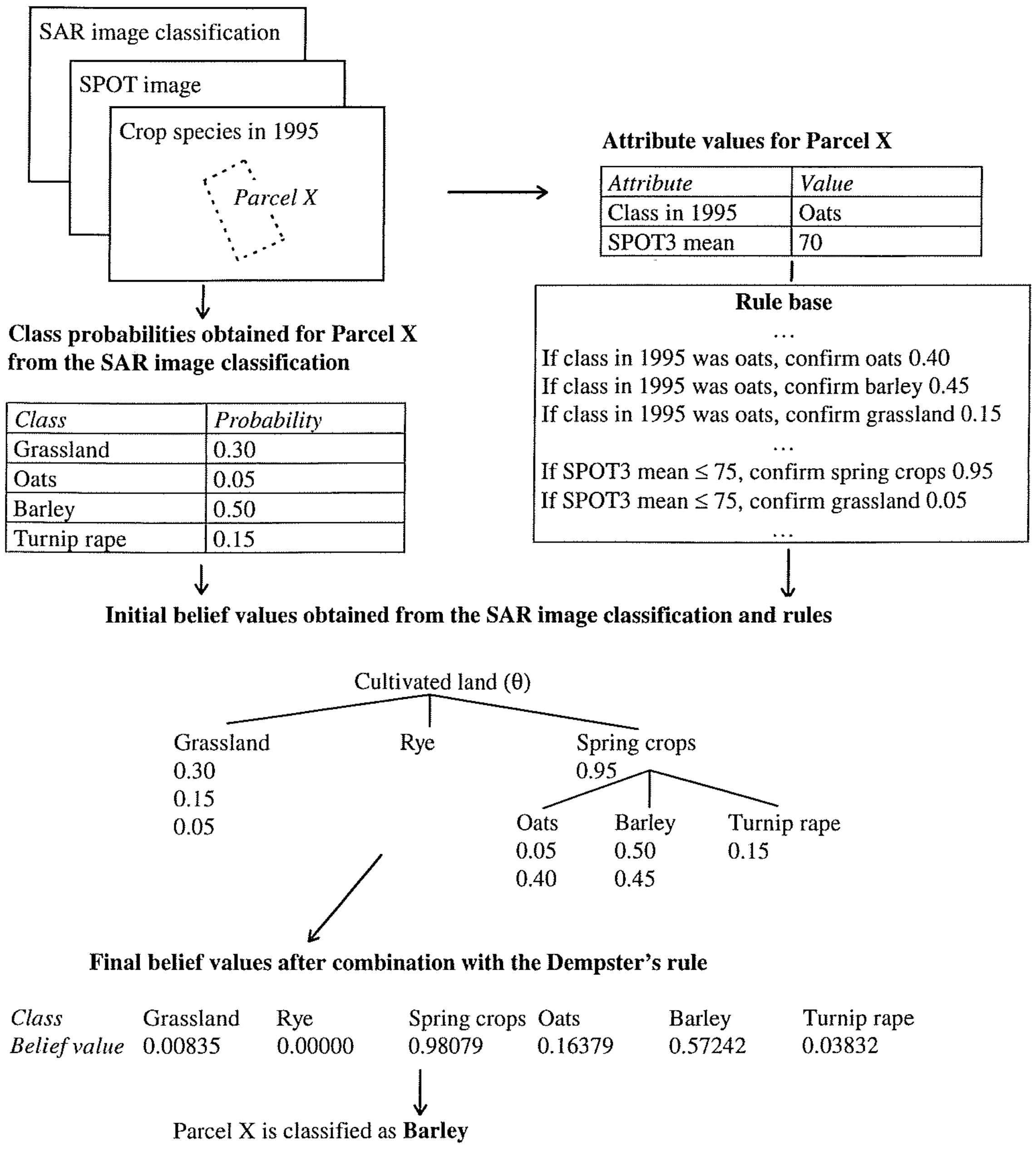

Figure 2. Interpretation of parcel X.

Logan (1987) have presented the exact implementation of the Dempster's rule in the hierarchical case. The evidence combination in the rule-based interpretation program used in this study is based on that algorithm. The hierarchy used is the same as in the example shown in Figure 2. Each rule and each class probability is treated as a distinct piece of evidence. For example, the rule *If value in the satellite image is less than 120, confirm grassland 0.80,* gives a belief of 0.80 to class grassland and a belief of 0.20 to θ, which is the set {grassland, rye, oats, barley, turnip rape}. The rule *If class in the previous year was turnip rape, disconfirm turnip rape 0.95* gives a belief of 0.95 to the complement of the class turnip rape, which is the same as the set {grassland, rye, oats, barley} and a belief of 0.05 to θ.

4.2 Classification of SAR images

In this study four SAR images were used, so four backscattering values were calculated for each digitized parcel. The backscattering value of a parcel is the mean of all SAR pixels that cover the parcel in question. The classification of the parcels is similar to classification of a multispectral image, e.g. a SPOT image. Each backscattering value is one element in the feature vector of the parcel.

The Maximum Likelihood (ML) method was used in the classification of the SAR images. The ML method is a statistical supervised classifier and rather easy to implement (Schalkoff 1992, pp. 59-62). The 156 parcels mentioned in Chapter 3.3 were used in training. After training, all the parcels were classified and the so called *a posteriori* probabilities were calculated. A series of probabilities was obtained for each digitized parcel. This series tells the probability of the parcel to belong to selected classes, such as barley, oats, turnip rape or grassland (see Figure 2). The classification of the SAR images is discussed in more detail in Karjalainen (1997).

The results of the SAR image classification were included in the knowledge-based interpretation by using an initial support file that contains the class probabilities calculated in the classification for each parcel. Class probabilities from ML-classification have also been used as belief values by Wilkinson and Mégier (1990). Belief values obtained from the SAR image classification were treated in the same manner as belief values obtained from rules. The belief values based on the SAR image classification gave belief to crop species grassland, oats, barley and turnip rape, which are all at the lowest level in the class hierarchy. Rye did not receive any belief from the SAR image classification because there were not enough rye parcels to calculate training statistics.

4.3 Rules

Rules were determined for the crop species information from 1995 and the SPOT image. The training parcels and crop species information from 1996 were used in the rule determination. To obtain information on typical changes in crop species between years 1995 and 1996 in the study area, a confusion matrix (Table 2) was formed. The information of the confusion matrix was then converted into rules and belief values (Table 3) by calculating the occurrence likelihood for each class in 1996 in case of a given class in 1995. Due to the very small number of training parcels in some classes, rules could not be determined for each case. If the crop species in 1995 had been turnip rape, a strongly disconfirming belief value was given to turnip rape. This rule is based on general knowledge of the usual agricultural practice; turnip rape is not normally grown in the same field in two successive years. For the SPOT image, rules were determined in a similar manner using histograms of training parcel means in classes spring crops, rye and grassland in channel 3, which is the infrared channel. These rules are shown in Table 4.

Table 2. Changes in the crop species of the training parcels between 1995 and 1996.

Crop species in 1996	Crop species in 1995					
	Oats	Barley	Turnip rape	Rye	Grassland	Total
Oats	15	10	2	0	2	29
Barley	16	49	0	1	3	69
Turnip rape	0	5	0	0	0	5
Rye	0	0	0	0	2	2
Grassland	6	7	0	0	29	42
Total	37	71	2	1	36	147

Table 3. Rules and belief values based on crop species in 1995.

Condition	Action
If Crop species in 1995 was Oats	Confirm Oats 0.40
If Crop species in 1995 was Oats	Confirm Barley 0.45
If Crop species in 1995 was Oats	Confirm Grassland 0.15
If Crop species in 1995 was Barley	Confirm Oats 0.15
If Crop species in 1995 was Barley	Confirm Barley 0.70
If Crop species in 1995 was Barley	Confirm Turnip rape 0.05
If Crop species in 1995 was Barley	Confirm Grassland 0.10
If Crop species in 1995 was Turnip rape	Disconfirm Turnip rape 0.9999
If Crop species in 1995 was Grassland	Confirm Oats 0.05
If Crop species in 1995 was Grassland	Confirm Barley 0.10
If Crop species in 1995 was Grassland	Confirm Rye 0.05
If Crop species in 1995 was Grassland	Confirm Grassland 0.80

Table 4. Rules and belief values based on the mean values of the parcels in channel 3 of the SPOT image.

Condition	Action
If SPOT3 mean ≤ 75	Confirm Spring crops 0.95
If SPOT3 mean ≤ 75	Confirm Grassland 0.05
If 75 < SPOT3 mean ≤ 95	Confirm Spring crops 0.30
If 75 < SPOT3 mean ≤ 95	Confirm Grassland 0.70
If 95 < SPOT3 mean ≤ 120	Confirm Spring crops 0.05
If 95 < SPOT3 mean ≤ 120	Confirm Rye 0.05
If 95 < SPOT3 mean ≤ 120	Confirm Grassland 0.90
If SPOT3 mean > 120	Confirm Rye 0.9999

5. RESULTS

Several tests using different types of input data and different numbers of SAR images were conducted. The main results of the study are listed in the following. The accuracy estimates shown in brackets were calculated based on class groups grassland, cereals (includes rye, oats and barley) and oil plants (includes turnip rape), while the other estimates were calculated based on the single crop species interpreted in the study. The confusion matrix and accuracy estimates of the interpretation in which all the available data were used are presented in Table 5. The change that occurred in the accuracy when new images were added to the interpretation is illustrated in Figure 3.

- The total accuracy of the ML classification of SAR images was 33–72% (45–79%). The accuracy increased as new images were added, and the best accuracy was achieved when all the four images were used.

- The total accuracy of the rule-based interpretation when using the crop species information from the previous year, the SPOT image and the ML classification result based on 1–4 SAR images was 63–83% (79–87%). The best result was obtained when all the images were used.

- The crop species information from previous year improved the total accuracy by 9–13% (5-17%). The most probable classes obtained high belief values, which improved the results. When the crop species information was used as the only data source in the interpretation, the total accuracy was 59% (72%).

- The SPOT image improved the total accuracy by 0–3% (1–5%). It was most useful in interpretation of grasslands. The number of rye parcels in the study area was too small for proper testing, but it is probable that a SPOT image from autumn or spring would also be useful in interpretation of winter crops.

- The idea of making the first interpretation early in the growing season and repeating the interpretation as new images are obtained seems applicable, e.g. grassland and spring crops as a group could be interpreted relatively accurately based on the SPOT image alone. The mean accuracy was 75% for grassland and 92% for spring crops. For the interpretation of single spring crops oats, barley and turnip rape, the sequence of SAR images obtained at different times of the growing season was important.

6. CONCLUSIONS

The interpretation results obtained in this study were satisfactory, and in the future the method can be further developed, e.g. parcel boundaries will be obtained directly from maps, which makes digitization unnecessary. More statistical data on crop species in previous years will also be available. This will increase the reliability of the rules and longer periods can be taken into account when giving belief to probable classes. For example, some crop species can be grown in the same parcel in two or three successive years, but then the species is normally changed. These changes could be predicted if data from several years were available. The developed method could be applied in inventorying crop areas for the EU's Rapid Estimates statistics.

Table 5. Confusion matrix and accuracy estimates of the interpretation in which all the available data sources were used.

	Reference classes					
Class	Grassland	Rye	Oats	Barley	Turnip rape	Total
Grassland	31	3	3	3	0	40
Rye	0	0	0	0	0	0
Oats	0	0	22	2	0	24
Barley	6	0	4	64	3	77
Turnip rape	0	0	0	1	3	4
Total	37	3	29	70	6	145
Interpretation accuracy	84%	0%	76%	91%	50%	
Object accuracy	78%	–	92%	83%	75%	
Mean accuracy	**81%**	**0%**	**83%**	**87%**	**60%**	
Total accuracy						**83%**
	Grassland	Cereals	Oil plants			
Interpretation accuracy	84%	90%	50%			
Object accuracy	78%	91%	75%			
Mean accuracy	**81%**	**91%**	**60%**			
Total accuracy						**87%**

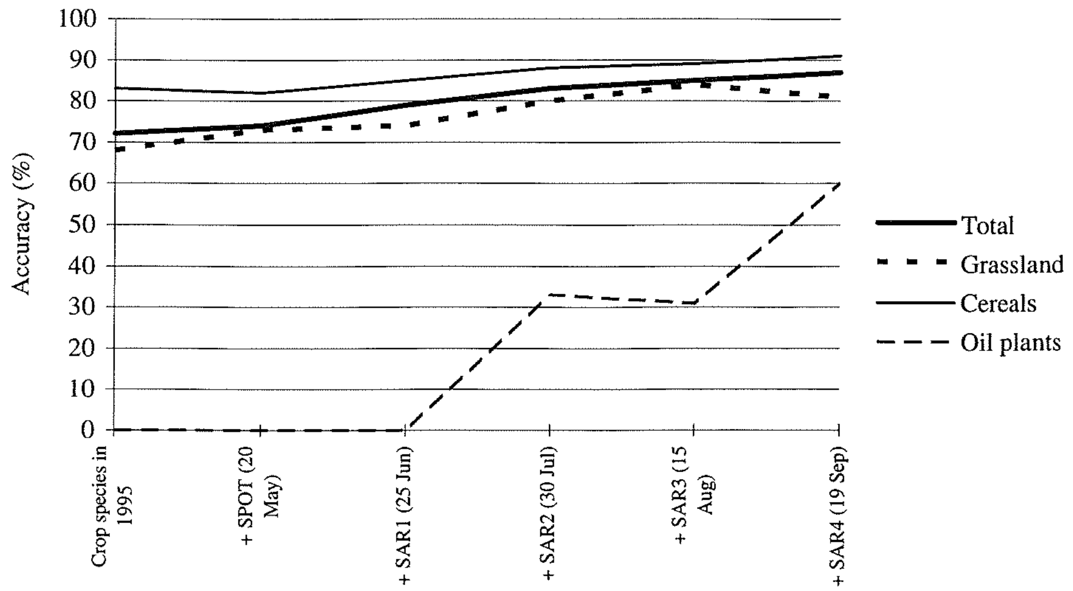

Figure 3. Change in the mean accuracy of classes and total accuracy of classification when new images were added to the interpretation.

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