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# Potenzial von multispektral und SAR Daten zum Monitoring von raum-zeitlichen Landnutzungsmustern

5. gemeinsame Jahrestagung der Arbeitskreise Fernerkundung (DGfG) und Auswertung von Fernerkundungsdaten (DGPF) , 28. bis 30. September, Halle/Saale

Björn Waske

# Introduction

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## Land cover classification and remote sensing

- Increased availability of (freely available) remote sensing data
- Applications become more interesting regarding recent and upcoming missions (e.g., ESAs Sentinel):
  - Increased revisit times
  - Better spectral and spatial resolutions
  - Increased availability of diverse data sets, e.g. multispectral and SAR; data sets with different spatial resolution

*multispectral RapidEye data*

*multitemporal SAR TerraSAR-X data*

# Introduction

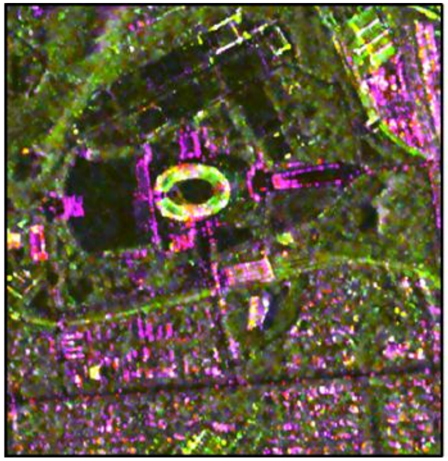
## Land cover classification and remote sensing

- Evolving EO technologies together with increasing performance requirements (e.g., speed, accuracy …) → increasingly improving algorithms.

- Processing power impacts pattern recognition algorithm development → enables faster processing of huge data sets.

➢ Users can choose between several – widely accepted – algorithms and between a multitude of diverse remote sensing data.

*TerraSAR-X (pauli composite)*



*Sentinel 2*

# Outline

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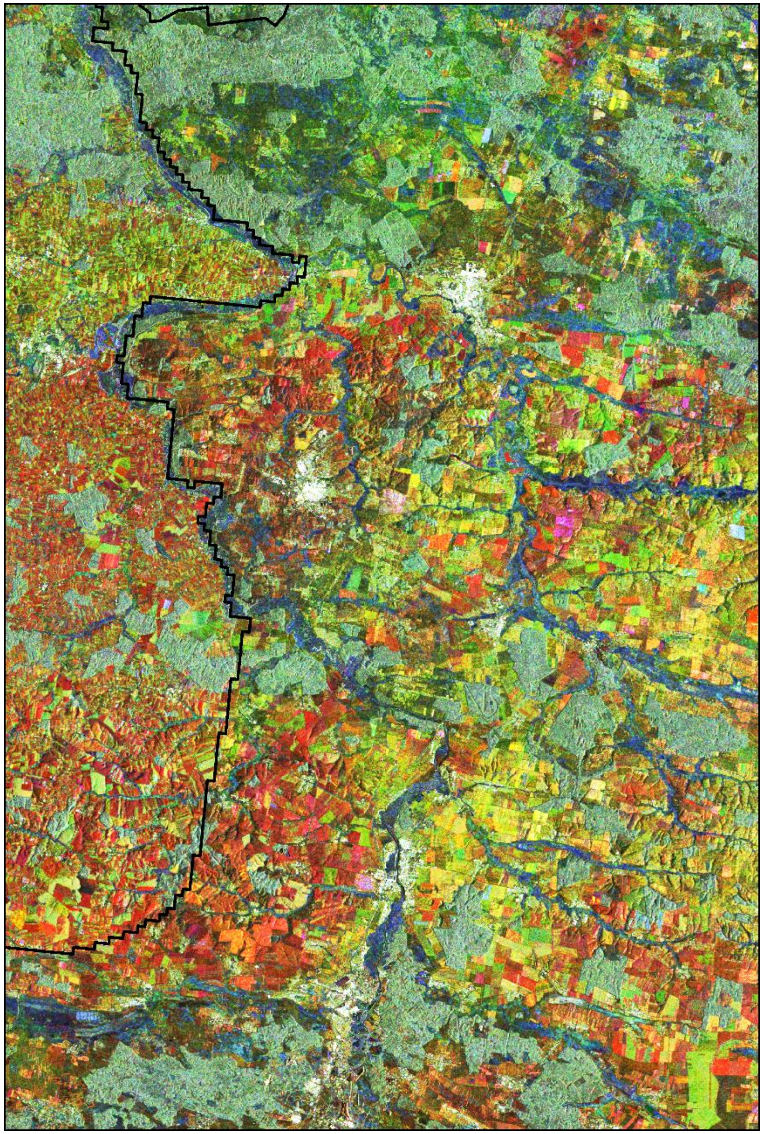
## Case studies

- Mapping land use and land use change in post-Soviet western Ukraine, using Landsat and ERS/Envisat ASAR data
- Mapping land use and deforestation in Brazilian Amazon, using TerraSAR-X data (and multisensor data)

# Ukraine – study site

- Breakdown Soviet Union in 1991 → significant changes in land-use management
- Industrialized and large agricultural fields
- Farmland abandonment → forest succession
- Large fields were converted to small field → change from intensive to extensive management



# Ukraine – study site



Large-Scale Cropland

Small-Scale Cropland

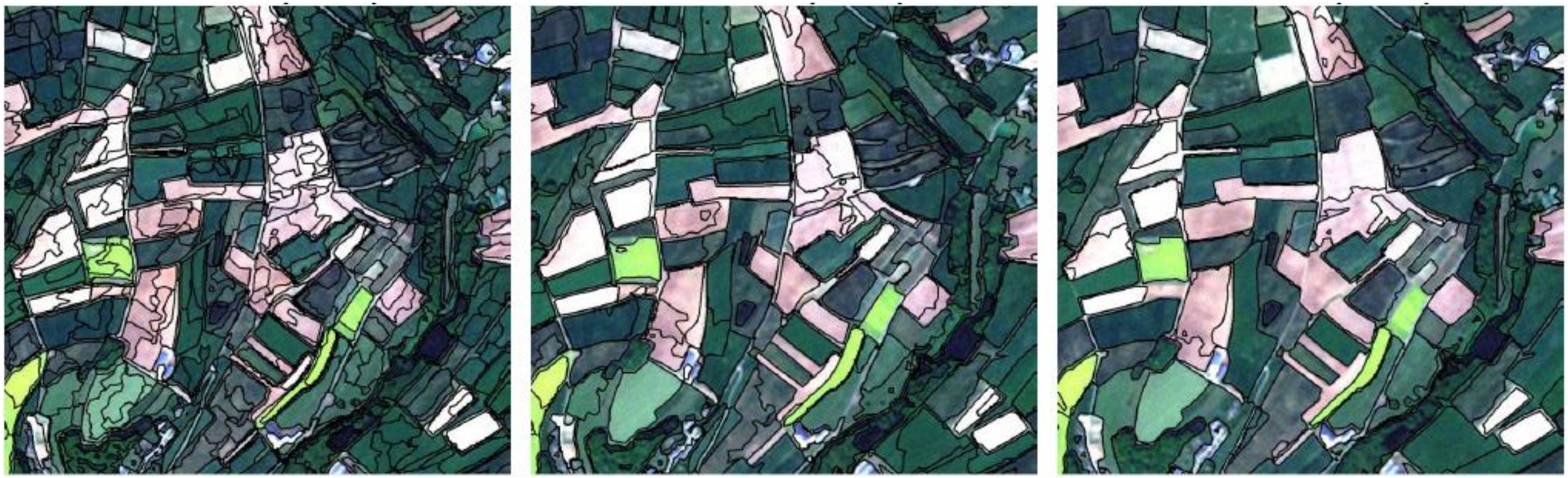

Pasture

Fallow/abandoned

# Ukraine – Methods & data



- Landsat 5 TM June / Nov. 2010 + 9 ERS-2 SAR scenes from 2010
- Random Forests, which is based on a combination of many decision trees and well suited for classifying multisensor data
- Segment-based classification, to integrate spatial information; new approach for a semi-automatic determination of the size



# Ukraine – Methods & data

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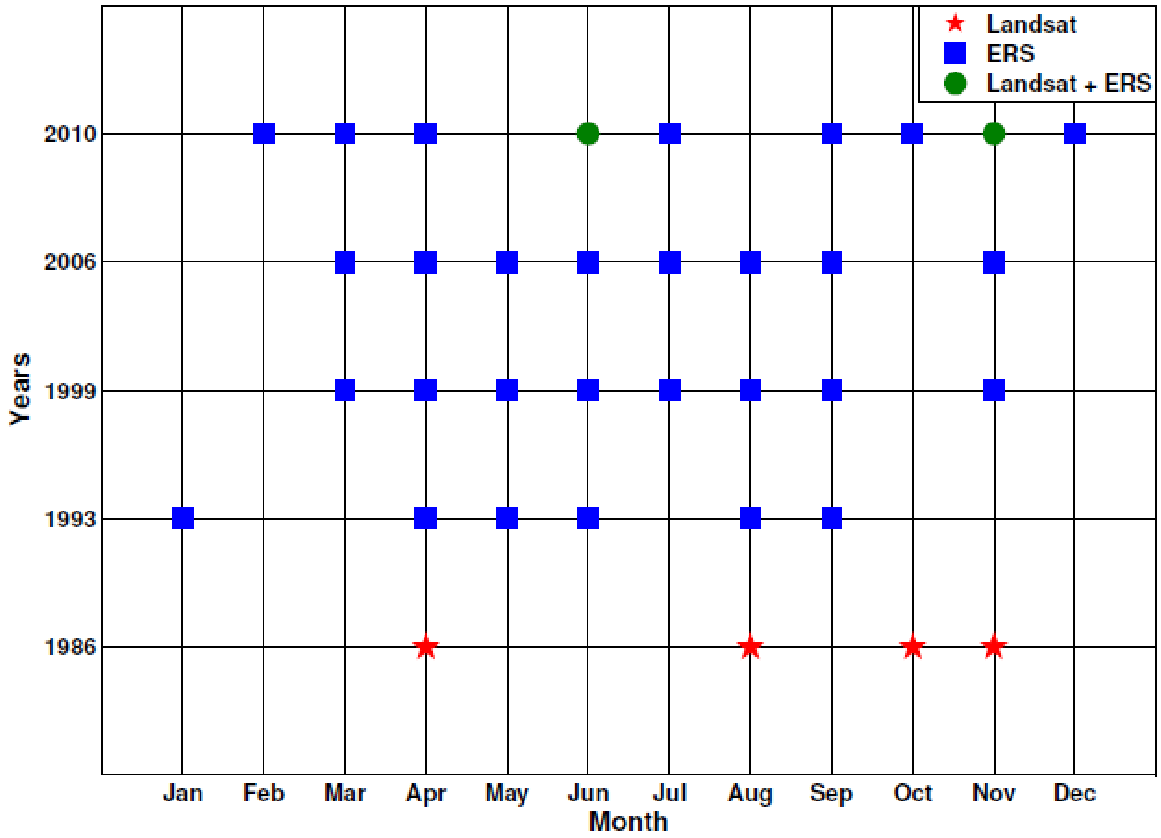
## Data sets and methods

- Image acquisition in every season
- 6 Landsat scenes
- 31 ERS SAR scenes
- “post-classificative” change detection



# Ukraine - Results

## Impact of different data sources on the mapping accuracy [%]

| LS Classes | Landsat (pixel-based) | | Landsat (object-based) | | SAR+Landsat | |
|---|---|---|---|---|---|---|
| | PA (%) | UA (%) | PA (%) | UA (%) | PA (%) | UA (%) |
| LSC | 51.6 | 70.8 | 85.4 | 89.0 | 85.1 | 89.7 |
| SSC | 73.2 | 43.3 | 92.5 | 56.3 | 91.8 | 71.4 |
| Pasture | 56.5 | 55.0 | 74.3 | 56.6 | 62.5 | 65.9 |
| Fallow | 67.3 | 69.4 | 58.0 | 81.9 | 74.0 | 79.2 |
| Forest | 96.8 | 95.1 | 92.3 | 96.1 | 94.1 | 96.2 |
| Urban | 54.5 | 76.9 | 29.5 | 77.8 | 63.2 | 80.0 |
| OA | 67.4% | | 78.3% | | 83.4% | |

(Stefanksi et al. 2013)

# Ukraine – Results

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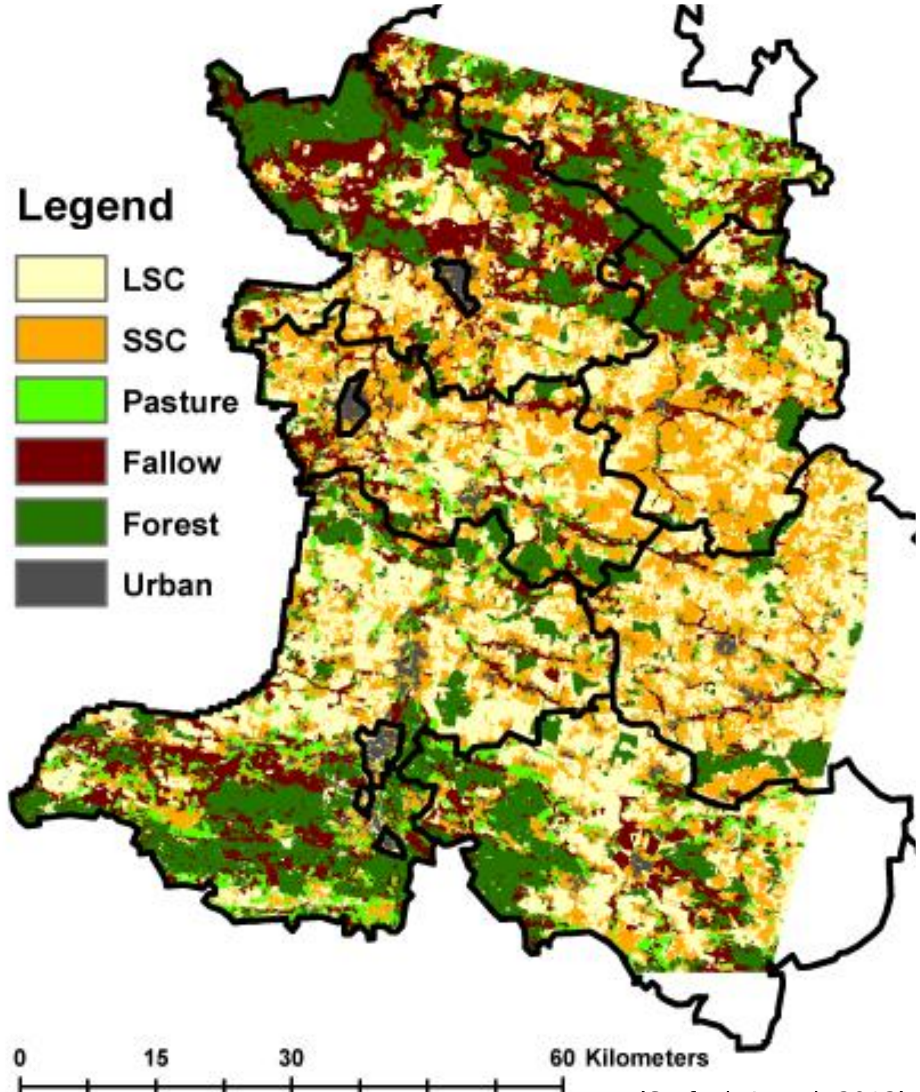
## Land use management 2010

The use of …

(1) multisensor data
(→ *fallow* vs. *pasture*)

(2) spatial information
(→ *large-scale* vs. *small-scale agriculture*)

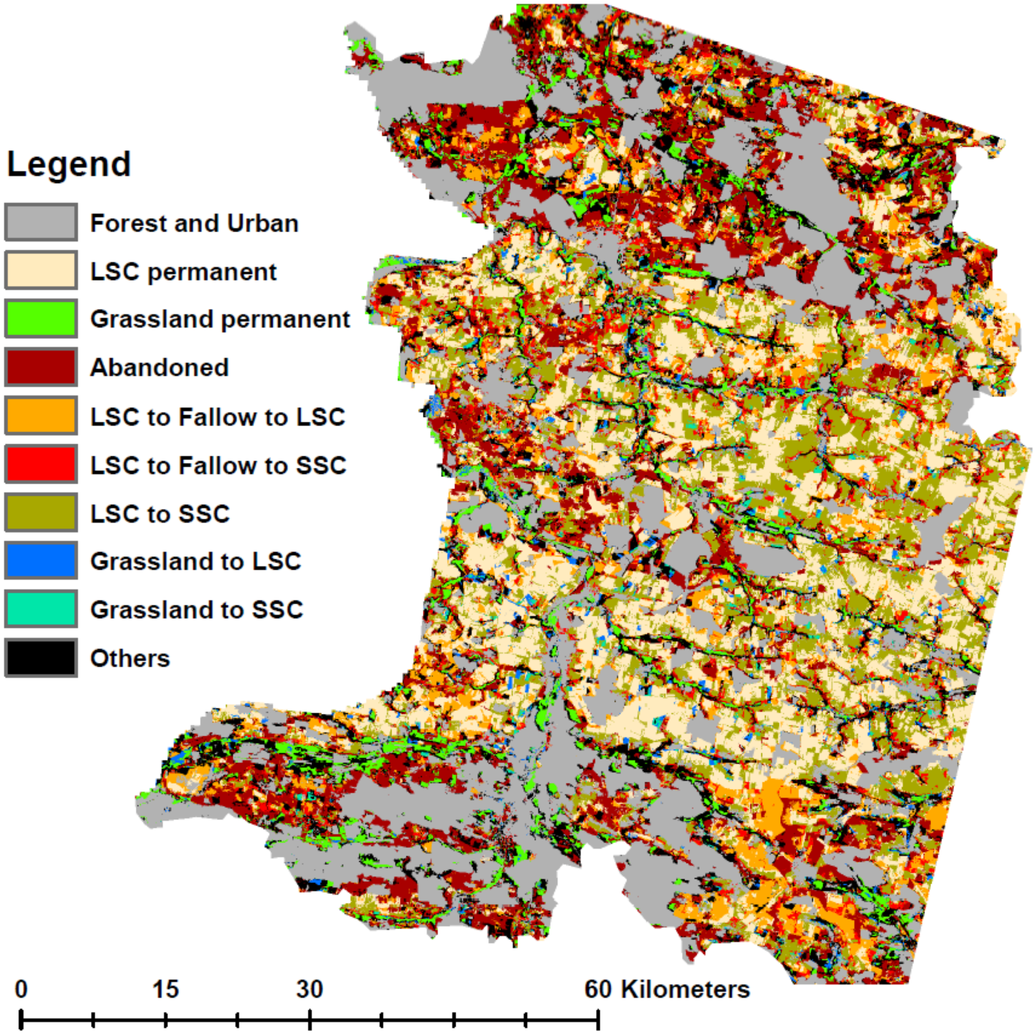
proved useful in terms of the mapping accuracy




(Stefanksi et al. 2013)

# Ukraine – Results






**Changes in land use management between 1986 and 2010**

- Cropland abandonment: ~18%
- Recultivation: ~17%
- ~25% permanently cultivated with large-scale cropland
- ~18% of large-scale cropland was transformed into small-scale cropland

(Stefanksi et al. 2014)

# Brazil – Study site

## SenseCarbon*

- Novo Progresso municipality (southern Pará, Brazil), close to the BR-163 highway

- Mapping forest degradation and deforestation in Brazil

- Based on the ESAs Sentinel missions (Sentinel-1 and Sentinel-2), their synergies among each other, and synergies with other systems (e.g. TerraSAR-X)


*funded by DLR / BMWi FKZ 50EE0917

# Brazil – Study site

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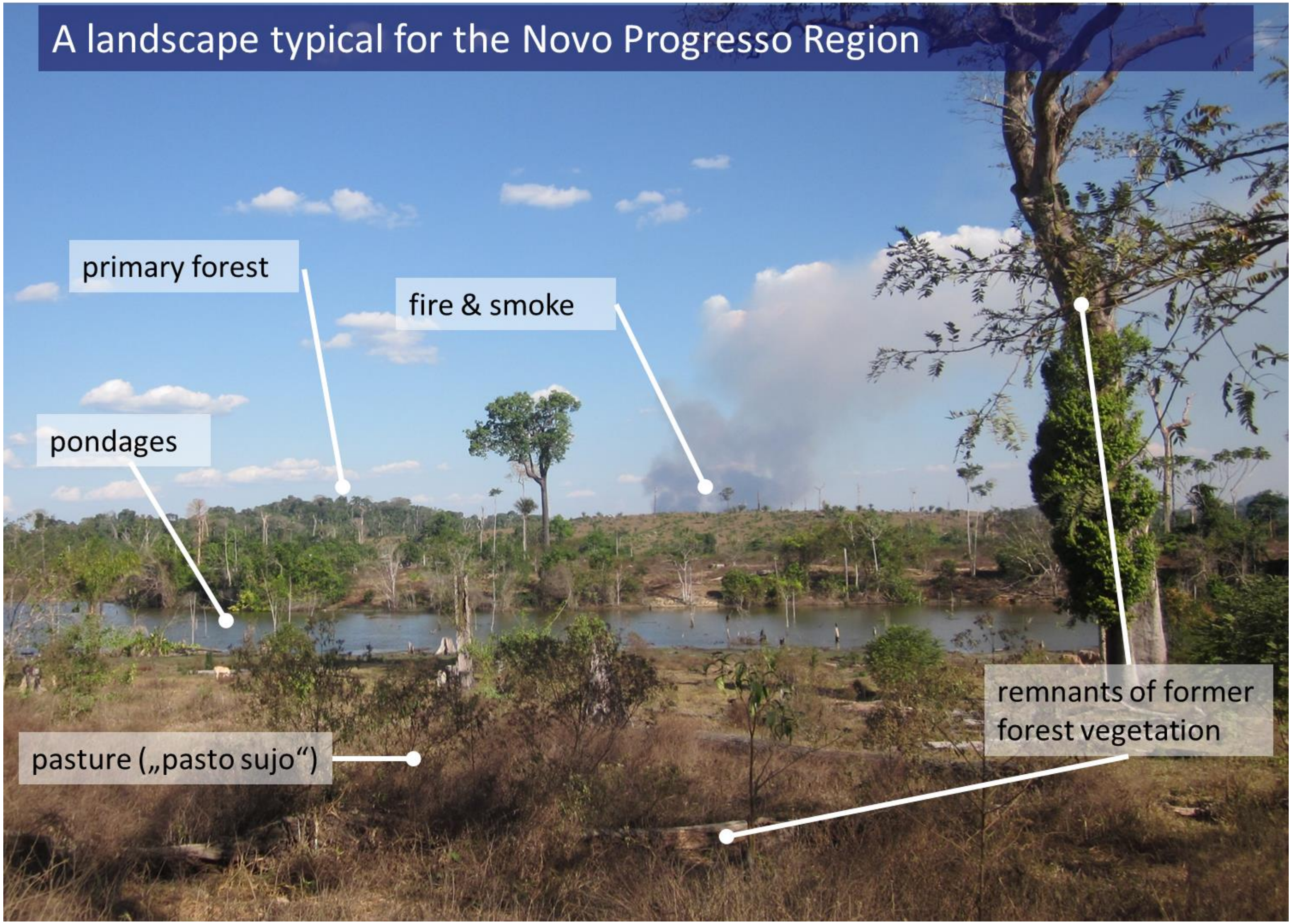
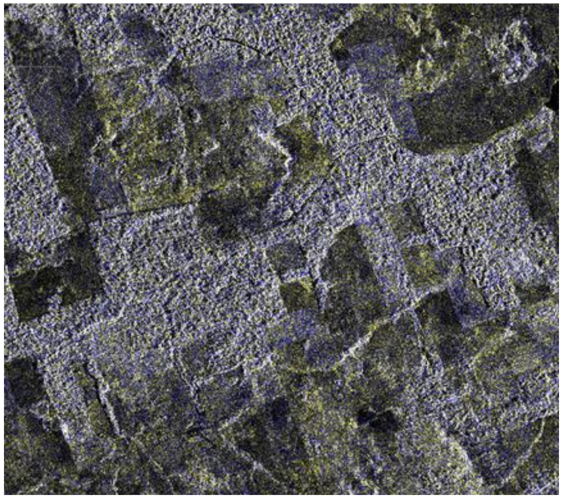


# Brazil – Study site

# Brazil – Study site

# Brazil – Methods

- The study area is temporally highly variable → land use land cover may have changed during the acquisitions
  - → stacking all data into one single data set results in one single map and is inadequate
  - → **classify each single scene, by using information from all other scenes**
- 5 TerraSAR-X images (June to September 2014) with different polarizations were used



# Brazil – Methods

## Land use and land cover classes

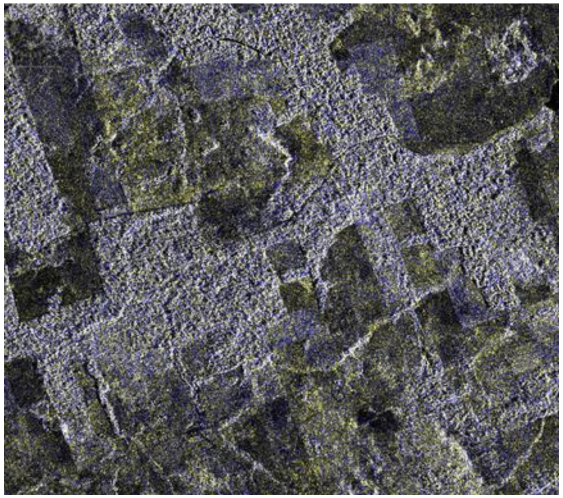
- ***Clean Pasture***, also called *pasto limpo:* pasture land that is intensively managed; including includes tillage and burning of land to support cattle ranching.

- ***Shrubby Pasture***, also called *pasto sujo*: not intensively managed and thus affected by bush encroachment.

- ***Burnt Pasture*, **includes recently burned clean and shrubby pasture tation residues.

- ***Forest/Secondary Vegetation***

- ***Water***



# Brazil – Methods

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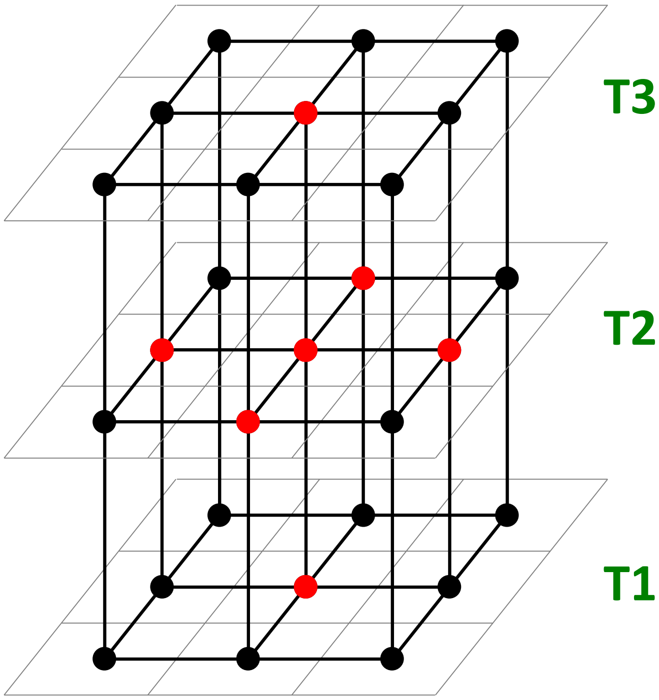
## Markov Random Fields

- MRF can be used to optimize land cover maps by spatial-temporal interactions between neighboring pixels
- Usually all interactions in space and time are equally weighted (using a so-called Potts model) → similar classes are more likely than different classes

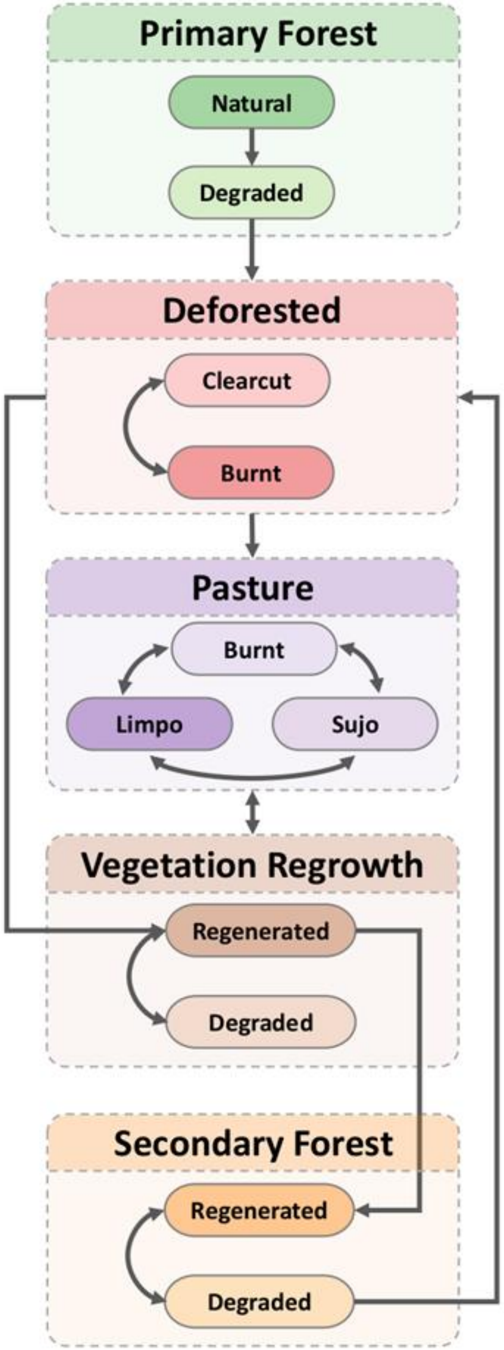


# Brazil – Methods

*Markov Random Fields*

- However, the relationship between classes can be different, e.g. a forest pixel can be deforested a few weeks later, while it is very unlikely that a reforestation process last only a few weeks

**→ We integrate expert knowledge in the Markov Random Field**



## Brazil – Methods

### Markov Random Fields

- We integrate expert knowledge in the Markov Random Field

$$U(Y|X) = -\sum_{i \in I} \ln p(x_i | y_i) + \beta \sum_{i_s \sim j_s} [1 - \delta_s(y_{i_s}, y_{j_s})] + \tau \sum_{i_t \sim j_t} [1 - \delta_t(y_{i_t}, y_{j_t})]$$

weights for **spatial neighborhoods**:
symmetric, given by spatial resolution

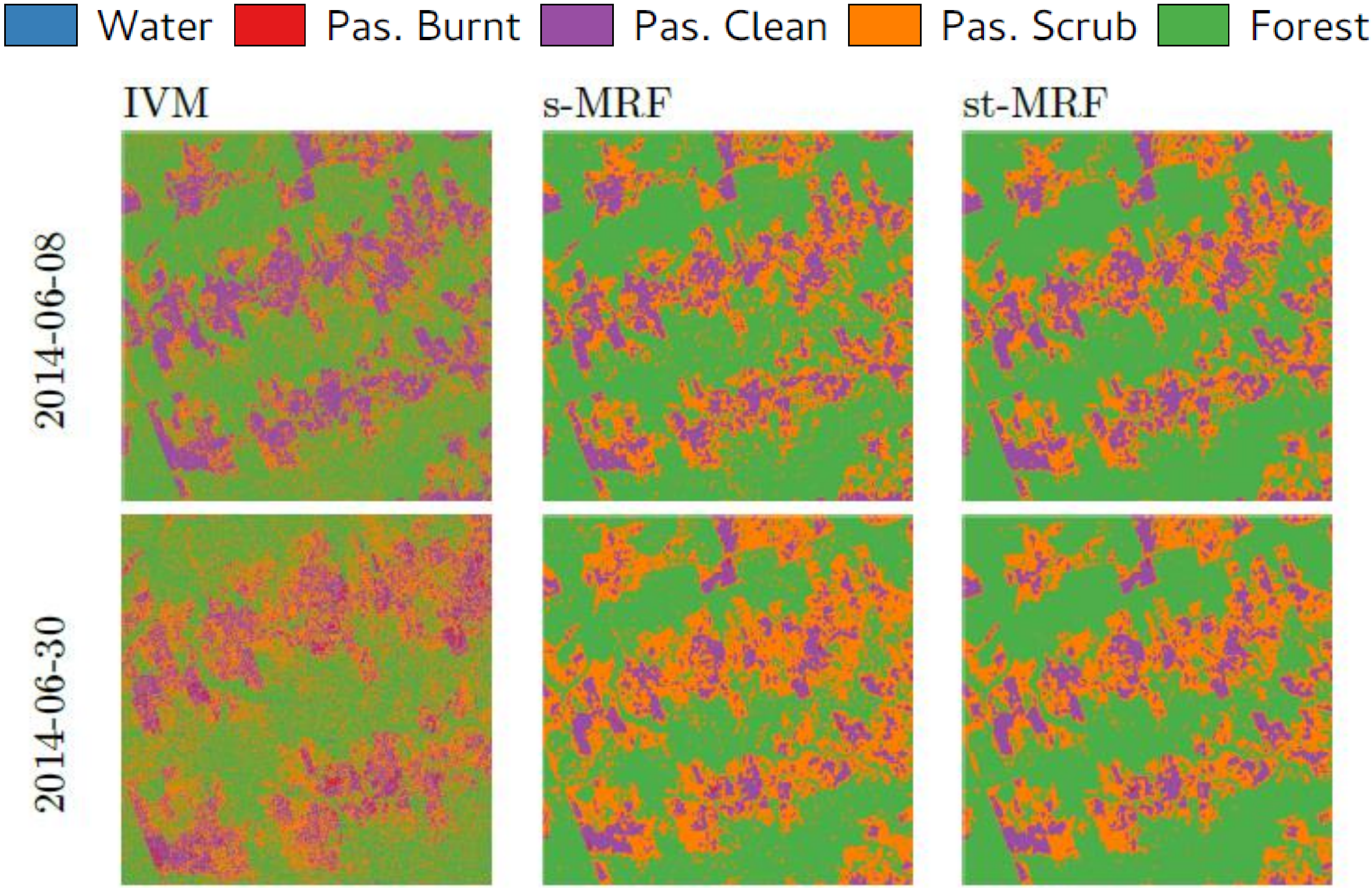
Typicial model (1/0), so-called Pott's model

δ(forest, forest) = 1
δ(forest, pasture) = 0
δ(pasture, pasture) = 1
δ(pasture, forest) = 0

weights for **temporal neighborhoods**:
depending on time between acquisitions dates, class-specific, non symmetric, e.g.:

Example:
δ(Forest, Forest) = 1
δ(Forest, Pasture) = 0.5
δ(Pasture, Forest) = 0.1

# Brazil – Results



# Brazil – Results

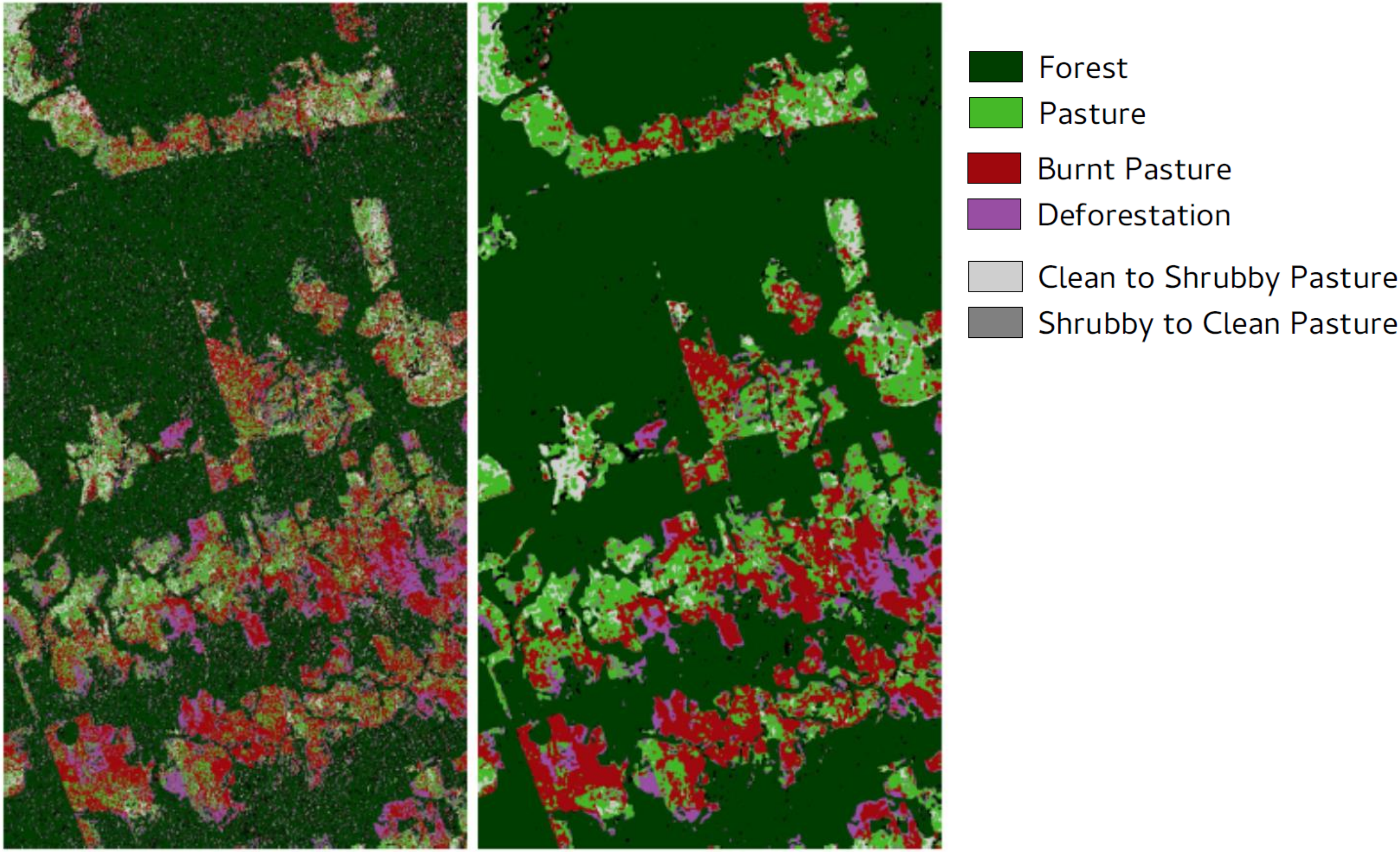


## Accuracy assessment

- Integration of spatial information by MRF improves classification results
- The proposed approach, a spatial-temporal MRF, results in the highest classification accuracies
- Visual assessment underlines these findings → typical random noise is considerably reduced

| Acquisition Date | IVM | s-MRF | st-MRF |
|---|---|---|---|
| 2014-06-08 | 0.65 | 0.75 | **0.77** |
| 2014-06-30 | 0.60 | 0.69 | **0.79** |
| 2014-07-22 | 0.66 | 0.76 | **0.78** |
| 2014-08-24 | 0.69 | 0.74 | **0.76** |
| 2014-09-04 | 0.68 | 0.77 | **0.78** |

# Brazil – Results



# Brazil - Discussion

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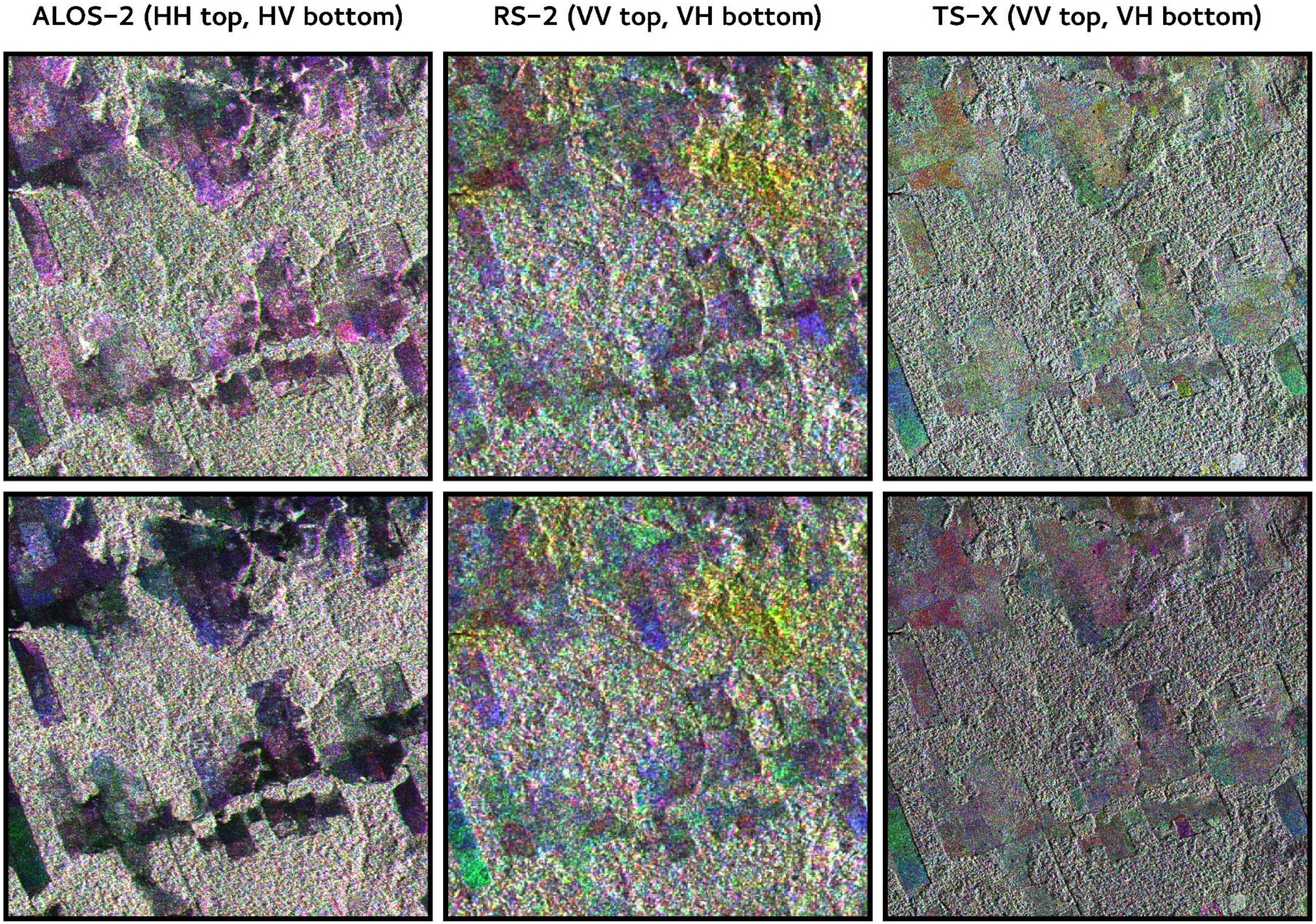
- In general an adequate classification strategy, is useful in terms of mapping accuracies
- Coupling machine learning / pattern recognition with geographical expert knowledge improves the mapping accuracies
- The proposed approach:
  - appears very well suited for mapping dynamic land use and land cover, using multitemporal SAR data
  - is based on probabilities → multisensor data

# Case study - Brazil



# Case study - Brazil

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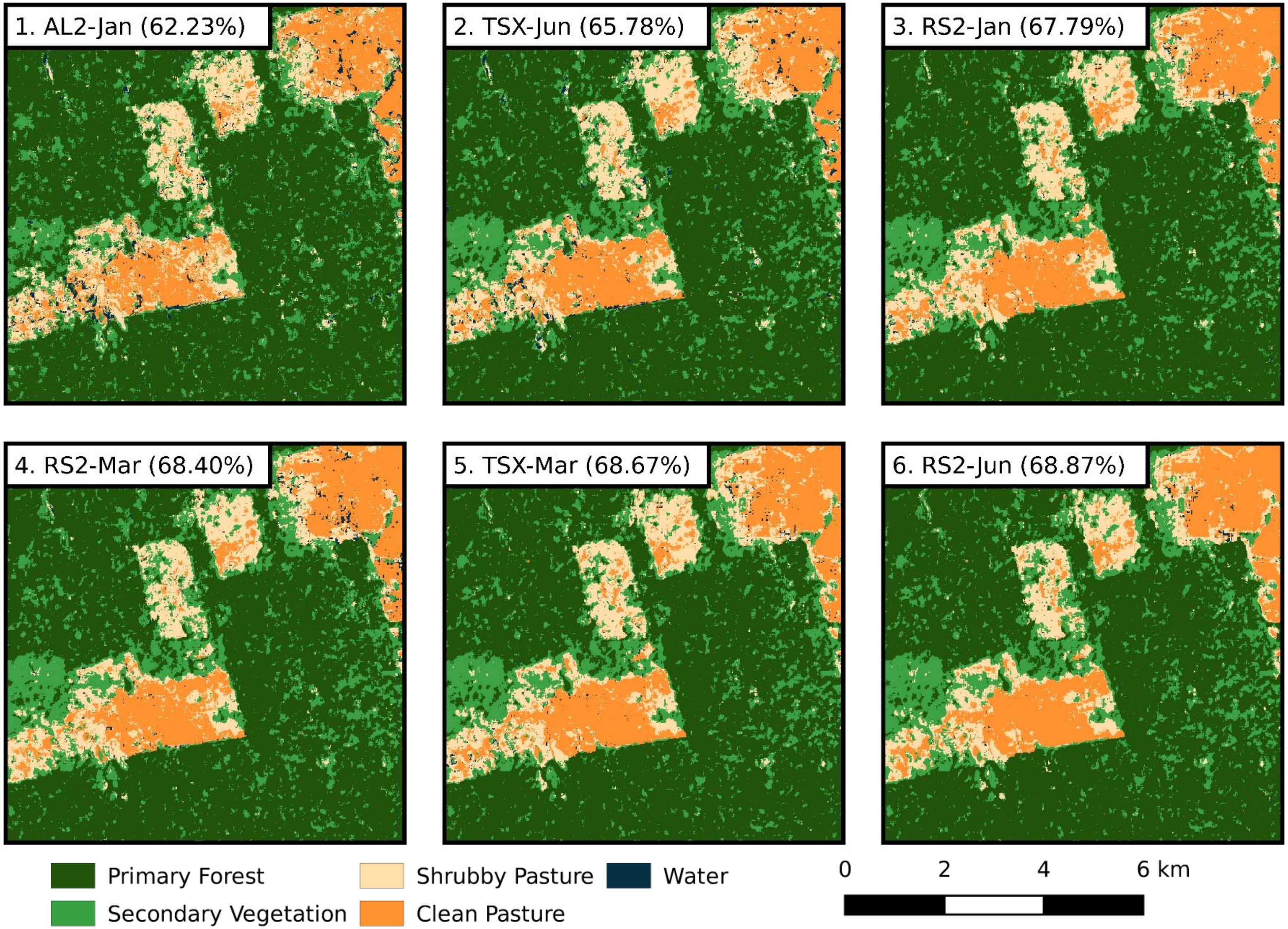


# Outlook

- Multisensor remote sensing data
  - provide different but complementary information
  - can fill gaps in time series

  and proofs useful in terms of mapping accuracy

- Upcoming missions such as ESAs Sentinel missions offer great potentials
- However,
  - these data sets, and
  - recent applications and performance requirements

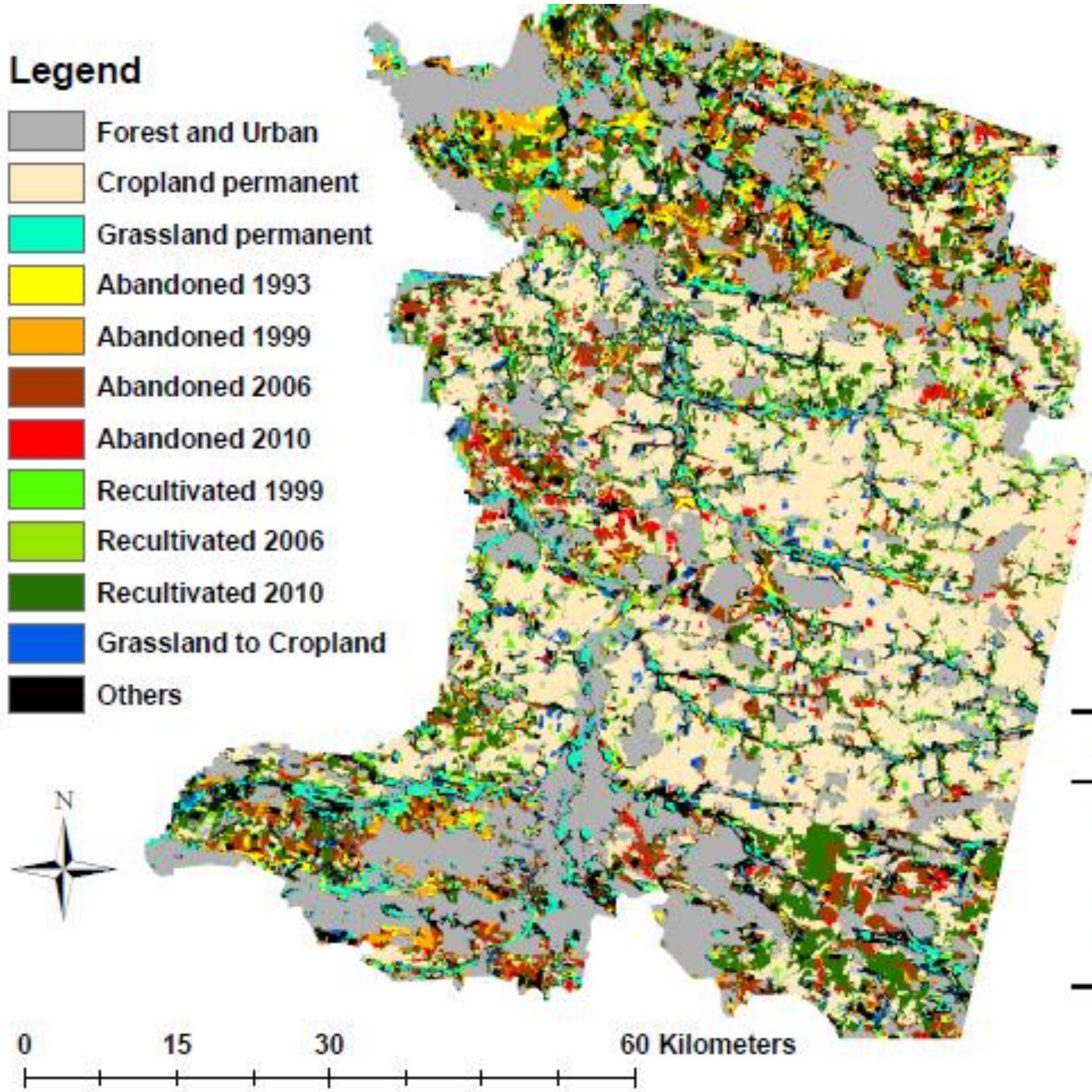
  demand increasingly improving algorithms

- Thus, the development of adequate methods for multisensor image analysis is an ongoing research topic


Sentinel 1 (jun-jul-aug 2015)


Thank you for your attention
Sentinel 2 (8-4-3)

# Case study - Ukraine




## Change analysis 1986-2010

| Change estimation | [%] |
|---|---|
| Total abandonment 1993 | 11.1 |
| Total abandonment 1999 | 13.7 |
| Total abandonment 2006 | 30.6 |
| Total abandonment 2010 | 19.7 |

(Stefanksi et al. 2014)

# Case study - Brazil

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**Methods:**

*Import Vector Machines*

- IVM (Zhu & Hastie 2005) are based on Logistic Regression and Kernel Logistic Regression
- Use only a subsets of samples (sparseness), whereas SVM (and Kernel Logistic Regression) use all samples
- Whereas SVM maximize the margin, IVM are aiming on the **optimization of the probabilities** and thus, **directly provide class probabilities**