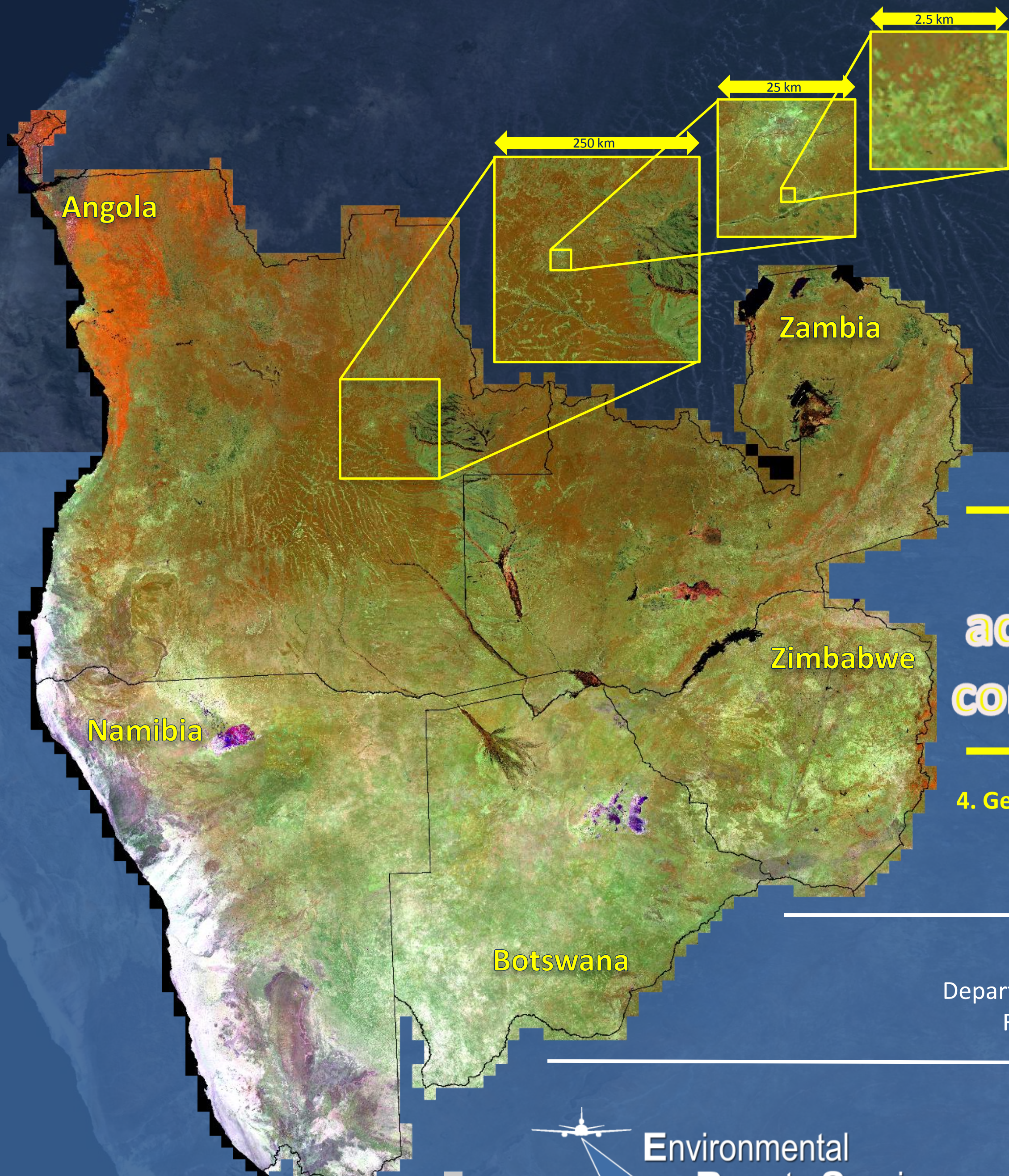
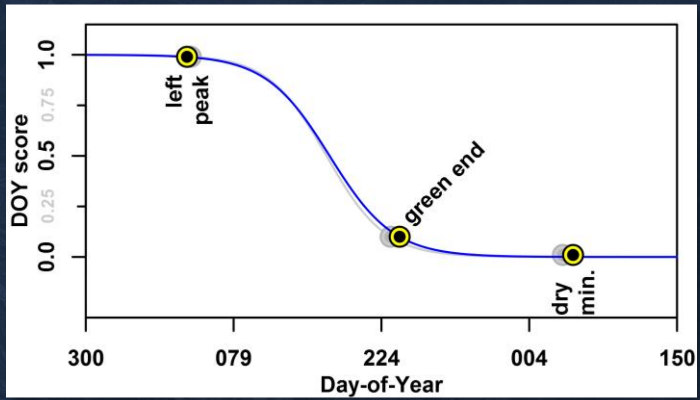




Generating phenology-adaptive pixel-based Landsat composites across large areas

4. Gemeinsame Jahrestagung der Arbeitskreise Fernerkundung
Daten – Informationen – Entscheidungen
24./25. Sept. 2015, Geozentrum der Universität Bonn

David Frantz, Achim Röder, Marion Stellmes, Joachim Hill
Department of Environmental Remote Sensing & Geoinformatics,
FB VI Regional and Environmental Sciences, **Trier University**

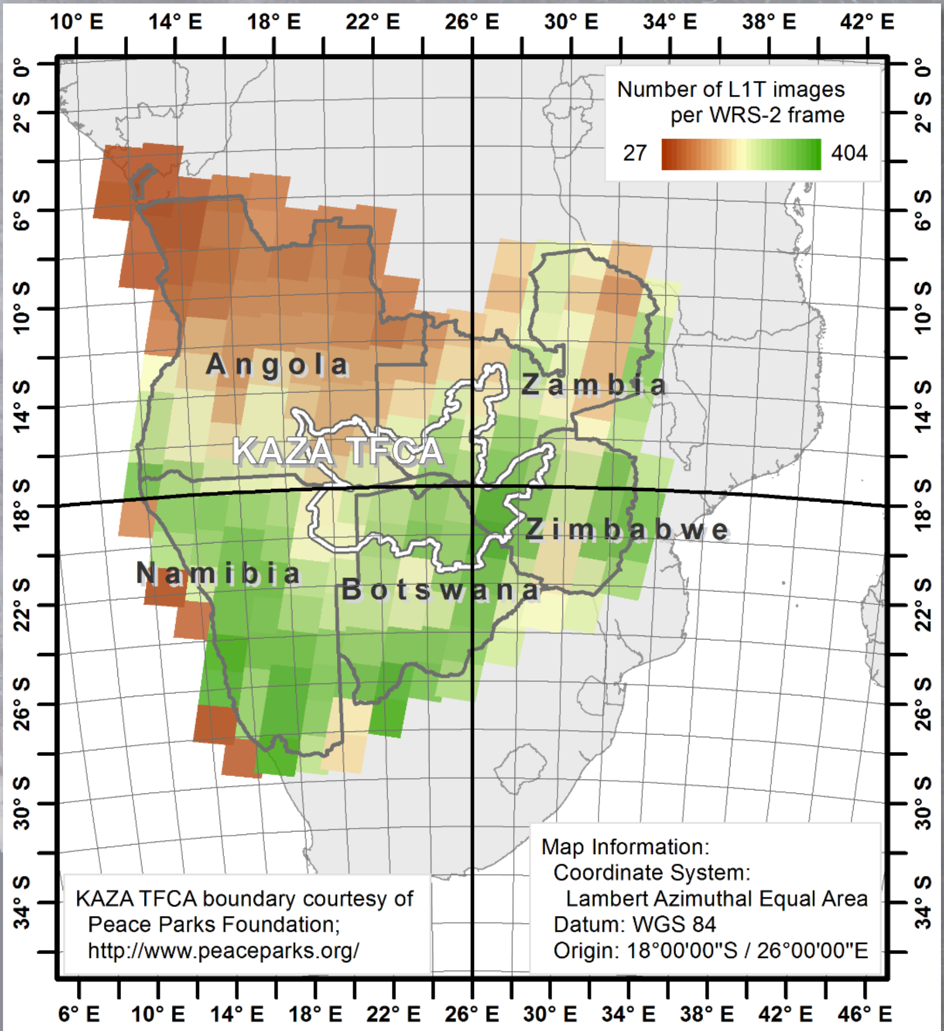
Universität Trier
Environmental Remote Sensing & Geoinformatics

SPONSORED BY THE
Federal Ministry of Education and Research

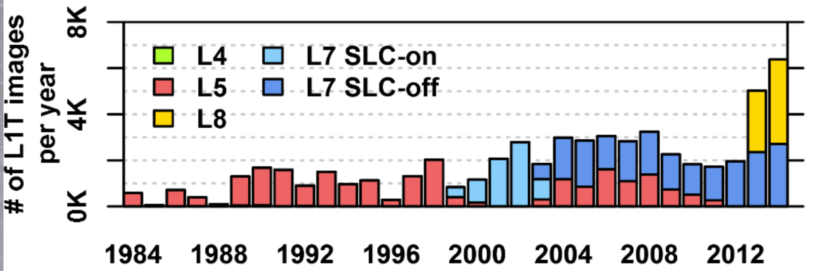
SASSCAL
Southern African Science Service Centre for Climate Change and Adaptive Land Management

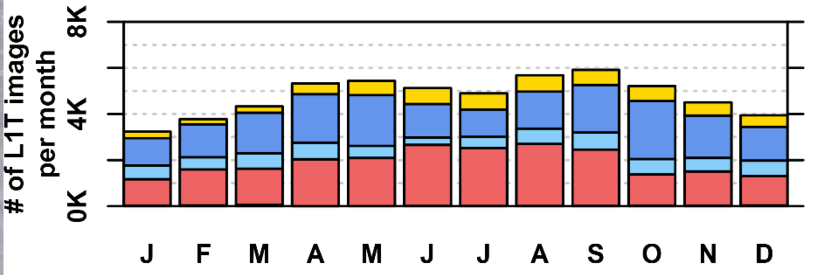
Study Area / Motivation

Centered at the upcoming Kavango-Zambezi Transfrontier Conservation Area (KAZA TFCA)



- ~ 3.7 Mio. km²
- 194 footprints
- 57,371 L1T images
- ~ 15 TB





→ **wall-to-wall applications**

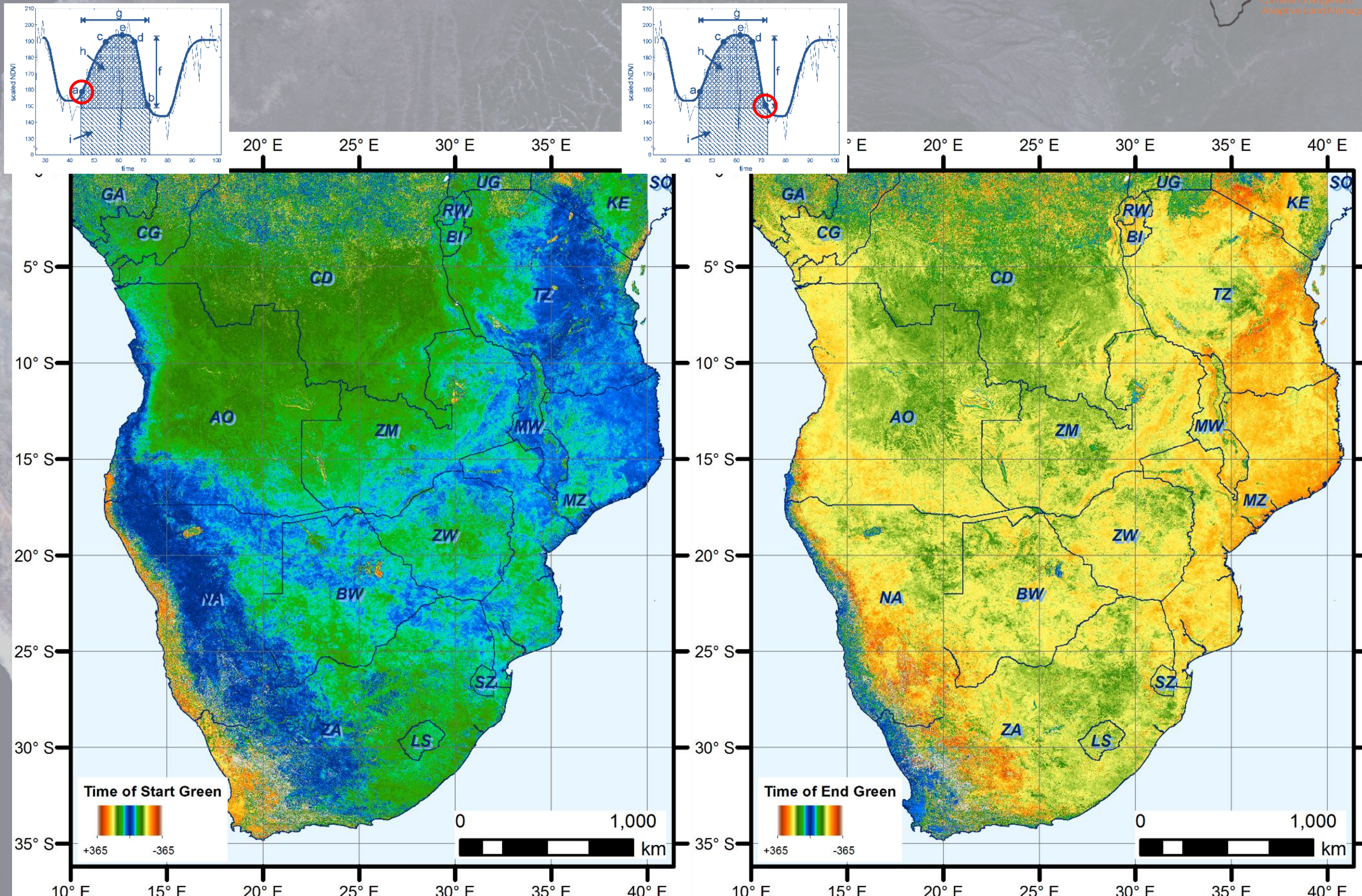
- e.g. forest cover + change/trend: deforestation/degradation
- Biophysical parameters: stand structure, tree height, biomass, …

→ **pixel-based composites**

state-of-the art: static target DOY

Study Area / Motivation

SASSCAL
Southern African Science Service Centre for Climate Change and Adaptive Land Management

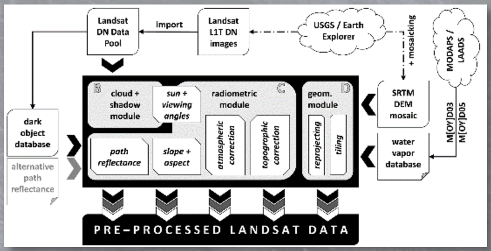


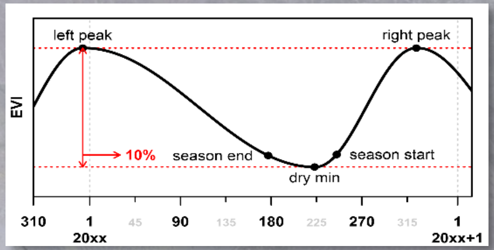
generation of wall-to-wall Landsat products

Structure

LANDSAT PRE-PROCESSING

- cloud masking
- radiometric correction
- gridded data structure



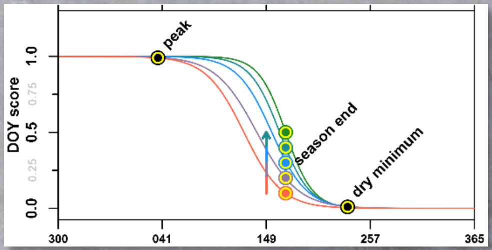


LAND SURFACE PHENOLOGY

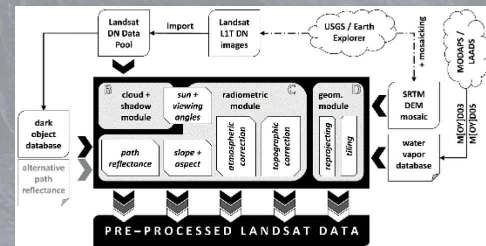
- MODIS phenology
- Data fusion by spatial unmixing → medium resolution phenology

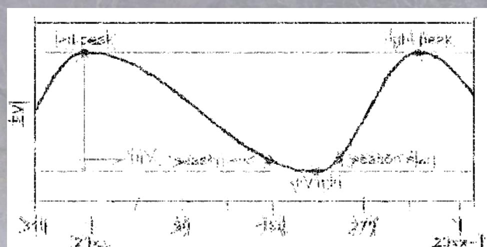
PIXEL-BASED COMPOSITES

- Generation of seamless large area baseline reflectance data
- Compositing guided by phenology



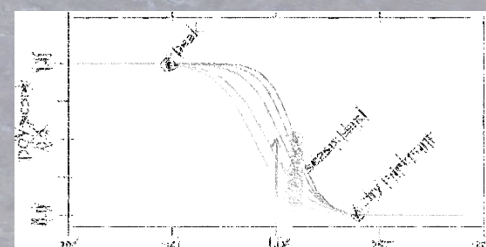
LANDSAT PRE-PROCESSING
- cloud masking
- radiometric correction
- gridded data structure





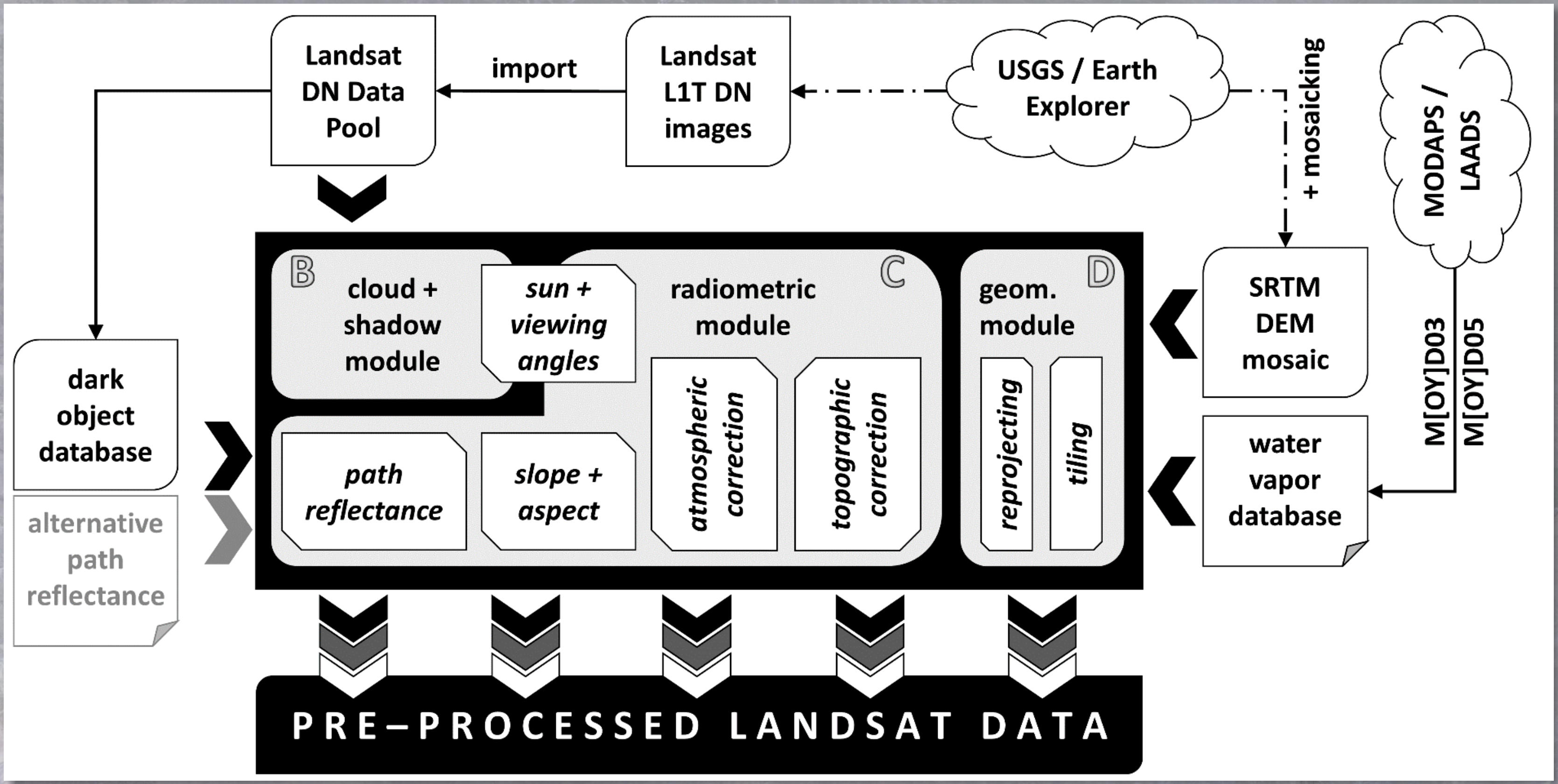
LAND SURFACE PHENOLOGY
- MODIS phenology
- Data fusion by spatial unmixing → medium resolution phenology

PIXEL-BASED COMPOSITES
- Generation of seamless large area baseline reflectance data
- Compositing guided by phenology



Landsat pre-processing framework

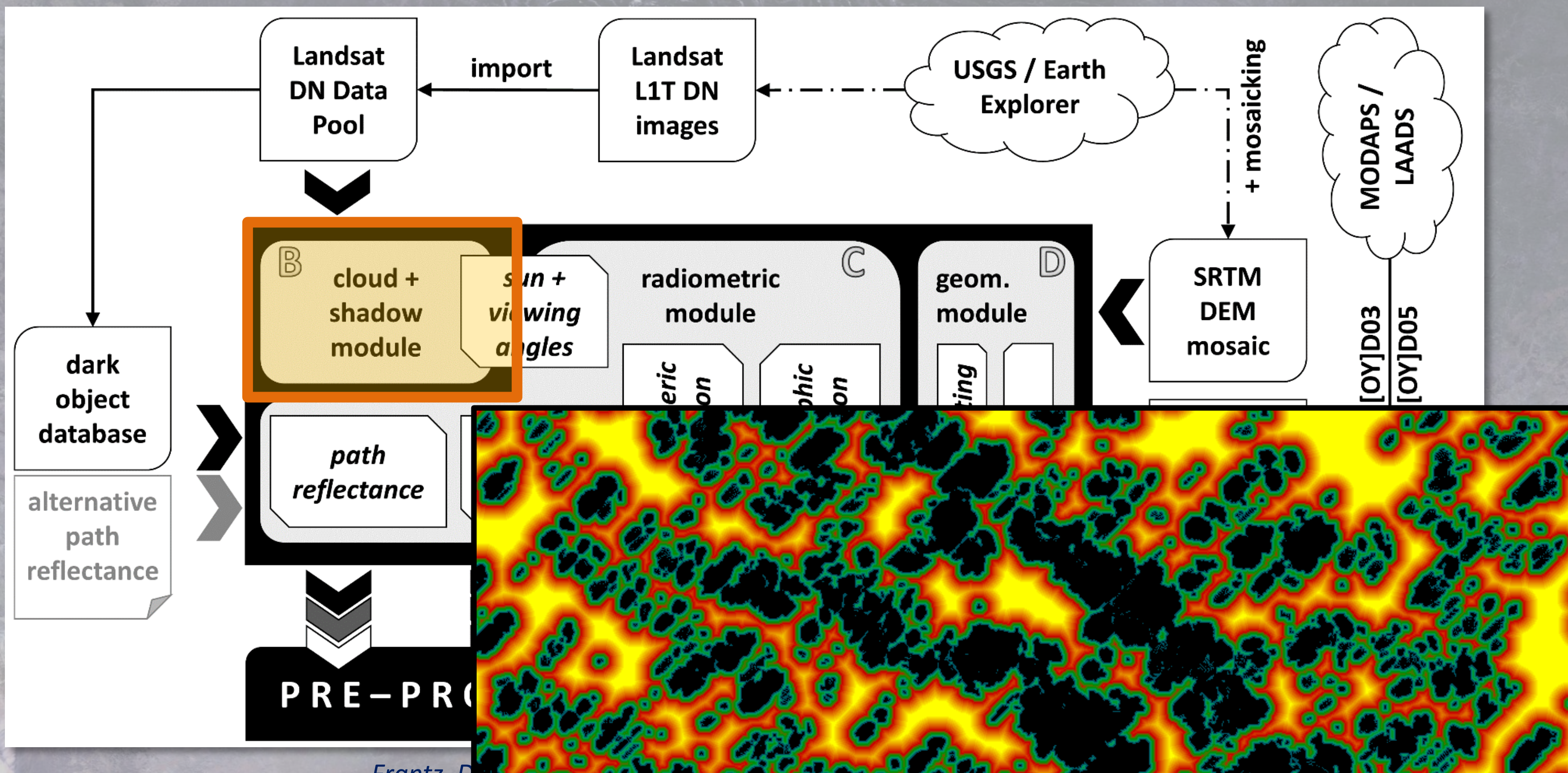
SASSCAL



Frantz, D., A. Röder, M. Stellmes, and J. Hill. "An Operational Radiometric Landsat Pre-Processing Framework for Large Area Time Series Applications." In Revision.

Landsat pre-processing framework

SASSCAL



Frantz, D

Fram

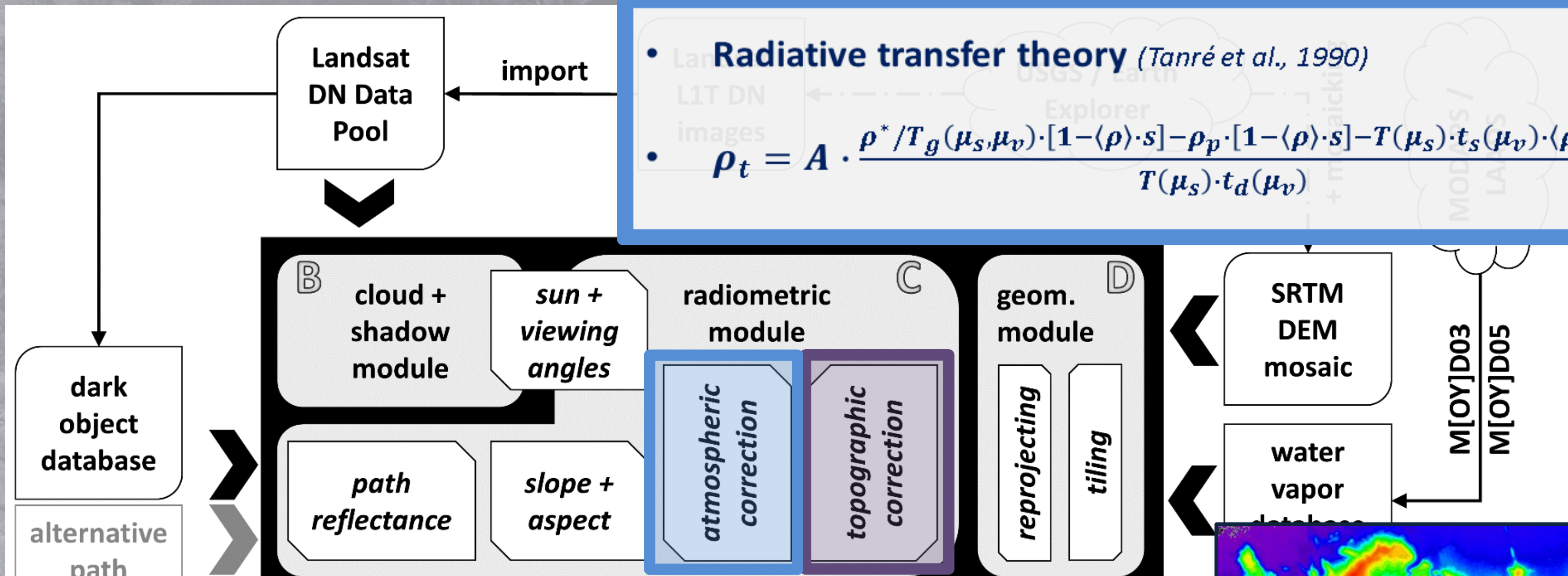
Fmask algorithm

(Zhu & Woodcock, 2012)

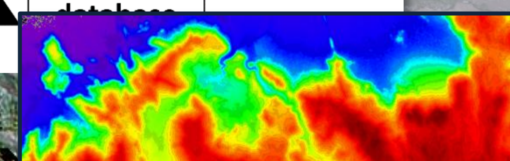
+ updates *(Zhu et al., 2015)*

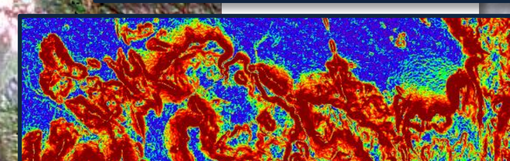
+ modifications *(Frantz et al., 2015a, Griffiths et al., 2013)*

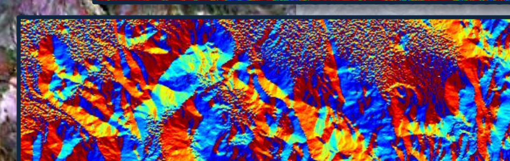
Landsat pre-processing framework



- **Radiative transfer theory** *(Tanré et al., 1990)*
- $$\rho_t = A \cdot \frac{\rho^* / T_g(\mu_s,\mu_v)\cdot[1-\langle\rho\rangle\cdot s] - \rho_p\cdot[1-\langle\rho\rangle\cdot s] - T(\mu_s)\cdot t_s(\mu_v)\cdot\langle\rho\rangle}{T(\mu_s)\cdot t_d(\mu_v)}$$





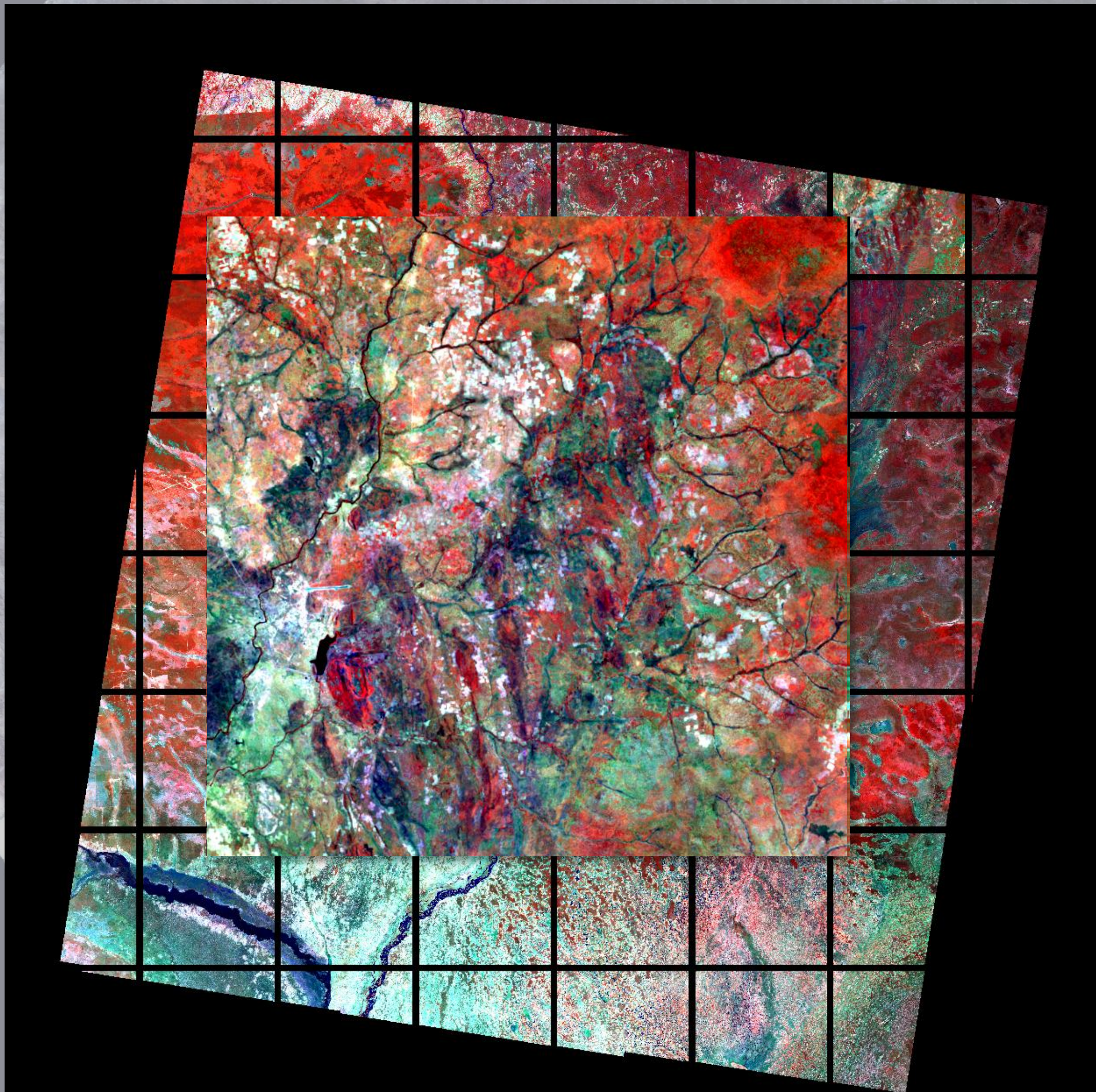


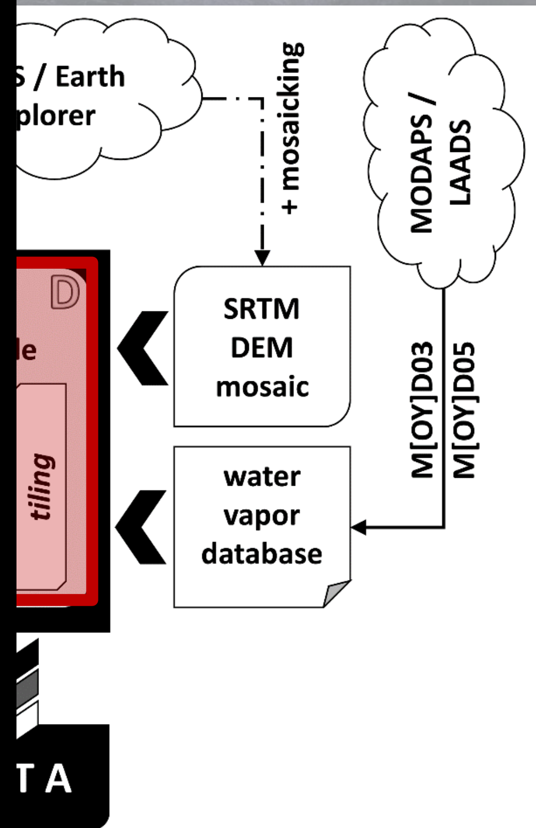
530m - 1530m

generation of wall-to-wall Landsat products

Landsat pre-processing framework

SASSCAL

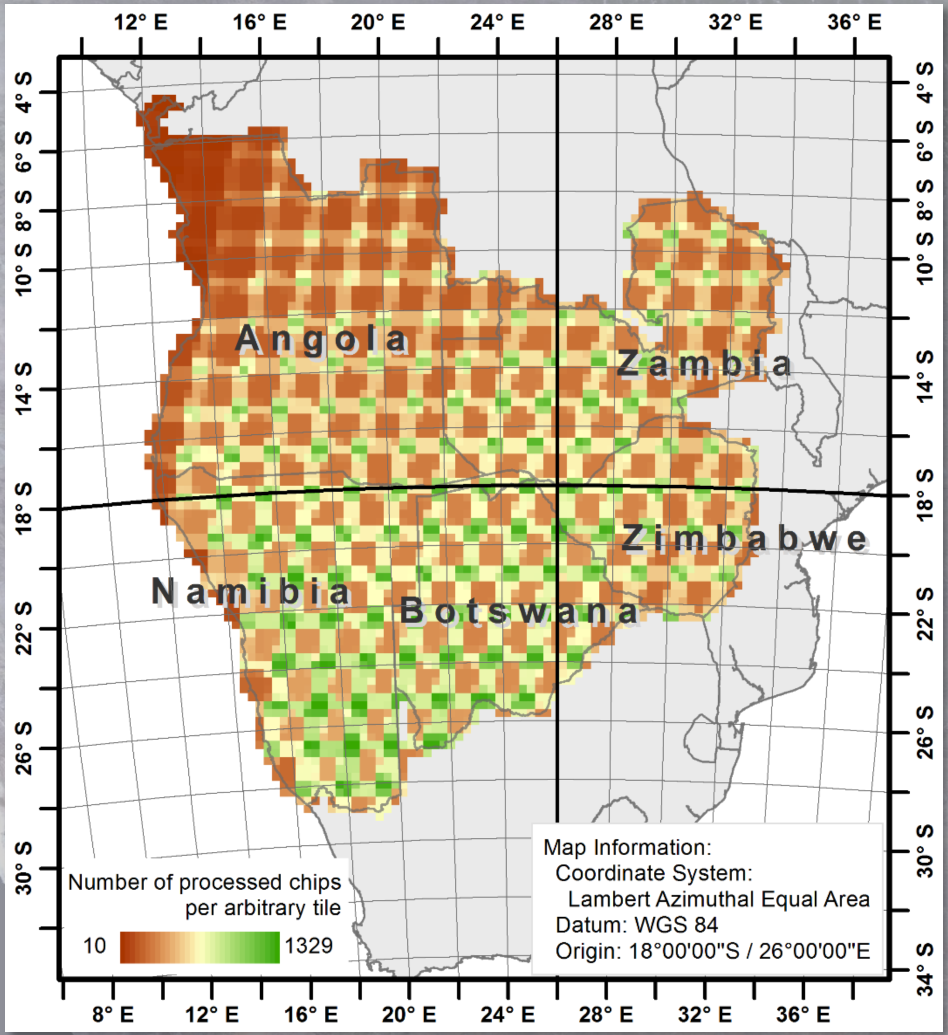




onal Radiometric Landsat Pre-Processing
rea Time Series Applications." In Revision.

generation of wall-to-wall Landsat products

Pre-processed dataset



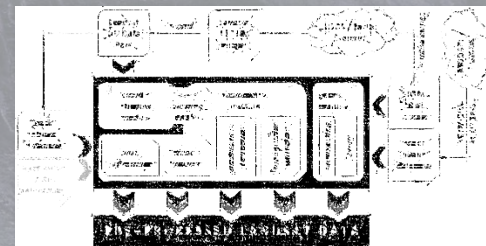
- 29% images not fully processed → cloud coverage exceeded threshold

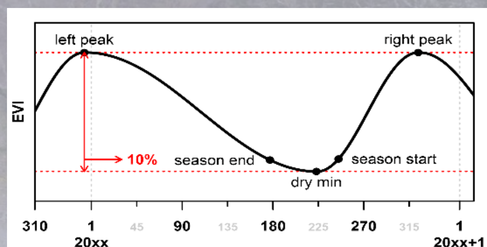
- 4,524 tiles
- 1,864,061 chips (i.e. tiled datasets)
- 27.18 TB processed data
- Processing time ~ 4days using 108 CPUs

Structure

LANDSAT PRE-PROCESSING

- cloud masking
- radiometric correction
- gridded data structure



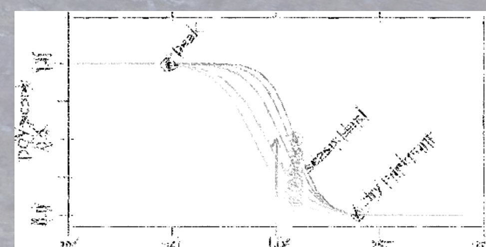


LAND SURFACE PHENOLOGY

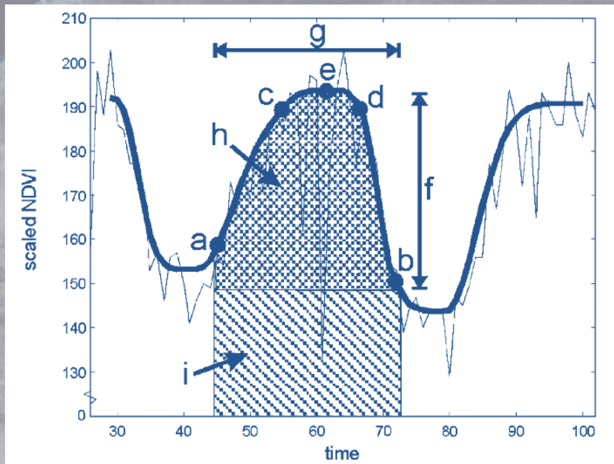
- MODIS phenology
- Data fusion by spatial unmixing → medium resolution phenology

PIXEL-BASED COMPOSITES

- Generation of seamless large area baseline reflectance data
- Compositing guided by phenology



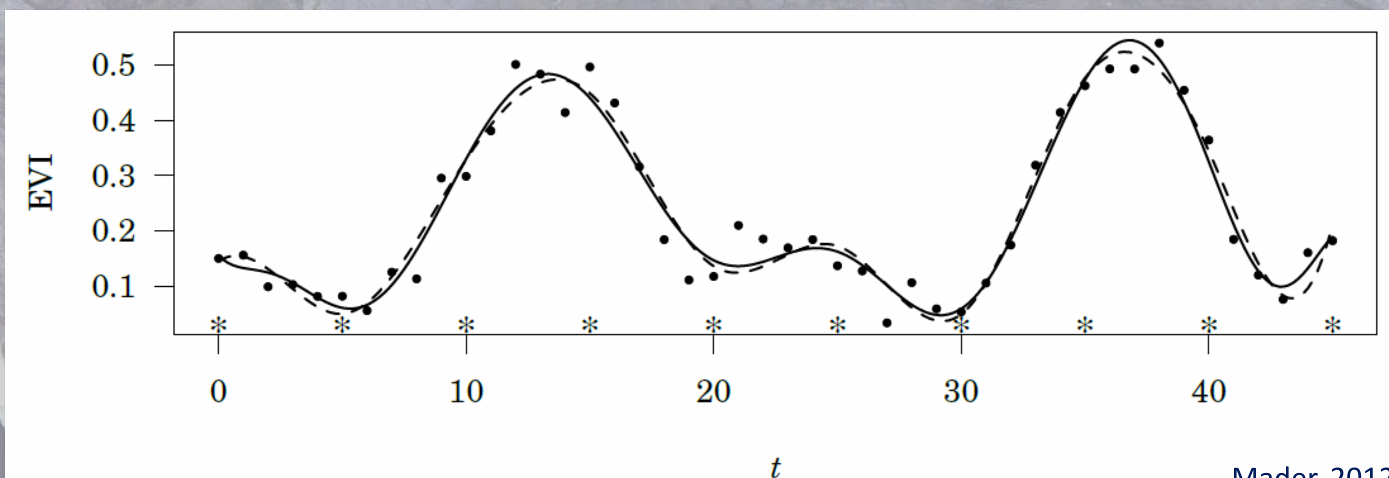
Land Surface Phenology LSP



Jönsson & Eklundh 2002

Phenological descriptors are derived from high temporal resolution time series, e.g. MODIS

- Start of season (a)
- End of season (b)
- Length of season (g)
- Base value (b)
- Middle of season (e)
- Maximum of fitted data (e)
- Amplitude (f)
- Left derivative (a-c)
- Right derivative (d-b)
- Large/Total integral (i)
- Small/Green integral (h)
- Latent integral (i-h)



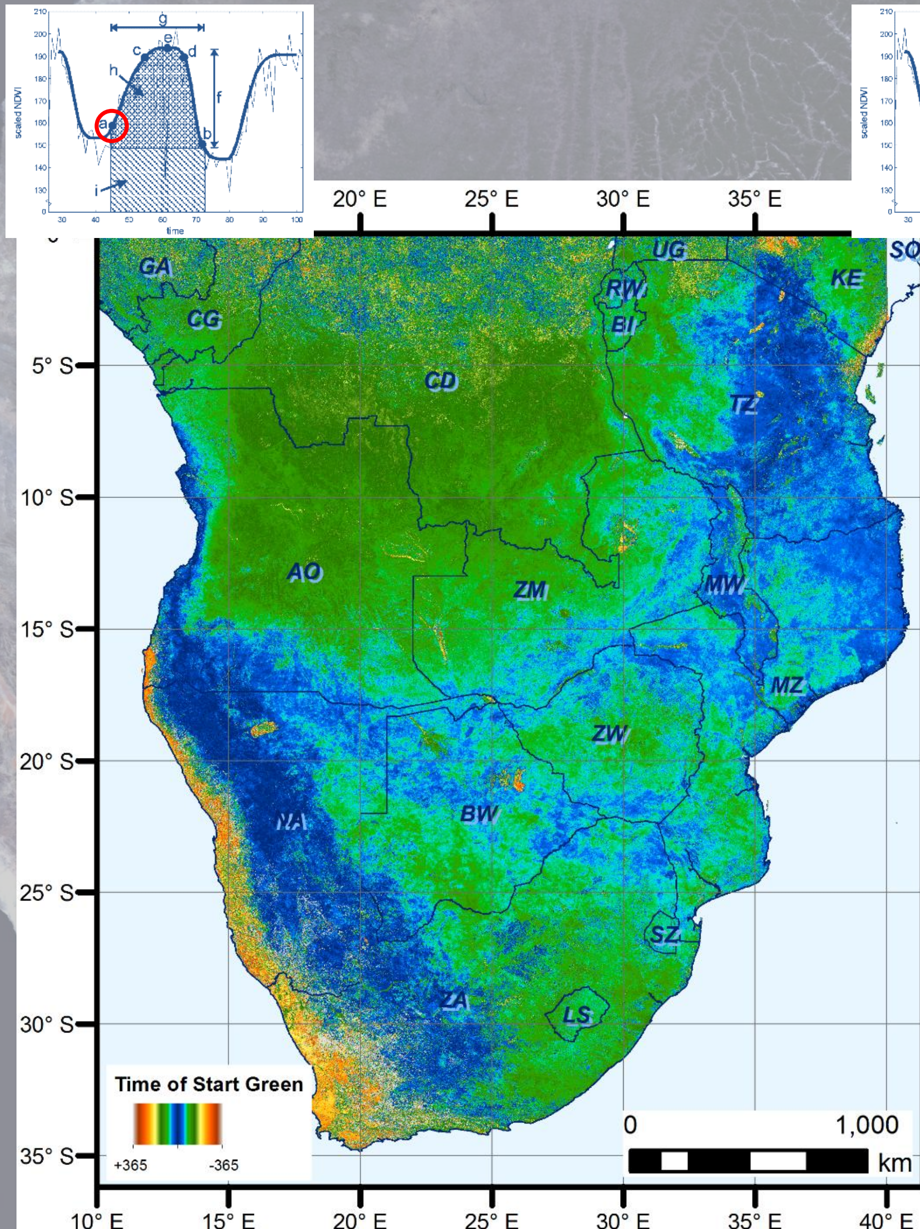
Mader, 2012

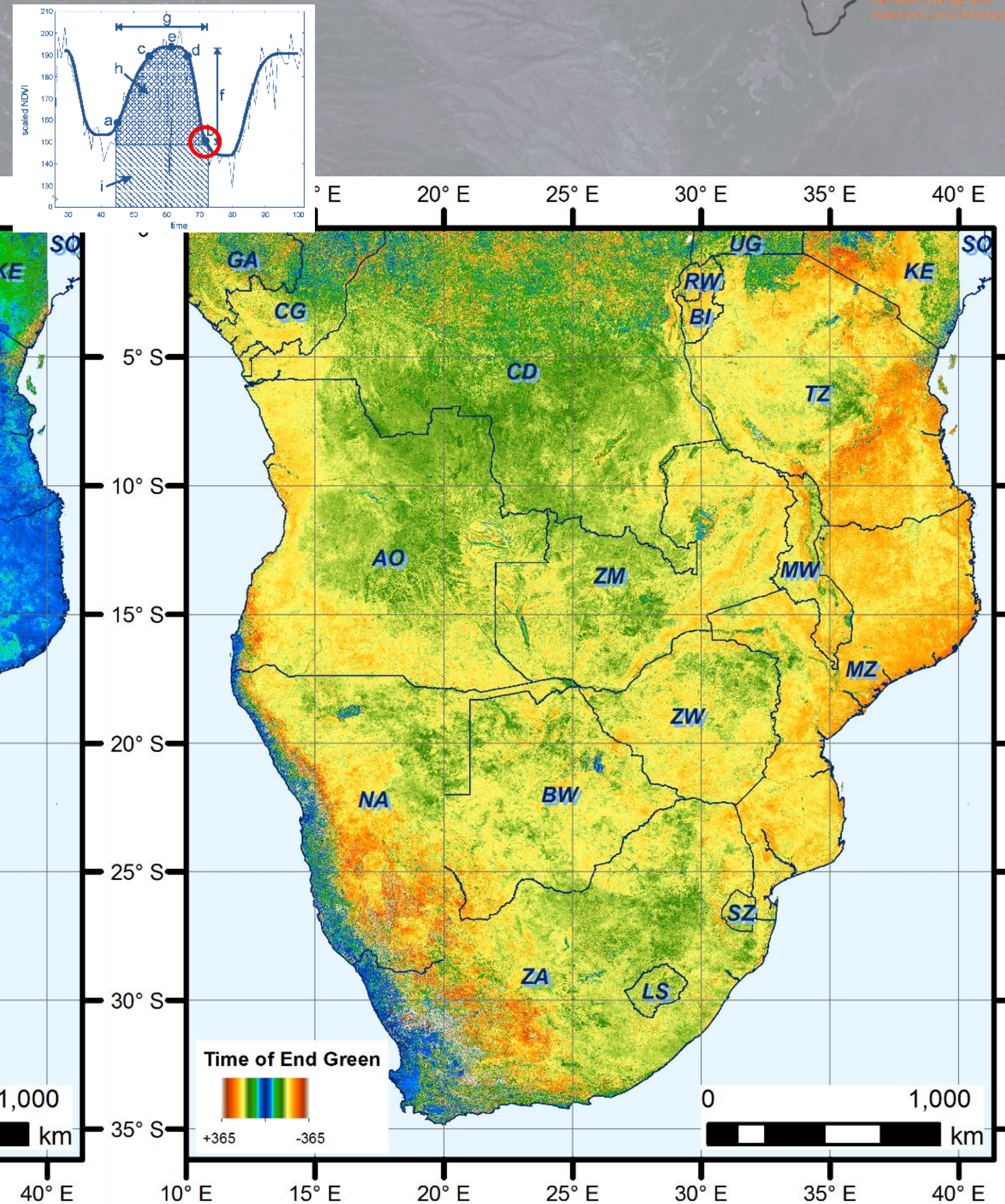
SpliTS (**Spli**ne Analysis of **T**ime **S**eries; Mader, 2012)

- framework for the analysis of remotely sensed time-series based on polynomial spline models
- data-driven, locally controlled fit without anticipation of a certain phenological shape
- Non-equidistant data

MODIS (Terra/Aqua) EVI time series (2000-2013) + day of composite
→ **PHENOLOGICAL DESCRIPTORS**

Land Surface Phenology LSP





generation of wall-to-wall Landsat products

Data fusion via spatial unmixing
→ increase of spatial resolution by a factor of 8.3

MODIS LSP and Landsat reflectance → Landsat LSP

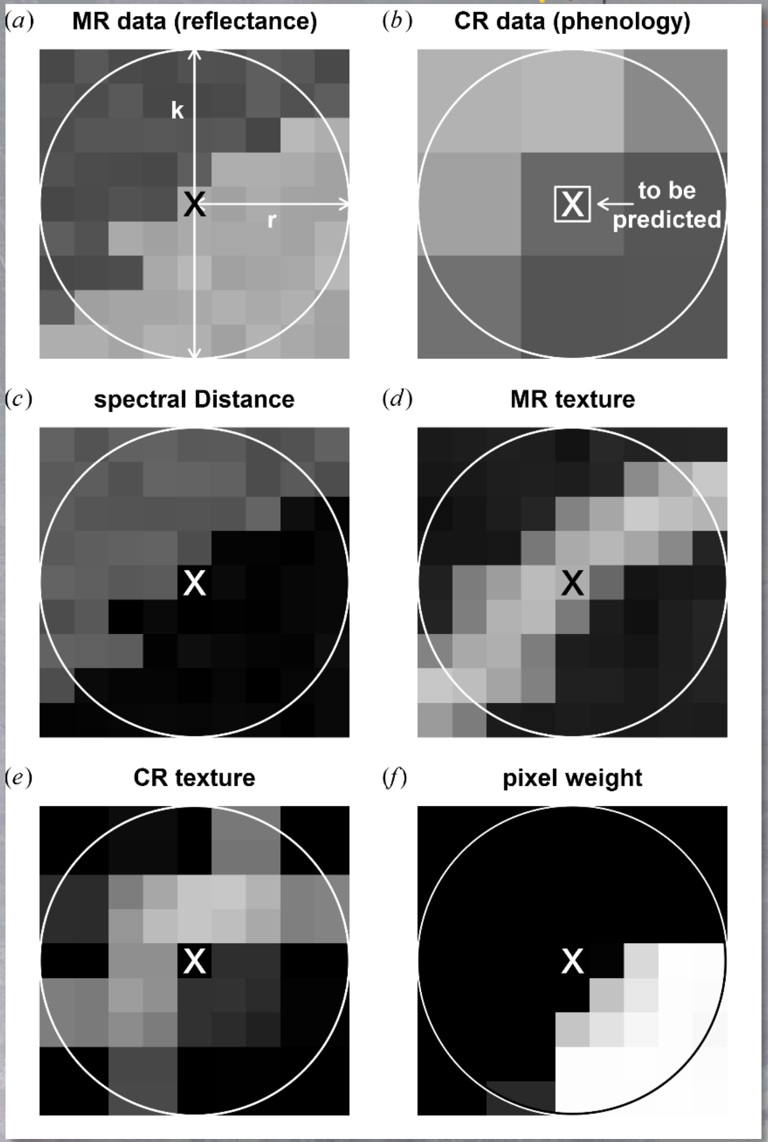
$$M_{xy,p} = \sum_{j=1}^{k}\sum_{i=1}^{k}(W'_{ji,p}C_{ji,p}) \Big/ \sum_{j=1}^{k}\sum_{i=1}^{k} W'_{ji,p}$$

Medium resolution (MR) LSP is modelled from coarse resoluton (CR) LSP

Based on the reliability of CR and MR data under different conditions, several proxies are defined:

S_{ji}	spectral distance	
T_{ji}	sub-pixel heterogeneity	(MR texture)
$U_{ji,p}$	super-pixel heterogeneity	(CR texture)

$$W'_{ji,p} = S'_{ji} \cdot T'_{ji} \cdot U'_{ji,p}$$

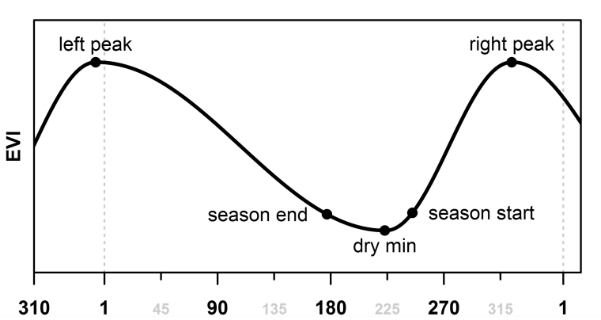


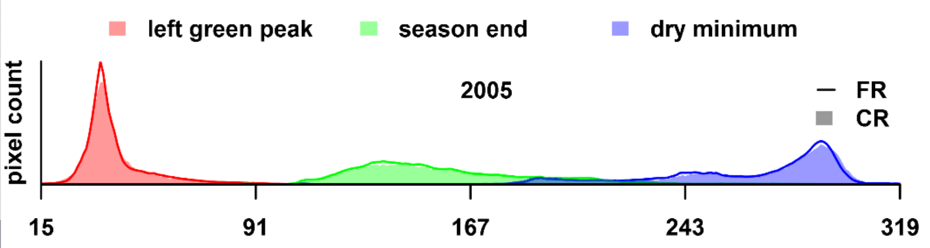
Land Surface Phenology LSP

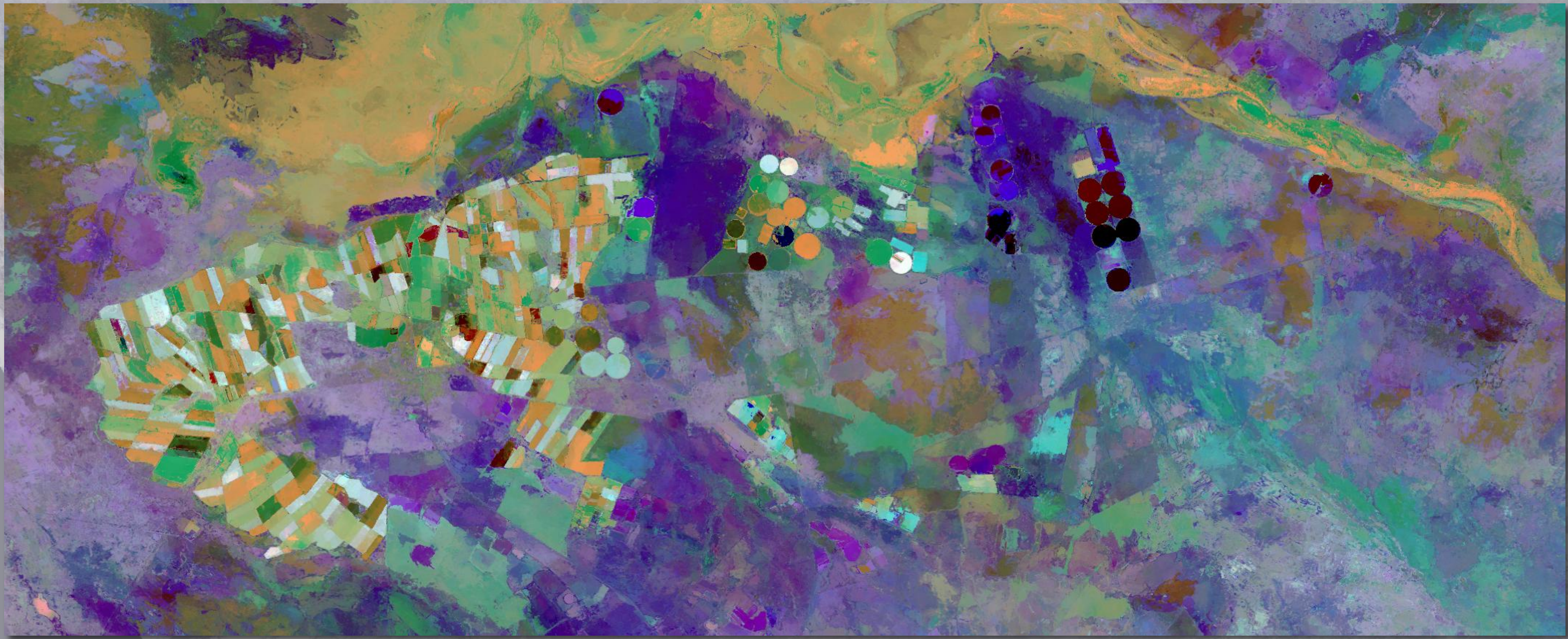
Data fusion via spatial unmixing
→ increase of spatial resolution by a factor of 8.3

MODIS LSP and Landsat reflectance → Landsat LSP

$$M_{xy,p} = \sum_{j=1}^{k}\sum_{i=1}^{k}(W'_{ji,p}C_{ji,p}) \Big/ \sum_{j=1}^{k}\sum_{i=1}^{k}W'_{ji,p}$$



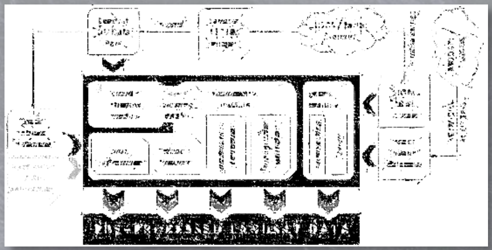


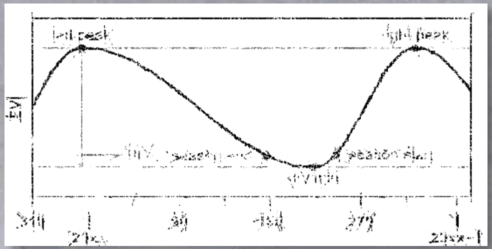


generation of wall-to-wall Landsat products

LANDSAT PRE-PROCESSING

- cloud masking
- radiometric correction
- gridded data structure



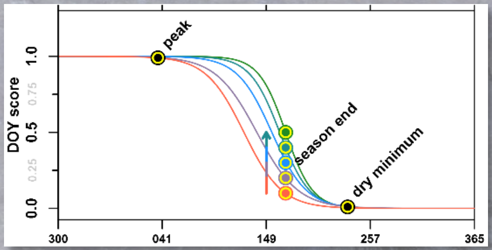


LAND SURFACE PHENOLOGY

- MODIS phenology
- Data fusion by spatial unmixing → medium resolution phenology

PIXEL-BASED COMPOSITES

- Generation of seamless large area baseline reflectance data
- Compositing guided by phenology



Selection of *"best"* observation

- Parametric weighting scheme based selection process *(based on Griffiths et al., 2013)*
- All Landsat images within a pre-defined time window are considered, e.g. Y_t = 2010±2 → 5 years

Total score is obtained from
DOY score, **Year** score, **Cloud** score, **Haze** score

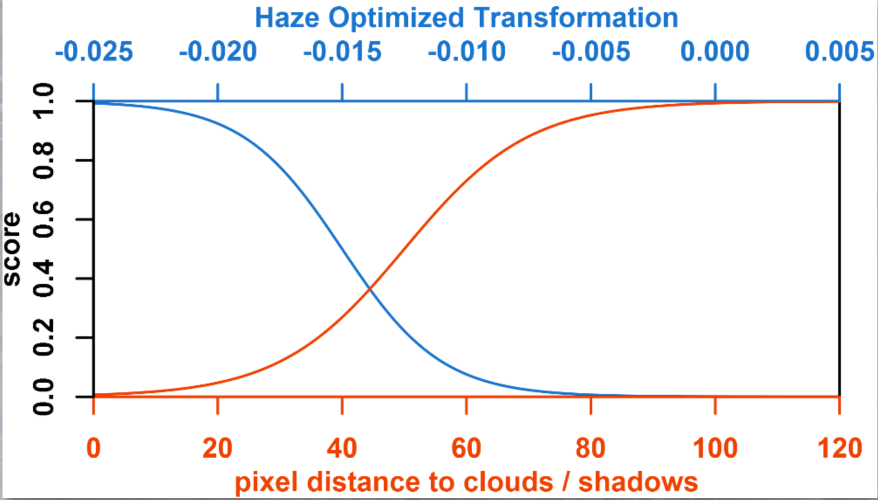
$$S_T = S_D \cdot S_Y \cdot S_C \cdot S_H$$

$$S_C = 1/\left(1 + \exp\left(-10/d_{req} \cdot \left[d_i - d_{req}/2\right]\right)\right)$$

d_{req}: distance after which the sky is assumed to be clear, e.g. 100px

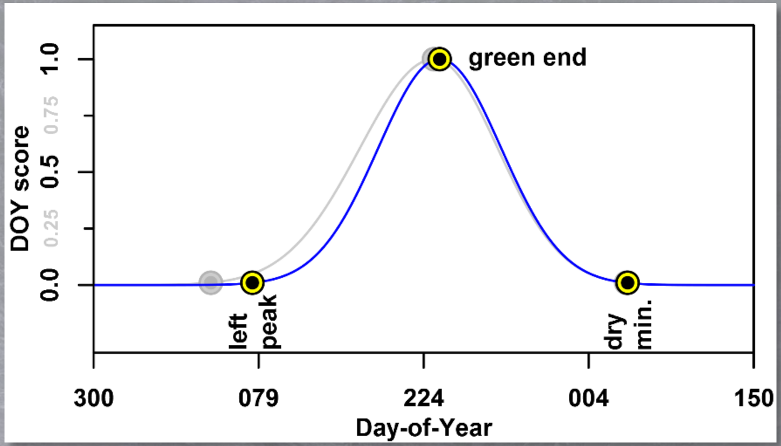
$$S_H = 1/(1 + \exp(500 \cdot HOT_i + 7.5))$$

HOT: Haze Optimized Transformation
proxy for Haze contamination *(Zhu & Woodock, 2012)*



Intra-annual contribution: acquisition day

SASSCAL



- 3 phenological descriptors are used, e.g.
  - left green peak, p_0
  - **season end,** $\boldsymbol{p_1}$
  - dry minimum, p_2
- A Gaussian scoring function is fit to the LSP for each pixel
- The Landsat observation is scored according to its acquisition DOY D_i:

$$S_D = \begin{cases} s_1 \cdot \exp\left(-0.5 \cdot [D_i - p_1]^2 / \sigma_l^2\right), & (D_i < p_1) \\ s_1 \cdot \exp\left(-0.5 \cdot [D_i - p_1]^2 / \sigma_r^2\right), & (D_i \geq p_1) \end{cases}$$

- The Gaussian width is derived from the LSP and pre-defined function values at p_0, p_1, p_2:
  - e.g. $s_0 = 0, s_1 = 1, s_2 = 0$

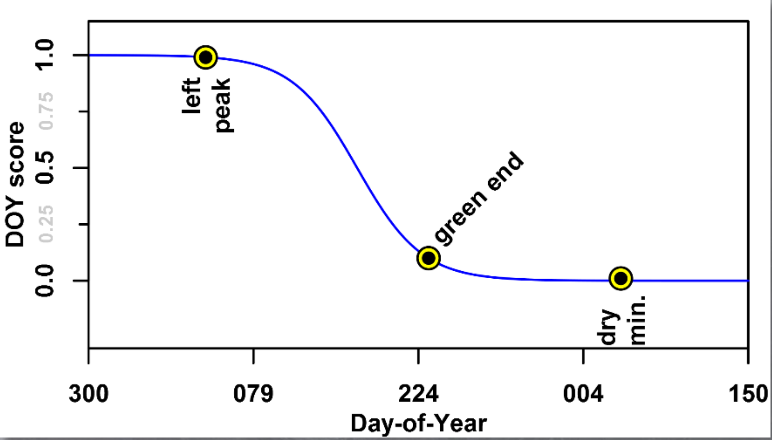
$$\sigma_l = [p_0 - p_1] / \sqrt{-2 \cdot \log(s_0 / s_1)}$$
$$\sigma_r = [p_2 - p_1] / \sqrt{-2 \cdot \log(s_2 / s_1)}$$

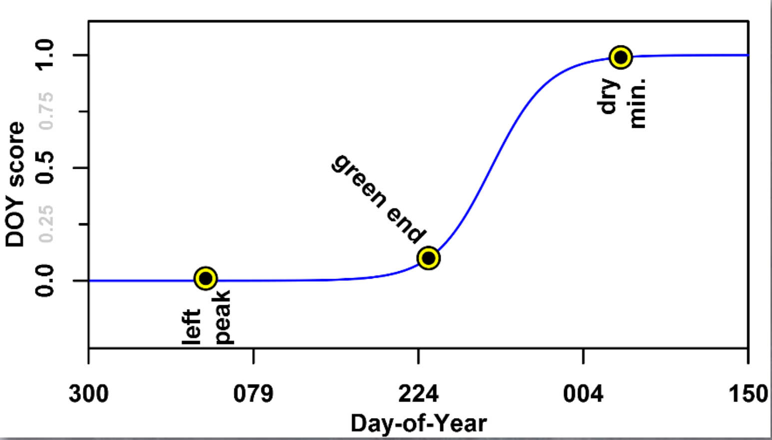
Intra-annual contribution: acquisition day

- 3 phenological descriptors are used, e.g.
  - **left green peak,** p_0
  - season end, p_1
  - **dry minimum,** p_2
- A logistics S-shaped scoring function is fit to the LSP for each pixel
- The Landsat observation is scored according to its acquisition DOY D_i:

$$S_D = \begin{cases} s_0/(1+\exp(a\cdot[D_i - p_1]+b)), & (s_0 > s_2) \\ s_2/(1+\exp(a\cdot[D_i - p_1]+b)), & (s_2 > s_0) \end{cases}$$

- The function parameters a and b are derived from the LSP and pre-defined function values at p_0, p_1, p_2:
  - e.g. $s_0 = 0.99, s_1 = 0.1, s_2 = 0.01$
  - Nelder-Mead Simplex Optimization *(Nelder & Mead, 1965)*





Inter-annual contribution: acquisition year

- Compositing should be mainly DOY-driven but data from the target Year should be preferred
  and cover change and inter-annual variability)
- with a dependency on the pixel‘s LSP
- S

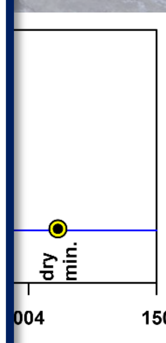
slic

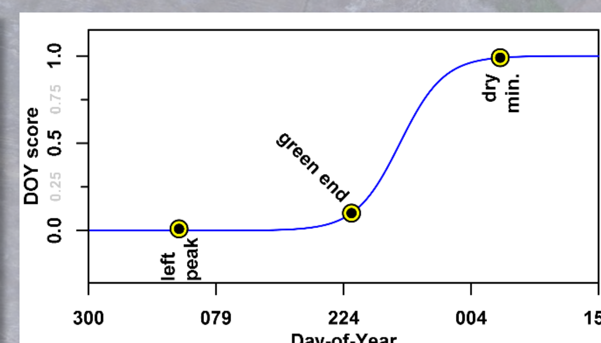
$(-0.5 \cdot [\Delta Y \cdot slice]^2/\sigma_l^2), \quad (D_i < p_1)$

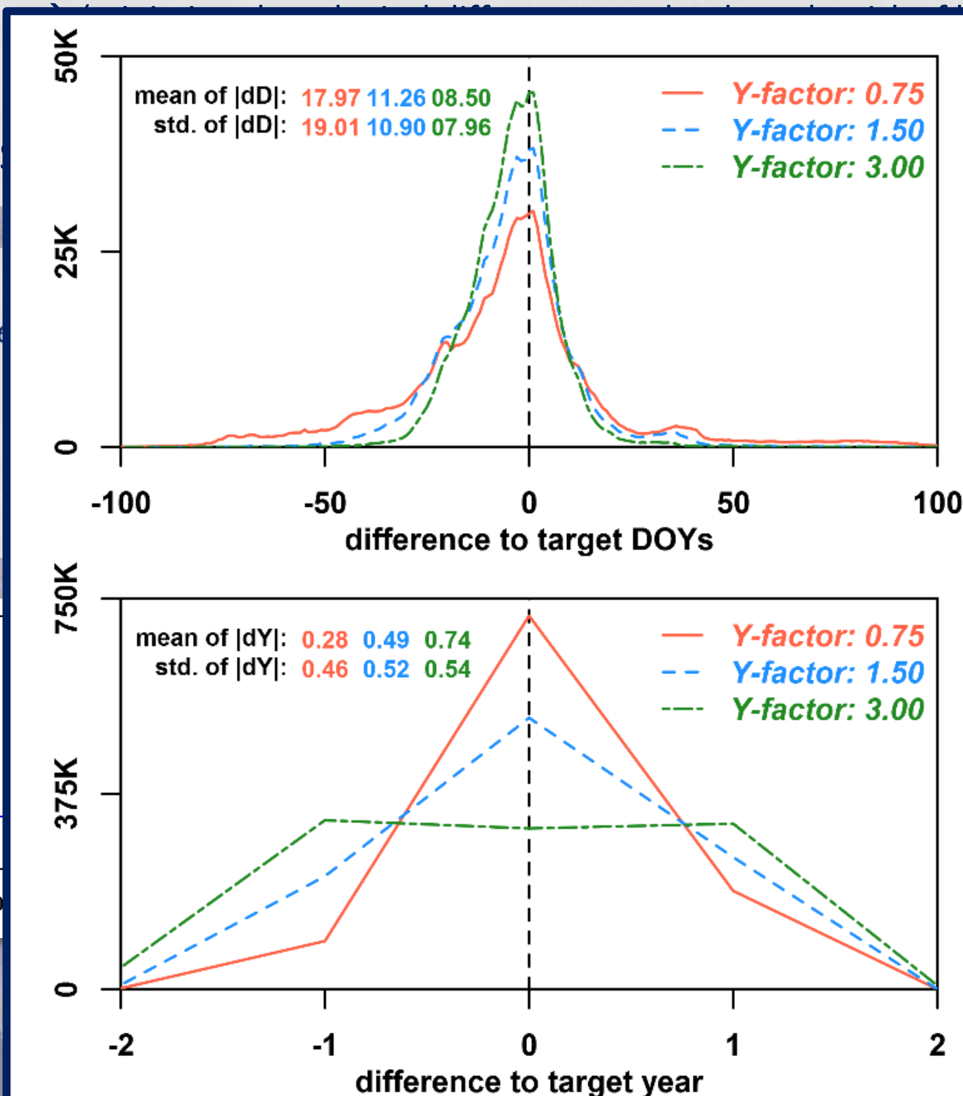
$(-0.5 \cdot [\Delta Y \cdot slice]^2/\sigma_r^2), \quad (D_i \geq p_1)$

$+ \exp(a \cdot [p_0 + \Delta Y \cdot slice - p_1] + b)), \ (s_0 > s_2)$

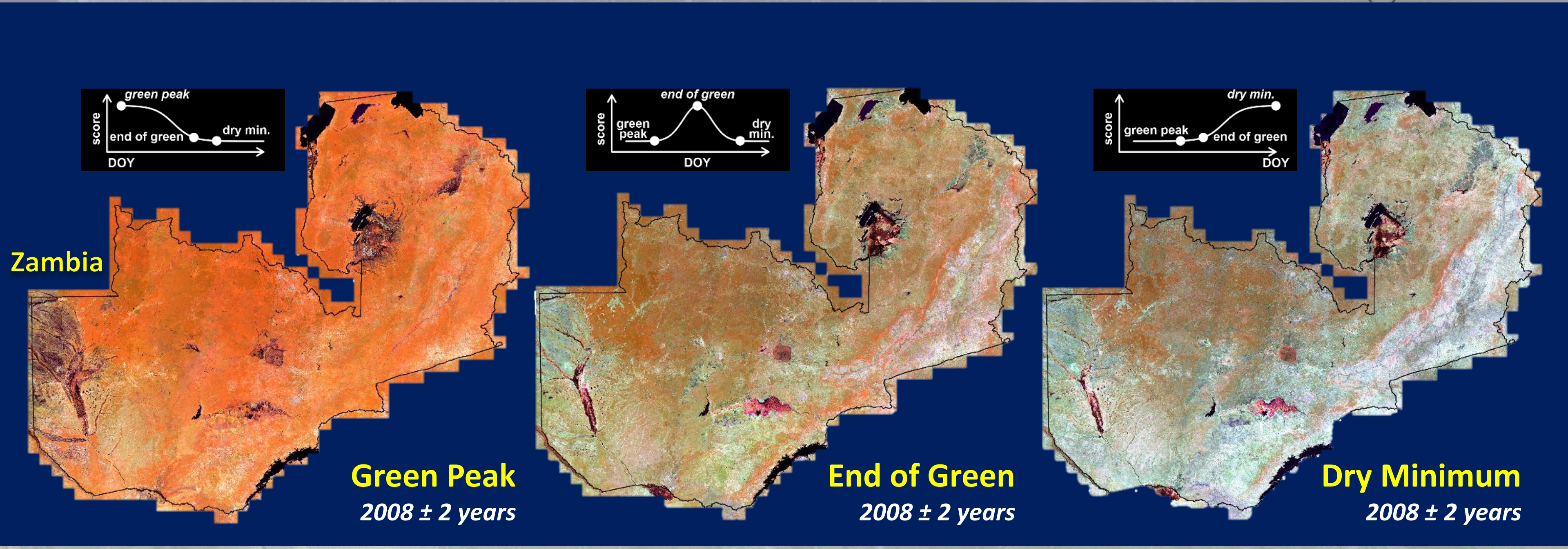
$+ \exp(a \cdot [p_3 - \Delta Y \cdot slice - p_1] + b)), \ (s_2 > s_0)$

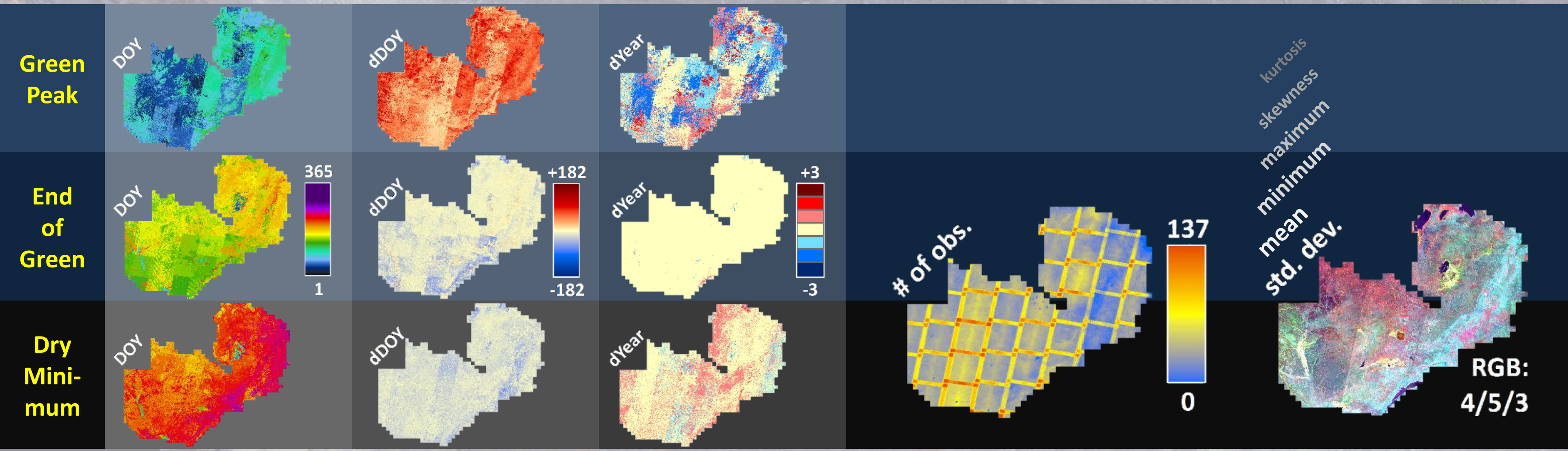






Multi-Seasonal Composites



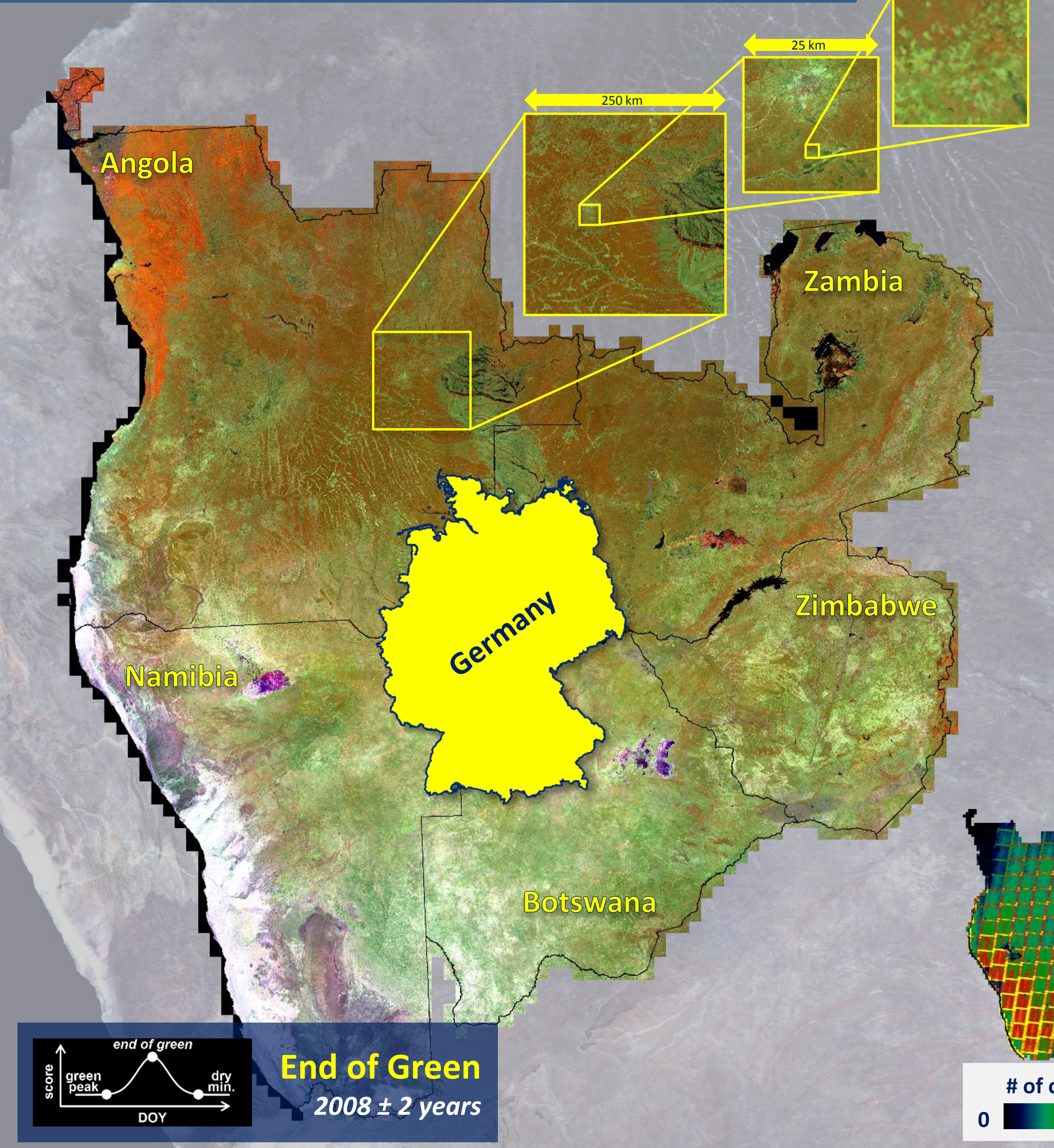


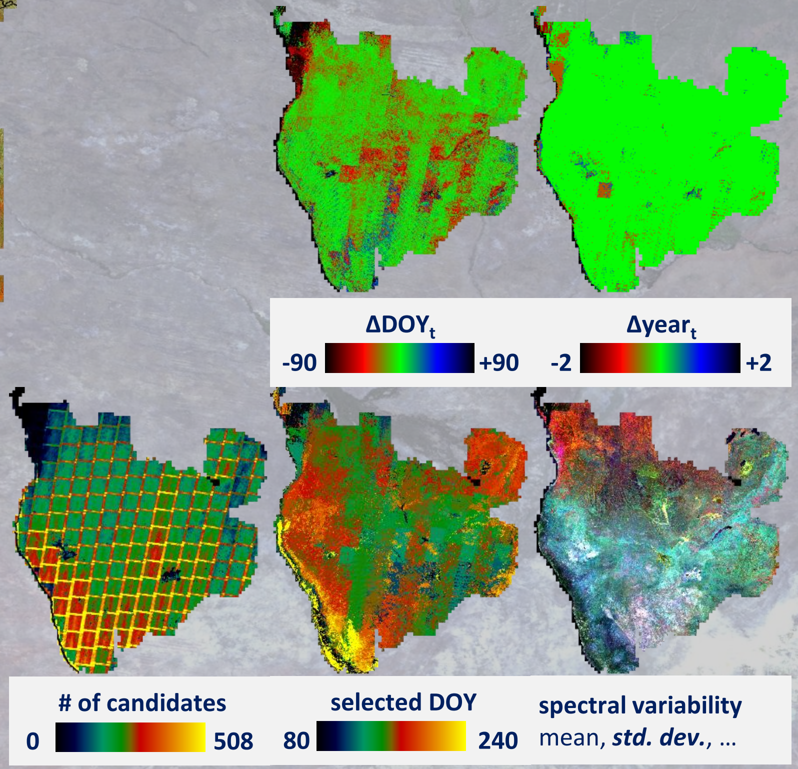
generation of wall-to-wall Landsat products

Wall-to-Wall Composites

- Composite size: 91000 x 82000 px
  → 2730 x 2460 km
- Spatial resolution: 30 m
- ~ 208 bn. observations were considered, i.e. 46 obs. / px on average
- ~ 14h processing time
- Data volume:
  - composite (6-bands): 83GB
  - composite criteria (9 bands): 125GB
  - standard deviation (6 bands): 83GB
    mean, min, max, range, skewness, kurtosis
  - compositing scores (6 bands): 83GB

  → **13.9 GB / band**





generation of wall-to-wall Landsat products

References

Thank you for your attention!

Questions? / Fragen?

- Frantz, D., A. Röder, et al. "An operational radiometric Landsat pre-processing framework for large area time series applications." In Revision.
- Frantz, D., A. Röder, et al. (2015). "On the derivation of a spatially distributed aerosol climatology for its incorporation in a radiometric Landsat pre-processing framework." Remote Sensing Letters 6(8): 647-656.
- Frantz, D., A. Röder, et al. (2015). "Enhancing the Detectability of Clouds and Their Shadows in Multitemporal Dryland Landsat Imagery: Extending Fmask." IEEE Geoscience and Remote Sensing Letters 12(6): 1242-1246.
- Griffiths, P., S. van der Linden, et al. (2013). "A Pixel-Based Landsat Compositing Algorithm for Large Area Land Cover Mapping." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 6(5): 2088-2101.
- Hill, J. (1993). High precision land cover mapping and inventory with multitemporal earth observation satellite data: the Ardèche experiment. Faculty of Geography/Geosciences, Trier University. Ph.D.: 121.
- Hill, J. and B. Sturm (1991). "Radiometric correction of multitemporal Thematic Mapper data for use in agricultural land-cover classification and vegetation monitoring." International Journal of Remote Sensing 12(7): 1471-1491.
- Jonsson, P. and L. Eklundh (2002). "Seasonality extraction by function fitting to time-series of satellite sensor data." IEEE Transactions on Geoscience and Remote Sensing 40(8): 1824-1832.
- Mader, S. (2012). A Framework for the Phenological Analysis of Hypertemporal Remote Sensing Data Based on Polynomial Spline Models. Geographie/Geowissenschaften, Trier University. Dr. rer. nat.: 101.
- Nelder, J. A. and R. Mead (1965). "A Simplex Method for Function Minimization." The Computer Journal 7(4): 308-313.
- Röder, A., T. Kuemmerle, et al. (2005). "Extension of retrospective datasets using multiple sensors. An approach to radiometric intercalibration of Landsat TM and MSS data." Remote Sensing of Environment 95(2): 195-210.
- Tanré, D., C. Deroo, et al. (1990). "Description of a computer code to simulate the satellite signal in the solar spectrum: the 5S code." International Journal of Remote Sensing 11(4): 659-668.
- Zhu, Z., S. Wang, et al. (2015). "Improvement and expansion of the Fmask algorithm: cloud, cloud shadow, and snow detection for Landsats 4–7, 8, and Sentinel 2 images." Remote Sensing of Environment 159(0): 269-277.
- Zhu, Z. and C. E. Woodcock (2012). "Object-based cloud and cloud shadow detection in Landsat imagery." Remote Sensing of Environment 118(0): 83-94.