Detecting the Change-point of Urbanization Process in Landsat Data

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Overview

Motivation

Urban Dynamics

Detecting when urbanization starts or ends would be helpful to understand the urbanizing process, develop urban growth models, and investigate further environmental impacts.

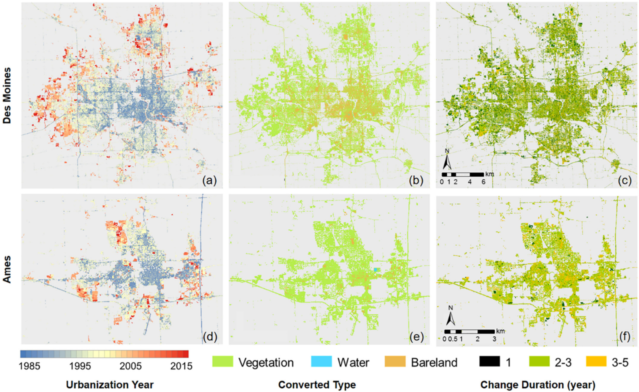


Figure: from Li et al., 2018

Areas and Datasets

- 143 locations in central Iowa(Des Moines and Ames): 4 non-urbanized areas and 139 urbanized areas.
- For each location, time ranges from 1985 to 2015 and B1(Blue), B2(Green), B3(Red), B4(NIR), B5(MIR), B7(SWIR) are included.

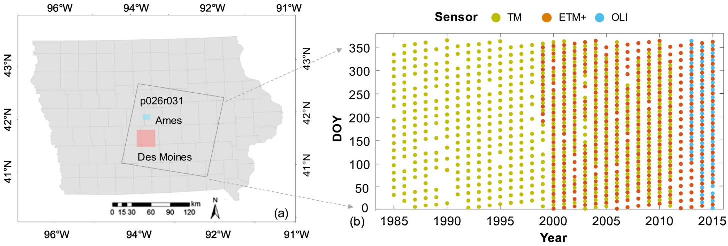


Figure: from Li et al., 2018

The Problem

We want to use the 6 bands to...

- test if there is urbanization happened for each location.

- estimate the year of urbanizaiton starts or ends for each location.

The change could be vegatation$\rightarrow$urban, water$\rightarrow$urban or bareland$\rightarrow$urban, corresponding to NDVI $=$ (NIR$-$Red)/(NIR$+$Red), MNDWI $=$ (Green$-$MIR)/(Green$+$MIR), and SWIR.

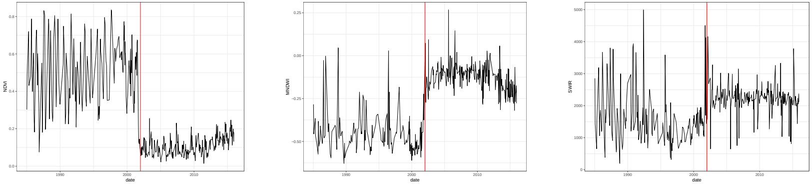


Figure: ending of change in the 74th location

Related Methods

Li et al., RSE (2018)

Regression based temporal segmentation approach:

- a linear regression was fitted to the annual time series, two turning points with maximum deviations are P_1 and P_2.
- dominant conversion type is determined by maximum absolute difference between two turning points.

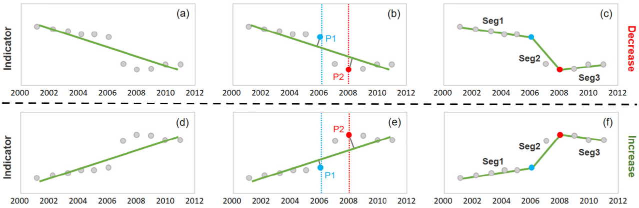


Figure: from Li et al., 2018

Berkes et al., JRSSB (2009)

Functional observations: $X_i(t)$, $1 \leq i \leq N$

$$P_k(t) = \sum_{1 \leq i \leq k} X_i(t) - \frac{k}{N} \sum_{1 \leq i \leq N} X_i(t)$$

Let $x \in [0, 1]$, $\widehat{\xi}_{i,l} = \int \{X_i(t) - \bar{X}_N(t)\} \widehat{\phi}_l(t) dt$, $l = 1, 2, \cdots, d$.

$$\int \left\{ \sum_{1 \leq i \leq Nx} X_i(t) - \frac{[Nx]}{N} \sum_{1 \leq i \leq N} X_i(t) \right\} \widehat{\phi}_l(t) dt$$

$$= \sum_{1 \leq i \leq Nx} \widehat{\xi}_{i,l} - \frac{[Nx]}{N} \sum_{1 \leq i \leq N} \widehat{\xi}_{i,l}$$

Berkes et al., JRSSB (2009)

Let $B_1(\cdot), \cdots, B_d(\cdot)$ denote independent standard Brownian bridges.

$$T_N(x) = \frac{1}{N} \sum_{l=1}^{d} \hat{\lambda}_l^{-1} \left(\sum_{1 \le i \le Nx} \hat{\xi}_{i,l} - x \sum_{1 \le i \le N} \hat{\xi}_{i,l} \right)^2$$

$$S_{N,d} = \frac{1}{N^2} \sum_{l=1}^{d} \hat{\lambda}_l^{-1} \sum_{k=1}^{N} \left(\sum_{i=1}^{k} \hat{\xi}_{i,l} - \frac{k}{N} \sum_{i=1}^{N} \hat{\xi}_{i,l} \right)^2 = \frac{1}{N} \sum_{k=1}^{N} T_N\left(\frac{k}{N}\right)$$

Under hypothesis H_0: $\mathrm{E}\{X_1(t)\} = \cdots = \mathrm{E}\{X_N(t)\}$,

$$S_{N,d} \xrightarrow{d} \int_0^1 \sum_{l=1}^{d} B_l^2(x)dx \equiv K_d$$

where K_d was derived by Kiefer (1959).

Berkes et al., JRSSB (2009)

To estimate the change-point θ, we can find the x which maximizes $T_N(x)$ over $[0,1]$.

$$\widehat{\theta}_N = \inf\left\{x : T_N(x) = \sup_{0\le y\le 1}\{T_N(y)\}\right\}$$

If assumptions hold, then $\widehat{\theta}_N \xrightarrow{p} \theta$.

Detecting Change-point of Time Series in Landsat Data

Preprocessing Data

- Modified NDVI formula as $\text{NDVI} = (-\text{NIR} + \text{Red})/(\text{NIR} + \text{Red})$ such that it increases after change, which is consistent with the other two indices
- Savitzky-Golay (S-G) filter was applied to remove abnormal observations in the raw time series.
- Three indices were joined within each year to be one time series which ranges from 1 to 3×366.
- Transformed into dense data by linear interpolation.

Preprocessing Data

- To make sure the covariance matrix has no missing value, we kept the days with more than 10 observations and remove years with observations all missing.
- Functional normalized data for each location.

Figure: data in the 10th location after preprocessing

Dense FPCA

Then we treated data as dense functional data.

$$\widehat{\mu}(t) = \frac{1}{N}\sum_{i=1}^{N} X_i(t)$$

$$R(s,t) = \frac{1}{N}\sum_{i=1}^{N}\{X_i(s) - \widehat{\mu}(s)\}\{X_i(t) - \widehat{\mu}(t)\}$$

Discretized decomposition, 85% explained, at most 2 principle components.

$$\widehat{\xi}_{i,l} = \int \{X_i(t) - \widehat{\mu}(t)\}\widehat{\phi}_l(t)dt$$

Detection of Change-point

We only focus on the estimation of change-point at this moment. To compare with the ending of change, we estimated change-point as

$$\left\lceil \max\{x : T_N(x) = \sup_{0 \le y \le 1} T_N(y)\} N \right\rceil$$

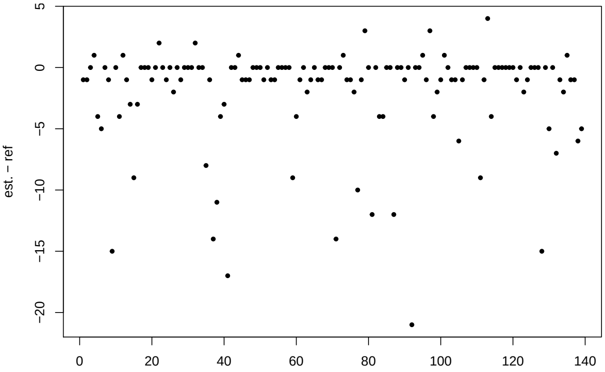


Figure: one year tolerance: 97/139

Comparison

Although our result is not better than the result showed in Li et al, 2018 in terms of overall accuracy and bias, it performs better when the change is not obvious enough to detect by simple regression.

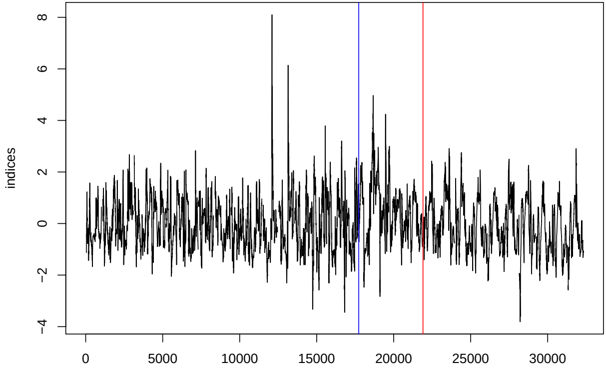


Figure: 54th location: blue is our method, red is regression method

Discussion

- The functional approach is not able to detect the ending of change. The estimate is better to be considered as the starting or middle phase of gradual change.
- We treated observations as dense data and estimated PC scores by numerical integration.
- The observatons have large noise, which may affect detection results.

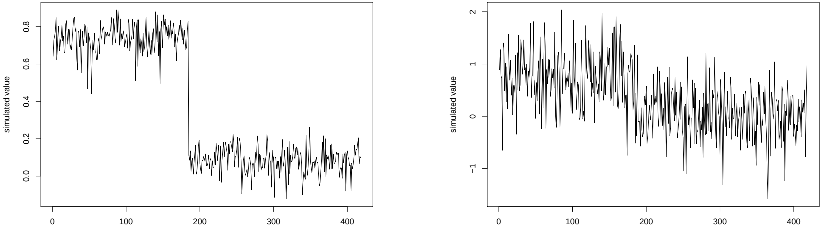
Simulation

Instant Change

$\mu(t)$ and $\phi_k(t)$ are from the estimation of NDVI in 118th location. $\forall i, 13 \leq t_{ij} \leq 348$. The change happens at 18th year: $\xi_{i,1} \overset{\text{iid}}{\sim} N(6I(i \leq 18) - 6I(i > 18), 0.4^2)$, $\xi_{i,2} \overset{\text{iid}}{\sim} N(0, 0.5^2)$. Before 1999, $m_i = 8$, while after 1999, $m_i = 18$.

$$Y_i(t_{ij}) = \mu(t) + \sum_{l=1}^{2} \xi_{i,l}\phi_k(t_{ij}) + \epsilon_{ij}$$

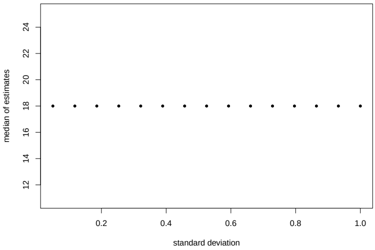
where $\epsilon_{ij} \overset{\text{iid}}{\sim} N(0, \sigma^2)$.

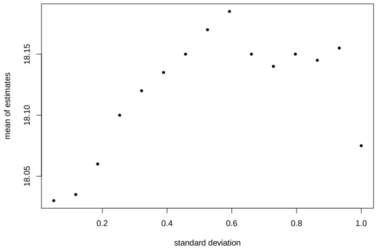


(a) $\sigma = 0.05$ (b) $\sigma = 0.5$

Instant Change

We used σ's changing from 0.05 to 1 and repeated 200 times for each σ.





Gradual Change

$\mu(t)$ and $\phi_k(t)$ are from the estimation of NDVI in 118th location.
$\forall i, 13 \leq t_{ij} \leq 348$. The change happens at 18th year:
$\xi_{i,1} \overset{\text{iid}}{\sim} N(6I(i < 18) - 6I(i > 18), 0.4^2)$, $\xi_{i,2} \overset{\text{iid}}{\sim} N(0, 0.5^2)$. Before 1999, $m_i = 8$, while after 1999, $m_i = 18$.

$$Y_i(t_{ij}) = \mu(t) + \sum_{l=1}^{2} \xi_{i,l}\phi_k(t_{ij}) + \epsilon_{ij}$$

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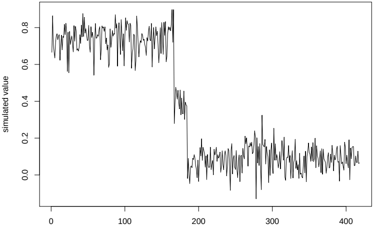

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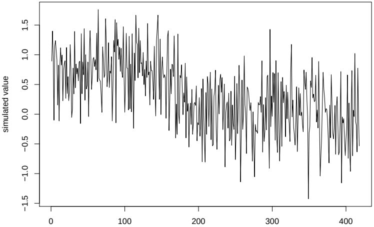
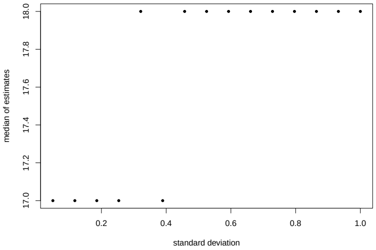
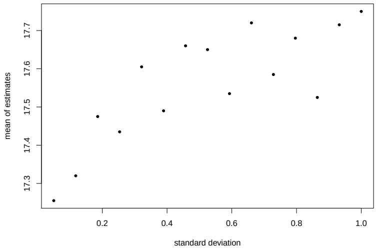


(b) $\sigma = 0.5$

Gradual Change

We used σ's changing from 0.05 to 1 and repeated 200 times for each σ.





Conclusion & Future Work

Conclusion

- The functional method is supposed to detect instant change or starting phase of gradual change.
- It performs better than the regression method for data with big noise and unobvious change.
- The noise in observation can have an effect on the estimation of change-point, making change procedure gradual.

Future Work

- We may use sparse FPCA for high dimensional data to estimate PC scores.
- We will compare our results with starting year of change from reference.
- Some methods for testing gradual change will be studied and applied to the data. And current method needs to be improved to adjust for gradual change, multiple changes and unregular change.

Q & A

Happy Halloween!