ESA–MOST Dragon Cooperation
中国科技部–欧洲空间局“龙计划”合作

2017 DRAGON 4 SYMPOSIUM
2017年“龙计划”四期学术研讨会

26–30 June 2017 | Copenhagen, Denmark

2017年6月26-30日，丹麦 哥本哈根

北京師範大學
BEIJING NORMAL UNIVERSITY

Spatial Downscaling Research for Urban Land Surface Temperature(LST) based on the Adjusted SVM Algorithm(A-SVM)

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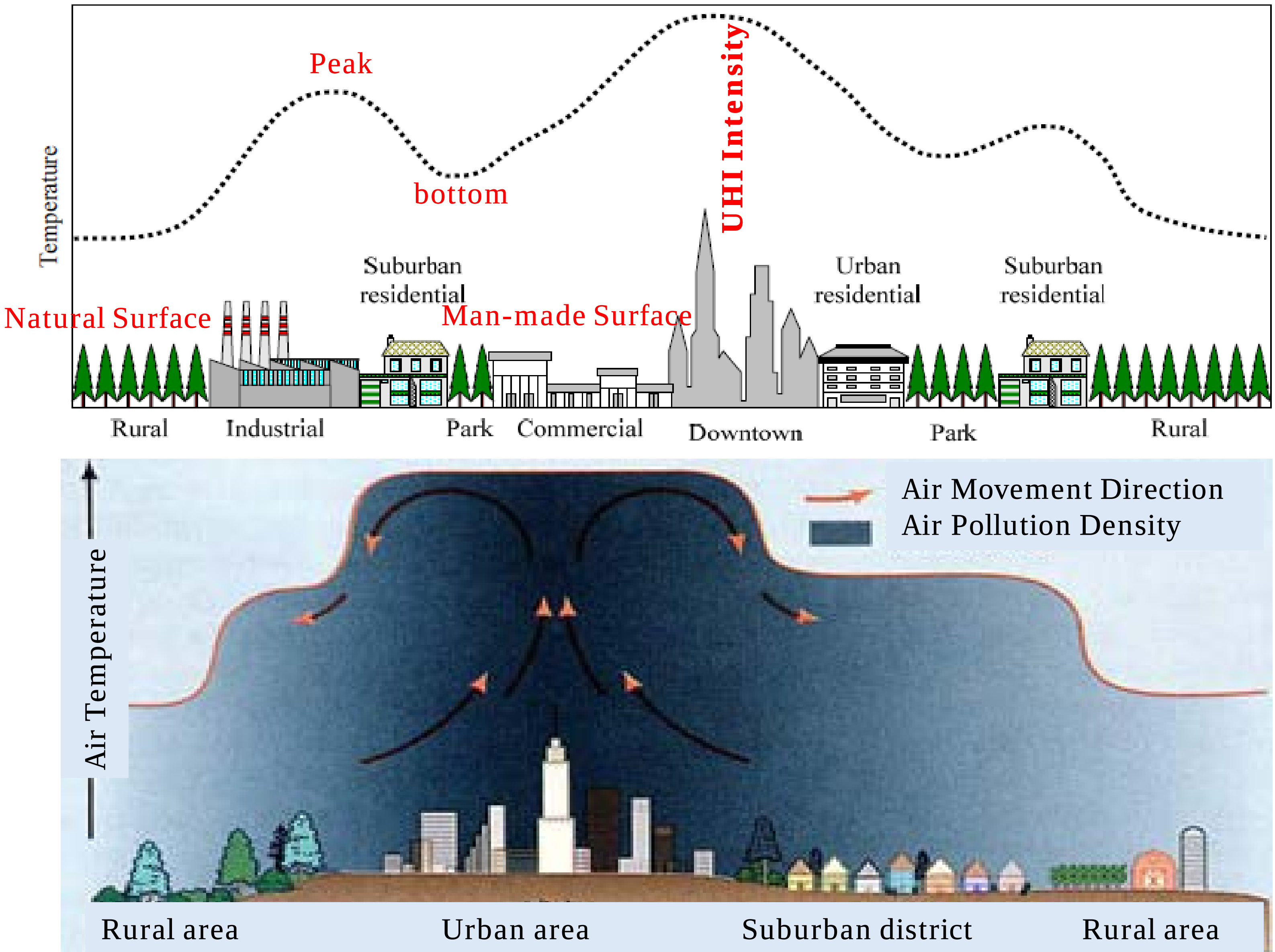
2017-06-29

Outline

1. Background
2. Present Research Progress
3. A-SVM LST Downscaling Algorithm
4. Summary
5. Future work

Urban Heat Island(UHI) Profile



1. Background

Land Surface Temperature(LST)

An important parameter:

---Showing the heat exchange of atmosphere,ocean and land

---Estimating some ecological parameters

---Monitoring the environmental change

How to obtain:

- Traditional way: fixed-point observation and mobile measurement
- Satellite technology: Thermal Infrared Radiation(TIR) - Continuous LST

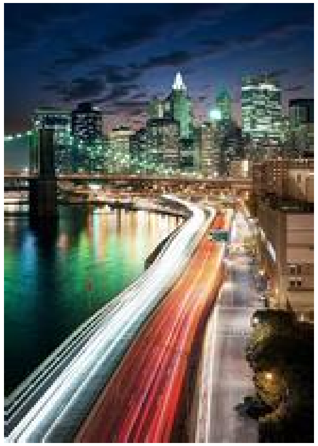
Two obvious problems we faced:

- 1----The complexity of Urban Land Surface(especially to image classification and LST retrieval)

- 2----The contradictions between the spatial resolution LST and the temporal ones. We can’t obtain both them synchronously from the present satellite images (especially to the TIR images, low resolution causes the thermal mixing effect)

Rural Surface---simple and smooth, mainly vegetation cover

Urban Surface---complex and rough, mainly impervious layer cover



The Spatial and Temporal Resolution of Different Satellite Images

Sensors	Satellite Platforms	VNIR/SWIR Spatial Resolution	TIR Spatial Resolution	Temporal Resolution
ETM+	Landsat 7	30m	60m	16days
TM	Landsat 5	30m	120m	16days
OLI/TIRS	Landsat 8	30m	100m	16days
ASTER	Terra	15m/30m	90m	15days
MODIS	Terra/Aqua	250/500m/ 1km	1km	4/day
AVHRR	NOAA	1km	1km	4/day
GEOS	GEOS	4km	4km	15mins

Sensors	Satellite Platforms	VNIR/SWIR Spatial Resolution	TIR Spatial Resolution	Temporal Resolution
ETM+	Landsat 7	30m	60m	16days
TM	Landsat 5	30m	120m	16days
OLI/TIRS	Landsat 8	30m	100m	16days
ASTER	Terra	15m/30m	90m	15days
MODIS	Terra/Aqua	250/500m/ 1km	1km	4/day
AVHRR	NOAA	1km	1km	4/day
GEOS	GEOS	4km	4km	15mins

contradictions between the spatial resolution LST and the temporal ones

However,

Some researches need high spatial-temporal resolution LST

- Agricultural application(such as farmland moisture estimation)
- Natural disaster monitoring and response(such as drought, forest fire)
- Environmental change periodic analysis in special region
- Urban heat island and its environmental effects research……

So,

it's very important to obtain the accurate LST by some ways when there are no high spatial-temporal resolution TIR data.

Sharpening, Disaggregation, Improvement, Unmixing, Sub-pixel, Fusion, Downscaling

It means the spatial resolution's variation of imagines.

Our goals in this study:

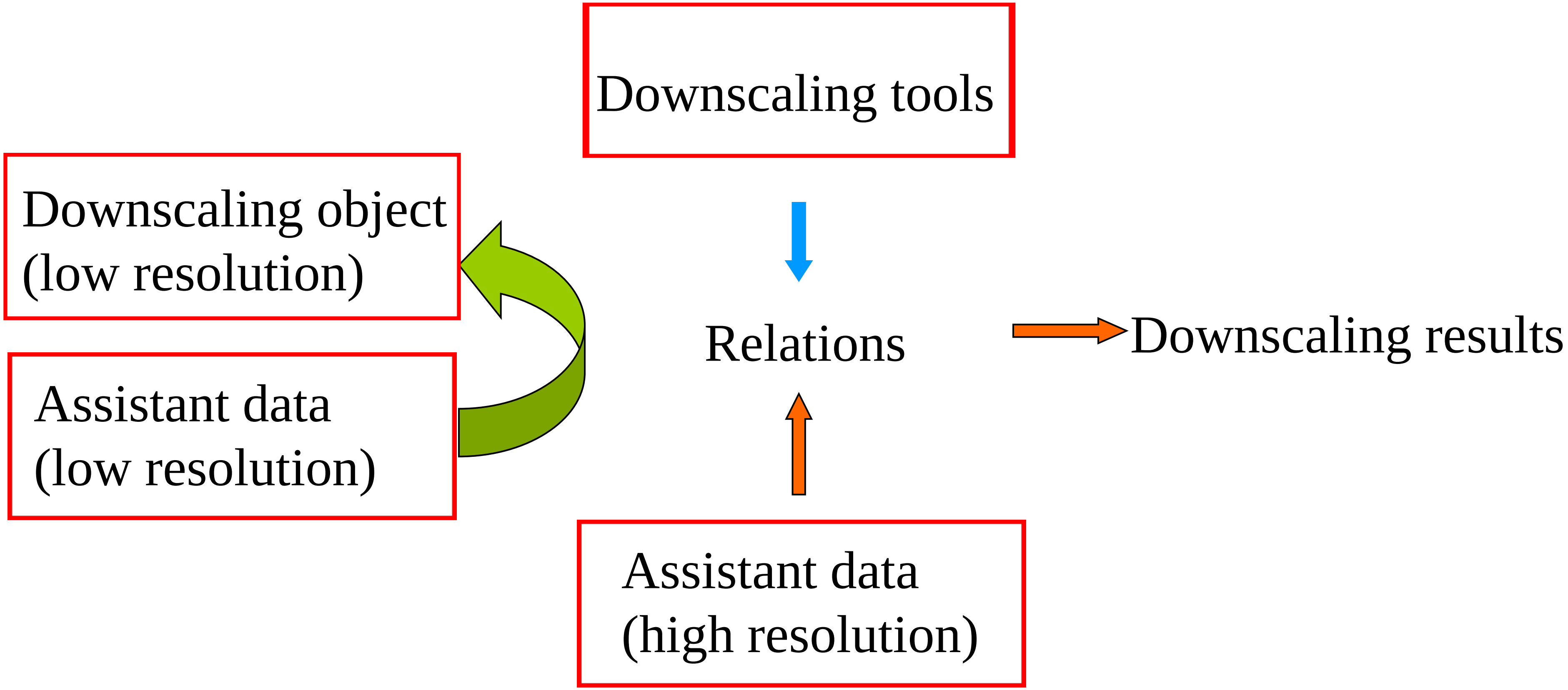
- Problem 1---The complexity of Urban LST retrieval

  One of possible ways--- Selecting and combining more typical parameters(such as NDVI,UI,MNDWI,VAP,BAP,WAP) except for NDVI derived from RS data to reflect the urban characteristic.

- Problem 2----not obtaining the high spatial-temporal resolution LST data synchronously from TIR images

  One of possible ways--- Using and improving SVM spatial downscaling algorithm to try to enhance the spatial resolution and also consider the effect of high-low spatial resolution change.

2. Present Research Progress



Present Research mainly focus on 3 aspects

Main Downscaling Methods

DN(Digital Number) level

Downscaling tools	Auxiliary datas	Advantages	Disadvantages
Statistical regression Co-kriging Bayesian	VNIR/SWIR /PAN	Started to the theoretical study of sharpening TIR	Most of the methods are similarity to visible fusion methods

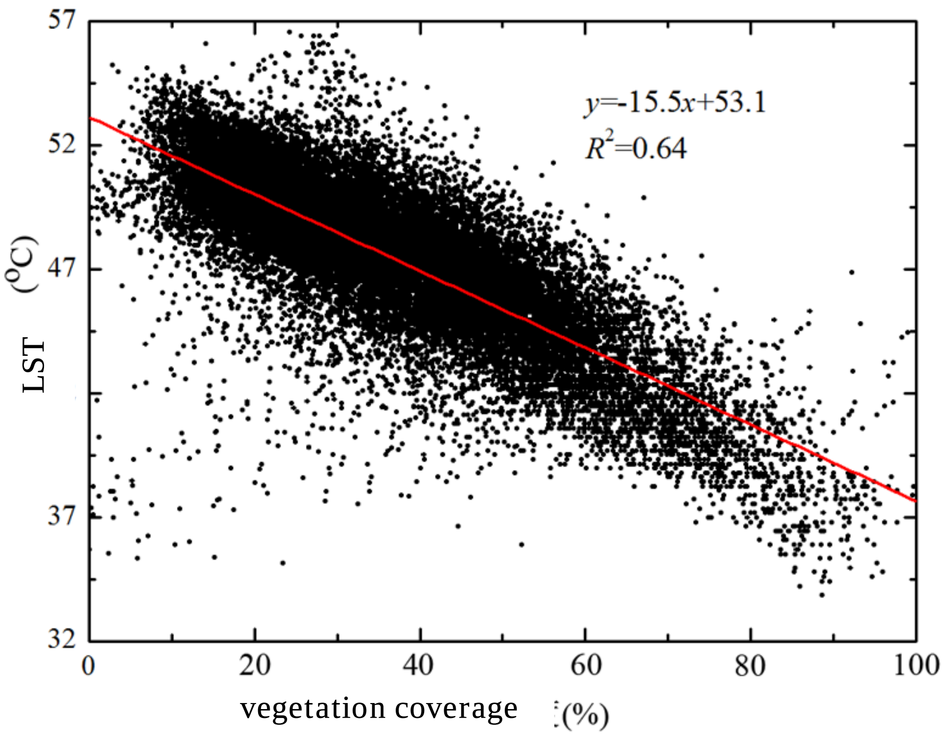
Ts/Rn(Surface Net Radiation) level ---for vegetation coverage area such as natural & simple surface (farmland, forest, grassland…)

Downscaling tools	Auxiliary datas	Advantages	Disadvantages
Statistical regression (Least-squares,Least median square and Pace regression)	NDVI	simple and easy to use	cannot be directly used for heterogeneity land surface like urban
	Fv	has a higher line relationship with LST than NDVI	
	Photosynthetic active Fv	consider the vegetation photosynthesis efficiency	
	establish NDVI-LST relations segmented based on SWI	consider the influence of soil moisture	
	TVDI	introduction the index sensitivity with water	

The LST value of main land cover types in center area of Beijing

Land cover type	LST Min(°C)	LST Max(°C)	LST AVE(°C)	Standard deviation(°C)
Water	34.1	53.0	43.4	3.4
Vegetation	34.6	53.3	44.4	3.1
Built-up	37.0	56.1	49.0	2.4
Soil	40.5	54.3	49.0	2.1

The scatter plots of LST and vegetation coverage in center area of Beijing



2. Present Research Progress

Ts/Rn(Surface Net Radiation) level----for high heterogeneity coverage area such as urban area

Downscaling tools	Auxiliary datas	Advantages	Disadvantages
Modulation-based	Effective emissivity,other some season high resolution LST, etc	simple	easy to produce plate effect
Statistical regression (Least-squares, stepwise regression)	single factor	improvements on NDVI-LST in urban	LST is influenced by multiple factors in urban area
	multiple factors	consider the diversity of the substrate type	they are linear models after all, and LST is the formation of multiple factors comprehensive production
Machine learning method（ANN、SVM）	multiple factors	consider the complexity of urban LST and establish the nonlinear model between many related factors with LST	ANN :overfitting LST, easy to produce extreme values

- In general, most statistical regression models of Urban LST downscaling focus on the linear correlation relationship between LST and other indexes（Zakšeka,2012; Zhu,2013）or the single regression kernel such as proportion modulation model（Nichol,2009; Stathopoulou,2009）
- However，LST is very complex and related to multiple factors, so the non-linear regression models is more better to indicate the multi-center thermal spatial distribution in urban area.

SVM (Supporting Vector Machine) Algorithms have been used successfully and widely in other fields

Author (Date)	Application	Conclusion
Camps-Valls(2006)	Ocean chlorophyll biomass estimation	have higher precision than ANN and classical optical estimation model
Yang(2006)	Evaporation estimation	better than ANN and multiple regression model
Bazi(2007)	Estimate the coastal boundary chlorophyll content	—
Xie(2008)	Calculate the amount of water inversion quantity of the Marine environment	have higher accuracy than the previous linear regression and reverse transmission NN model
Knudby (2010)	Reef fish biomass study	—
Lin Hui(2013)	Wheat LAI value inversion	—
Liang Dong(2013)	LAI inversion	better than linear statistical regression model and it points out that multibands (i.e., multiple factors) cooperative inversion for LAI have the highest accuracy

SVM Algorithm Advantages and Potentials used in Urban LST downscaling

- It’s very common to use SVM as a good classifier in RS image classification, but still rarely used on urban LST downscaling.
- SVM has more advantages and potentials than linear regression, ANN and other machine learning methods:

  ---Supporting multiple variables processing（Multi-dimensional & Non-linear）

  ---Supporting machine learning using fewer samples

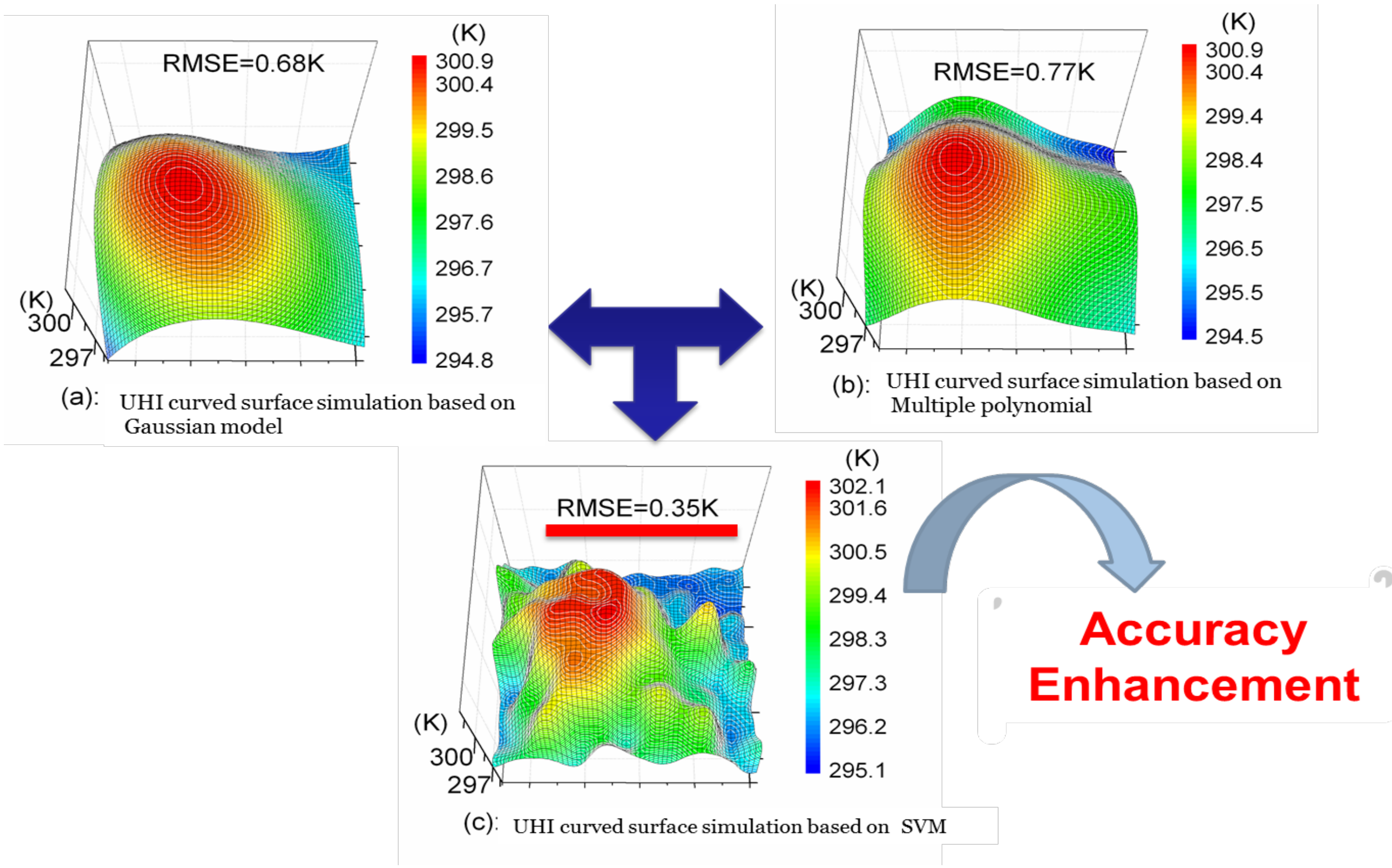
  ---Higher accuracy

  ---Better Generalization Ability

  ---Avoiding the structure selection and local minima of ANN(Aritificial Neural Network)

The Advantages and Potential of SVM in Urban LST downscaling

- So, it's possible to enhance the accuracy of LST downscaling using SVM regression model to replace multiple linear regression models ---- Zakšeka, 2012



(a): UHI curved surface simulation based on Gaussian model

(b): UHI curved surface simulation based on Multiple polynomial

(c): UHI curved surface simulation based on SVM

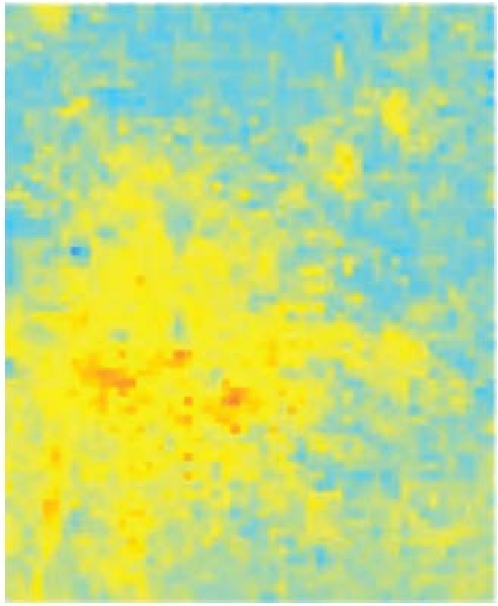
The disadvantage of SVM using to Urban LST downscaling

The basic assumption of SVM regression:

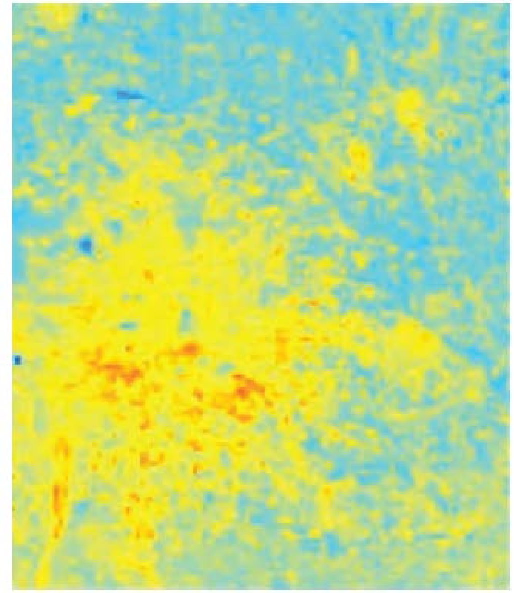
- It is strictly scale-invariant between LST and all the relevant regression kernels selected whether high resolution or low resolution RS images.
- But in fact, scale change will exactly cause errors during the process of resolution changing.

The disadvantage of SVM using to Urban LST downscaling

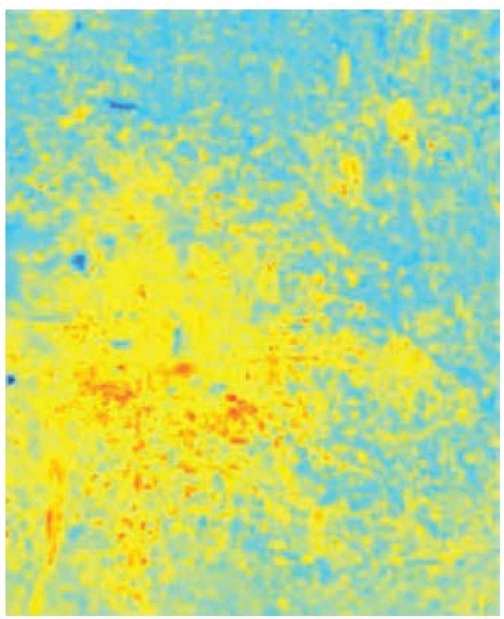
960m
LST from
simulation



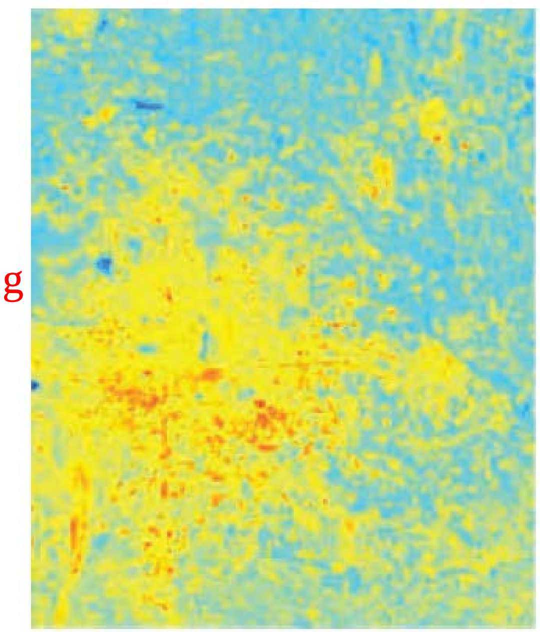
480m
LST from
downscaling



240m
LST from
downscaling



120m
LST from
downscaling



The target of this study

- So, we want to establish the new model to reduce the error caused by resolution change based on adding the scaling factors spatial adjustment model to SVM model to adjust the facing the characteristic factors of high resolution LST.
- In this study, we simulated TM low resolution LST data(to 960m) and then downscaled it to 120m (comparing with real 120m TM LST), because its resolution is suitable for the urban scale.

Several urban land cover indexes (or regress factors of SVM) used in this study：

—NDVI： Normalized Difference Vegetation Index

—MNDWI： Modified Normalized Difference Water Index

—UI： Urban Index

—VAP： Vegetation Area Percentage

—BAP： Built-up Area Percentage

—WAP： Water Area Percentage

—SAP： Soil Area Percentage

Several methods comparison in this study :

- Method1：Direct Resampling

  ---Using cubic convolution interpolation from low resolution to high resolution.

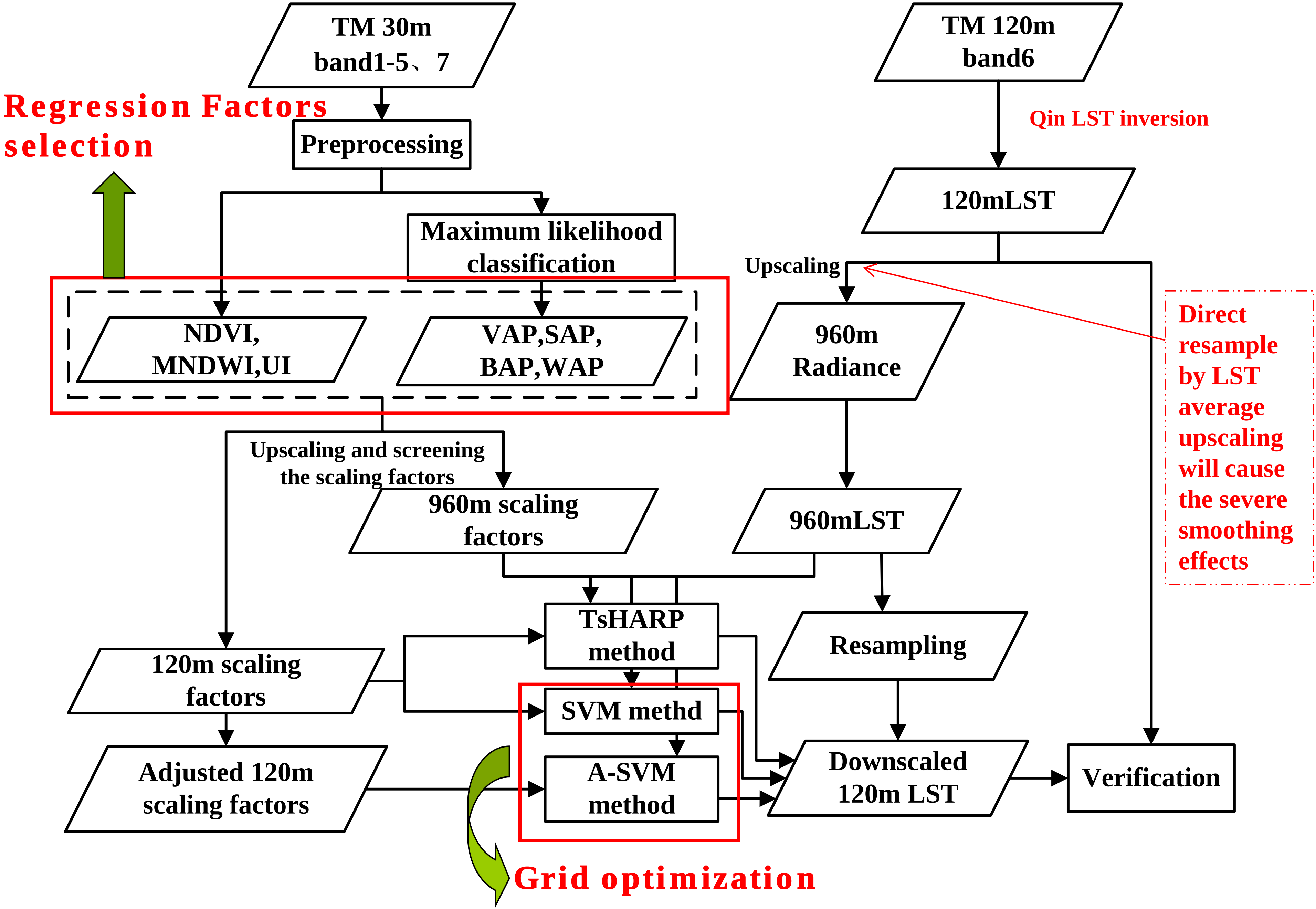
- Method2：TsHARP

  ---TsHARP (an algorithm for sharpening thermal imagery) is a classic linear regression model using single scale factor between NDVI and LST(negative correlation)

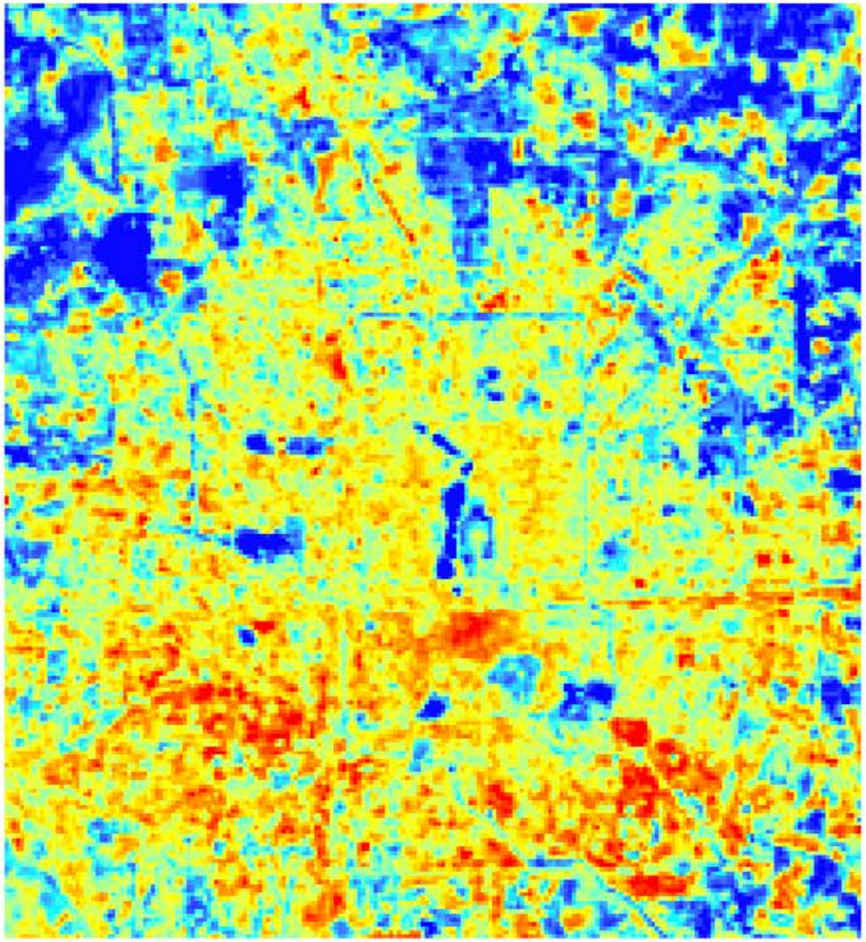
- Method3：SVM

- Method4：A-SVM

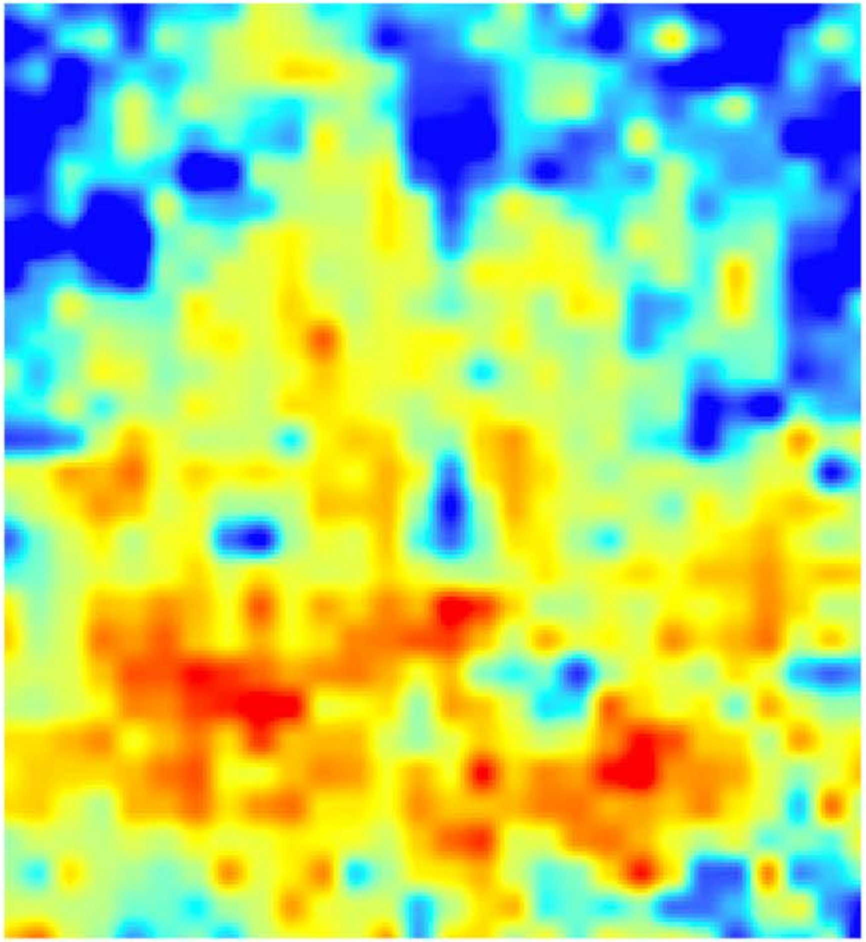
3. LST Downscaling based on A-SVM



Results



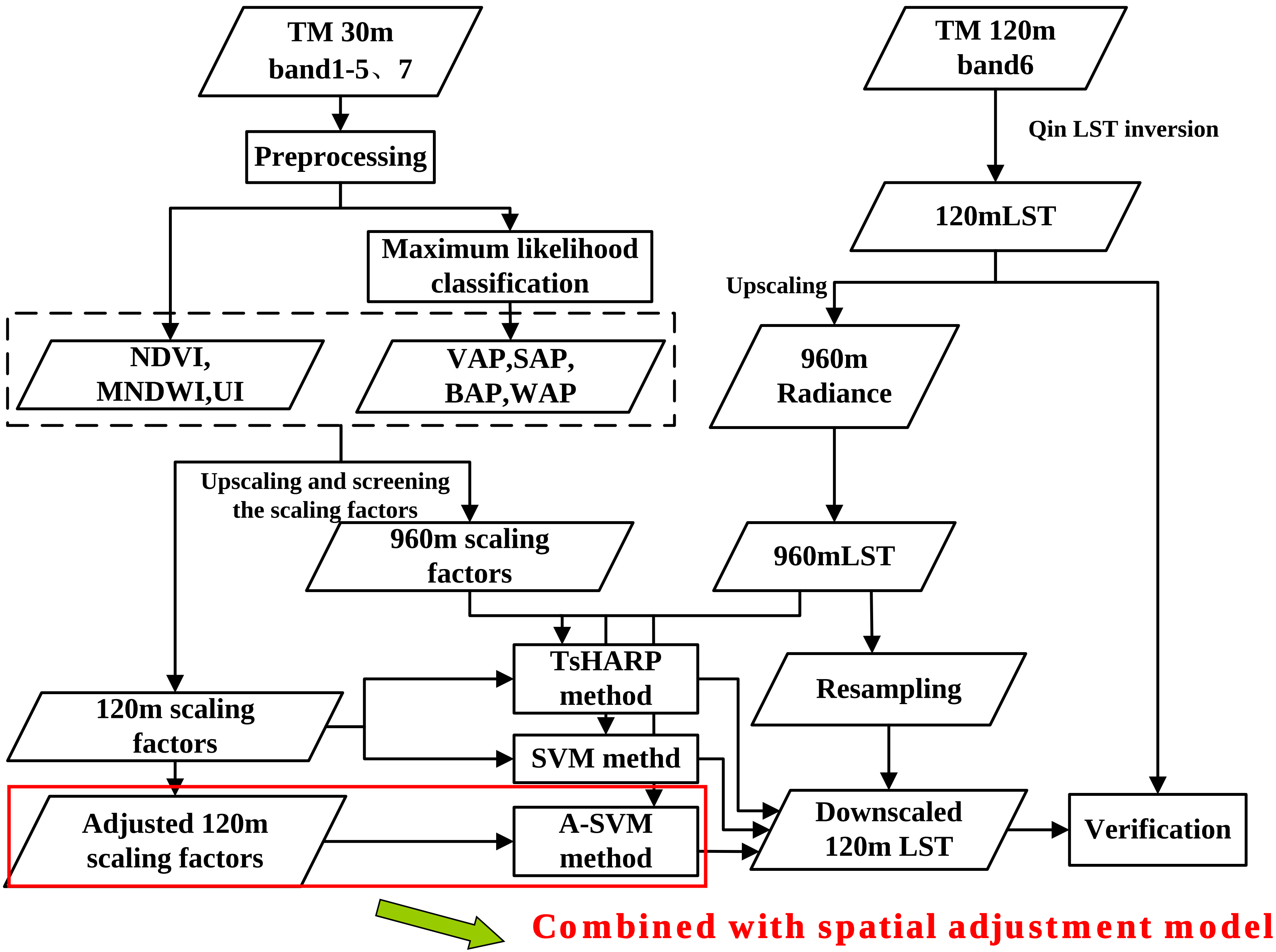
(a)The Real LST

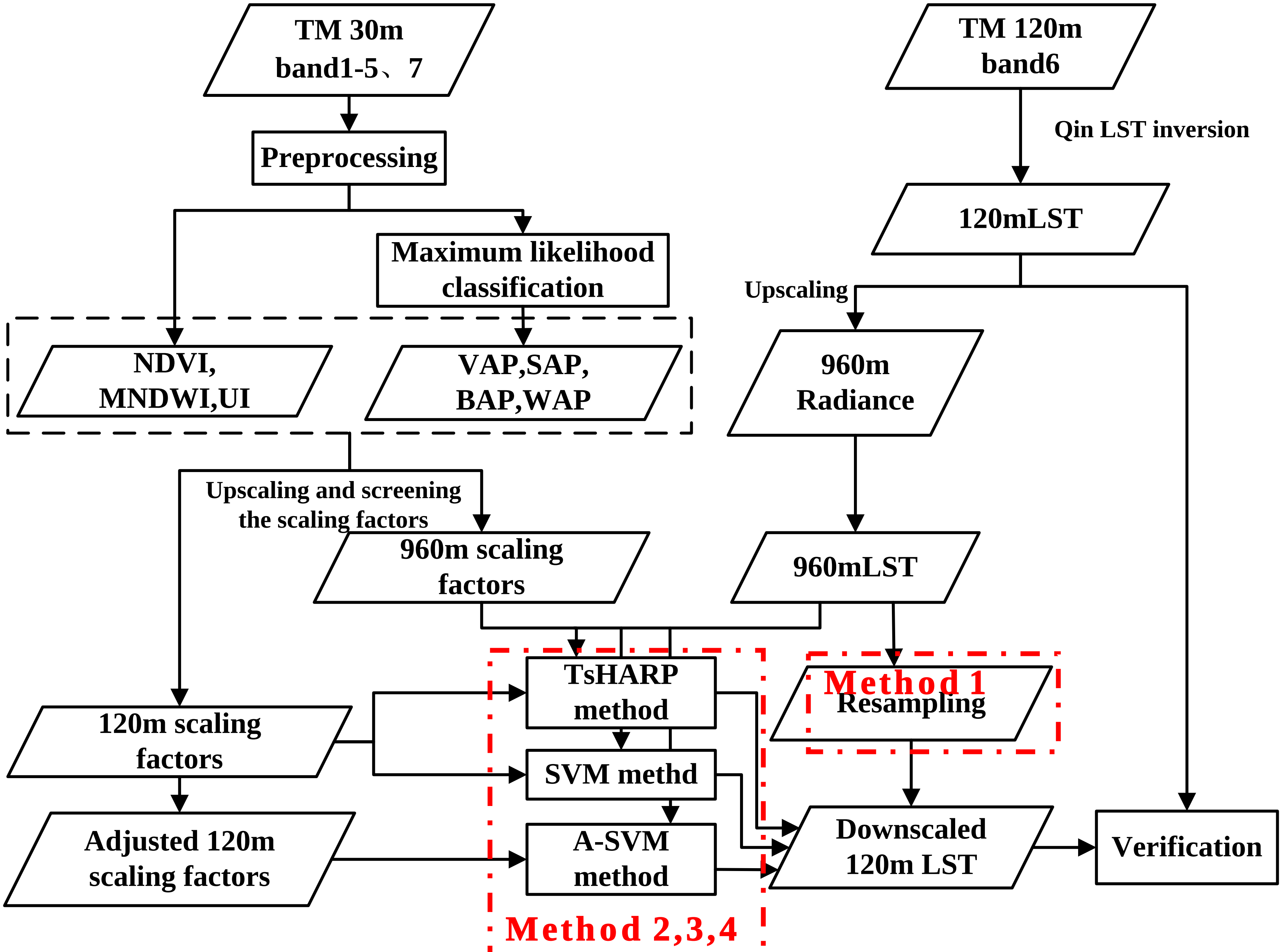


(b)Direct Resampling to 960m

severe smoothing LST caused by direct resampling

3. LST Downscaling based on A-SVM

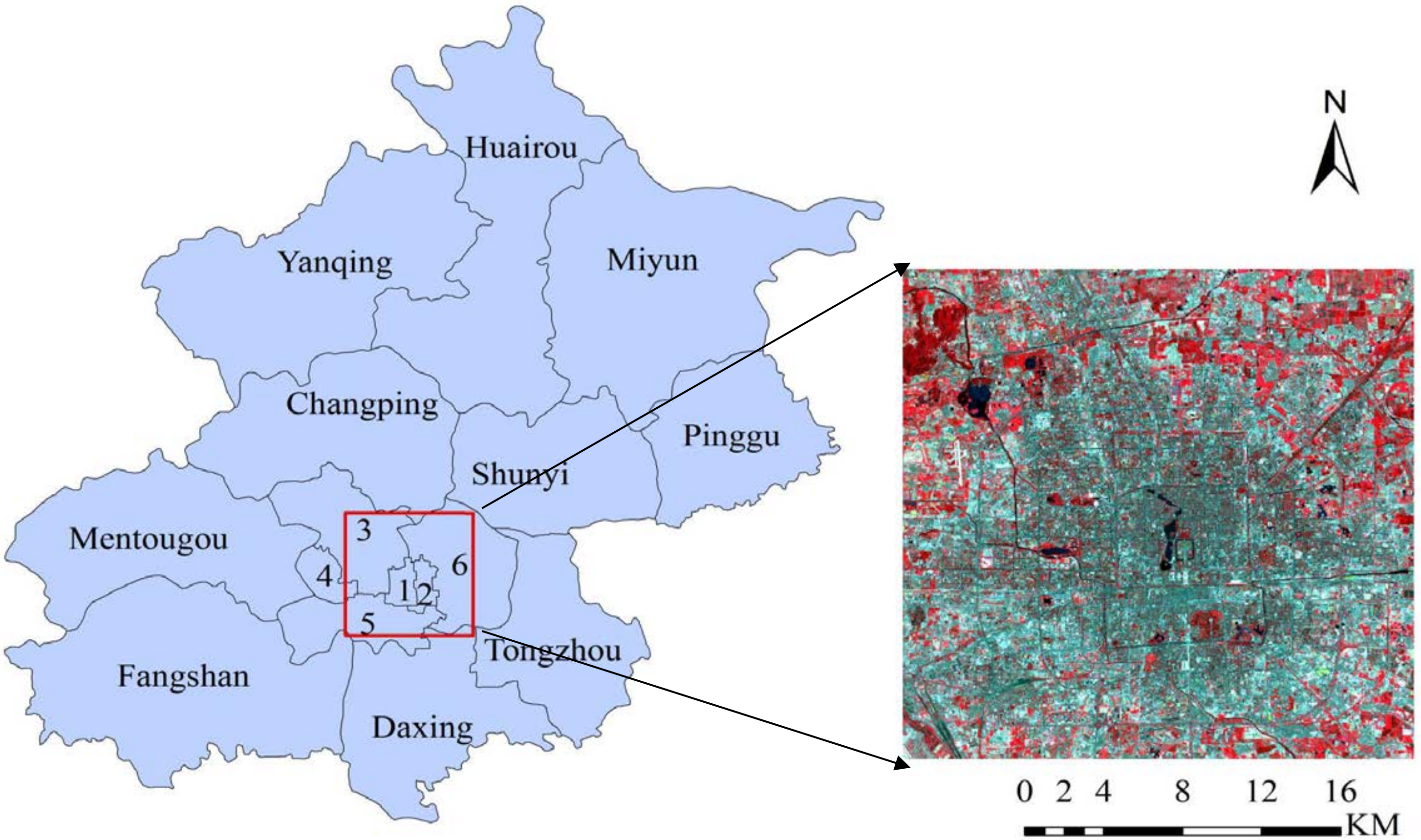



TM 30m
band1-5、7
Preprocessing
Maximum likelihood
classification
NDVI,
MNDWI,UI
VAP,SAP,
BAP,WAP
Upscaling and screening
the scaling factors
960m scaling
factors
120m scaling
factors
Adjusted 120m
scaling factors
TM 120m
band6
Qin LST inversion
120mLST
Upscaling
960m
Radiance
960mLST
TsHARP
method
SVM methd
A-SVM
method
Method 2,3,4
Method 1
Resampling
Downscaled
120m LST
Verification

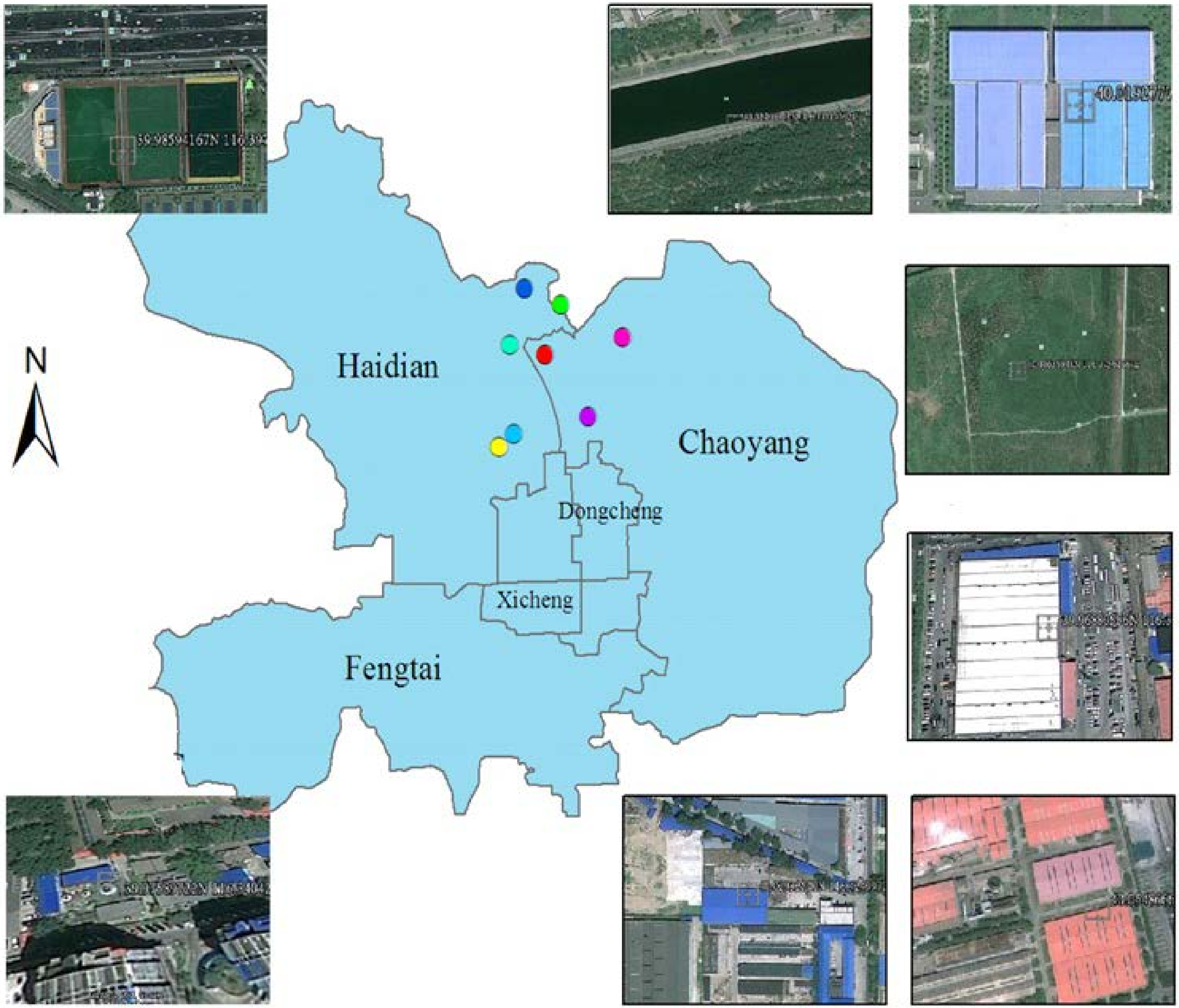
Data and Study Area

RS Data: **Landsat TM, 2004/07/06, Clear sky**
N39° 48'—40° 04', E116° 13'—116° 32'

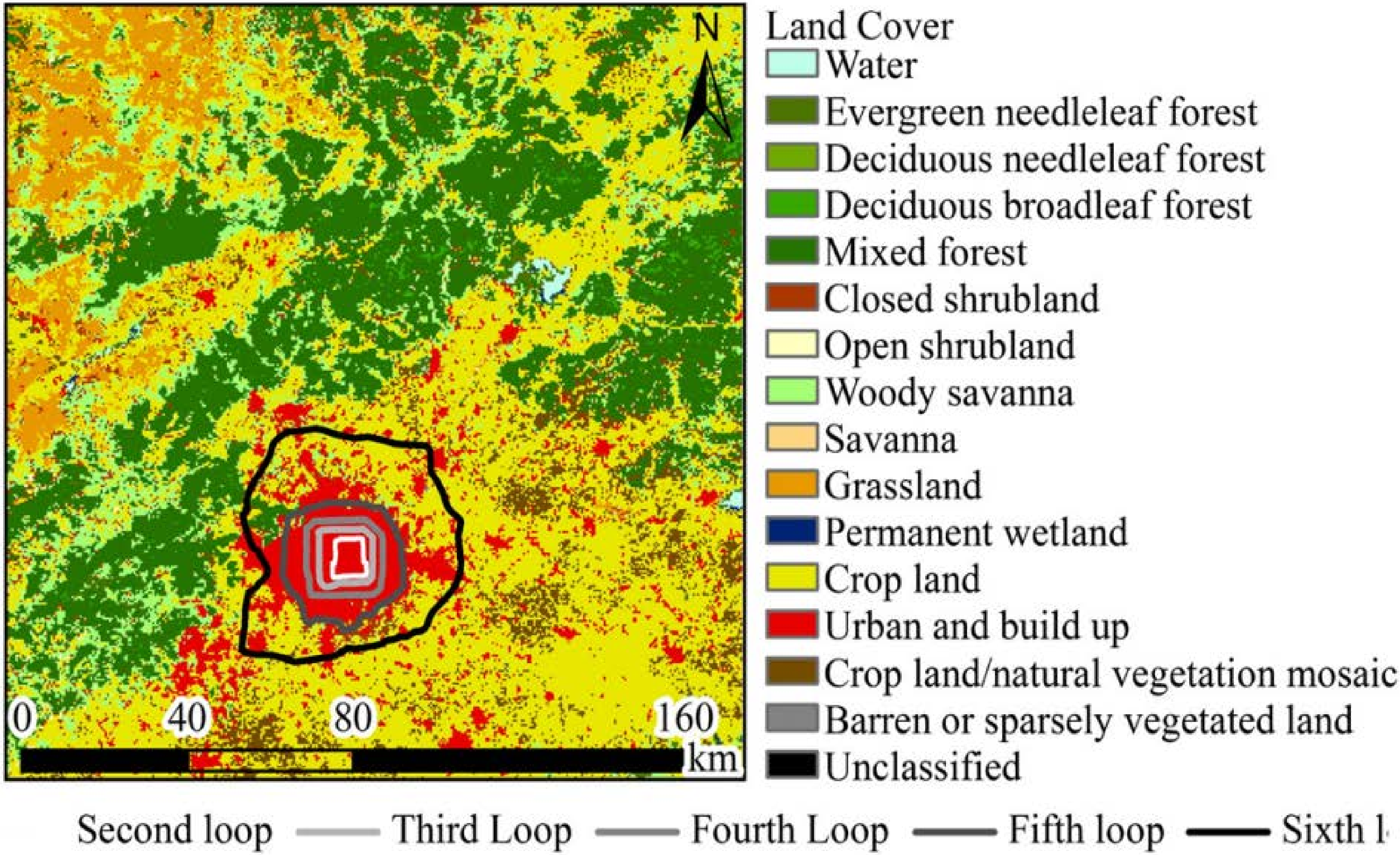
Research Area: **Urban area and part suburban districts in Beijing**



1-Xicheng;2-Dongcheng;3-Haidian;4-Shijingshan;5-Fengtai;6-Chaoyang



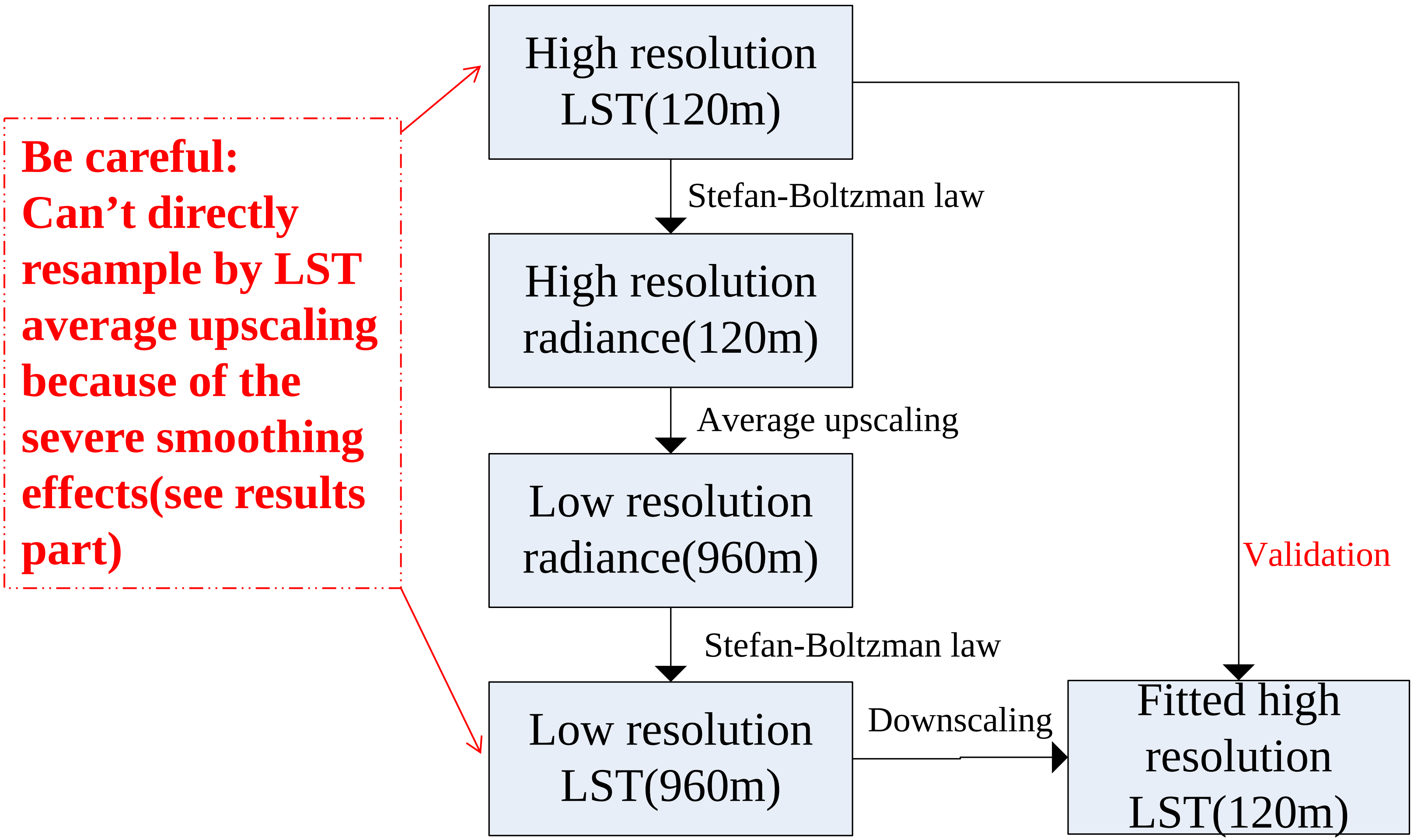
The typical objects in Beijing



The whole Land cover around Beijing(From MODIS)

LST downscaling procedure based on SVM

Because of the lack of validation data, this study adopts the simulation TM data to validate the feasibility of the downscaling method



Step 1: Classification and scaling factors selection

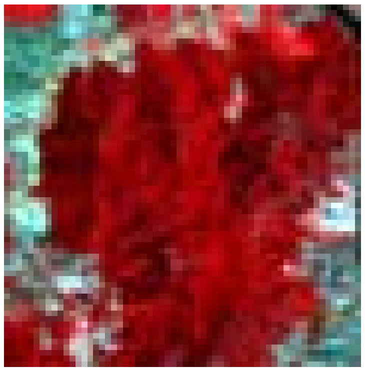
Multiple Regression Kernels (scaling factors) Selection and Combination is very Important

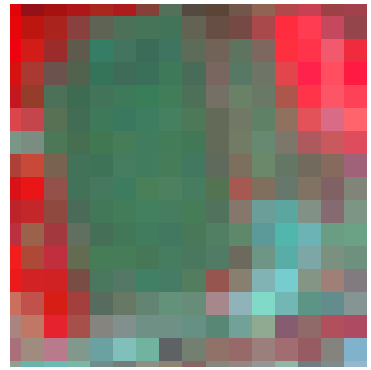
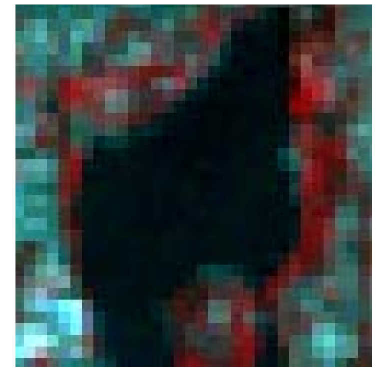
- By correlation analysis and PCA(Principal Component Analysis), selecting the parameters strongly related-to LST but independent respectively as the regression kernels (scaling factors) to do downscaling regression.
- Usually, the principal components with high value (>95%)will be selected to do the regression.

Step 1: Classification and scaling factors selection

Maximum Likelihood Classification(MLC, TM): 4 main types

Vegetation | Built-up | Soil | Water



Index NDVI | UI | | MNDWI

% VAP | BAP | SAP(not used) | WAP

scaling factors selected & their percentage:

- ---NDVI: Normalized Difference Vegetation Index
- ---UI: Urban Index;
- ---MNDWI: Modified Normalized Difference Water Index
- ---VAP: Vegetation Area Percentage ---WAP, SAP

Step 1: Classification and scaling factors selection

Selecting the scaling factors by correlation analysis and PCA

Raleted factors	MNDWI	UI	NDVI	VAP	SAP	BAP	WAP
MNDWI	1.00(1.00)						
UI	0.46(0.44)	1.00(1.00)					
NDVI	-0.83(-0.80)	-0.88(-0.87)	1.00 (1.00)				
VAP	-0.76(-0.68)	-0.87(-0.81)	0.95 (0.87)	1.00(1.00)			
~~SAP~~	-0.24(-0.07)	0.11(0.22)	0.04(-0.12)	0.09(-0.09)	1.00(1.00)		
BAP	0.63(0.51)	0.82(0.70)	-0.85(-0.72)	-0.93(-0.86)	-0.38(-0.35)	1.00(1.00)	
WAP	0.53(0.55)	-0.38(-0.26)	-0.04(-0.11)	0.07(-0.01)	-0.08(-0.04)	-0.26(-0.23)	1.00(1.00)

- Selecting 6 kinds of scaling factors to do SVM regression(NDVI, UI, MNDWI,VAP,BAP,WAP)
- High correlation between VAP & NDVI/BAP in high & low resolution.
- SAP is eliminated because soil area is very infrequent in urban area and the classification type of soil is usually ignored in the low resolution images during the scaling transforming process(960m &120m)

Step 2: SVM Model building

SVM Principles:

•Converting the algorithm of searching optimal hyperplane to solve the optimization problem.

•Based on Mercer core, mapping the sample space to a feature space with high dimensional or even infinite dimensional using non-linear mapping method.

•Carrying out the linear regression in the high dimensional space, finally converting the non-linear model to linear model.

•Using the radial basis kernel function(RBF)to convert the point multiplication in feature space to the kernel function in the low-dimensional original space.

Step 2: SVM Model building

SVM model combining LST and regression Kernels for low resolution

$$\min\left\{\frac{1}{2}\|W\|^2 + C\sum_{i=1}^{t}(\xi_i + \xi_i^*)\right\}$$

$$\text{subject to:}\begin{cases} y_i - (W \cdot X_i) - b \le \varepsilon + \xi_i \\ (W \cdot X_i) + b - y_i \le \varepsilon + \xi_i^* \end{cases}$$

$$\hat{T}_L = f(X_L) = (W \cdot X_L) + b = \sum_{i=1}^{S} W_i \cdot \boxed{\exp(-\|X_L - X_i\|}^2 / p^2) + b$$

$$\Delta T_L = T_L - \hat{T}_L$$

ξ_i/ ξ_i^*: sample points lie in the above and below of the optimal regression hyperplane

W: slope b: constant c: penalty coefficient given ε: non-sensitive loss function

a_i/a_i^*: lagrange multiplier X_i: support vector S: groups

exp: the radial basis kernel function p: width of the radial basis kernel function(RBF)

X_L/T_L: scale factor and LST in low resolution

$\hat{T}_L$: estimated LST from model in low resolution

ΔT_L: model estimation error

Step 2: SVM Model building

SVM model combining LST and regression Kernels for high resolution

Using the above SVM model for low resolution to high resolution, replacing the low-resolution scale factors to high-resolution scale factors and further adding the model estimation error， high-resolution LST can be obtained.

$$T_H = \sum_{i=1}^{S} W_i \cdot \exp(-\| \boxed{X_H - X_i} \|^2 / p^2) + b + \boxed{\Delta T_L}$$

W: slope b: constant X_i: support vector S: groups
exp: the radial basis kernel function p: width of the radial basis kernel function(RBF)
X_H/T_H: scale factor and LST in high resolution
ΔT_L ：model estimation error

Step 2: SVM Model building

- On the basis of comparing with three algorithms (Grid Search , GA, PSO), finally selecting Grid Search algorithm to do SVM model parameters optimization(including the penalty coefficient C， the width of the radial basis kernel function(RBF) p.

Step 3: Adding the scaling factors spatial adjustment model

The basic assumption of SVM regression:

- It is strictly scale-invariant between LST and all the relevant regression kernels selected whether high resolution or low resolution RS images.
- But in fact, scale change will exactly cause errors during the process of resolution changing.

Step 3: Adding the scaling factors spatial adjustment model

Zhu(2013) build a simple model to dynamically adjust the scale factor spatial distribution according to the Standard Deviation of scale factors from high resolution and low resolution LST.

Scaling factors spatial adjustment model

$$\boxed{X_{AH}} = (X_H - \boxed{X_L})\sigma_L / \sigma_H + X_L$$

X_H: high resolution scaling factors with the position-corresponding to pixel to X_L

X_L: low resolution scaling factors with the position-corresponding to pixel to X_H

σ_L/σ_H: Scaling factors standard deviation of low and high resolution

X_{AH}: adjusted scaling factors with spatial distribution model

Step 3: Adding the scaling factors spatial adjustment model

By considering the relationship between high-resolution and low-resolution images, the purpose of the model-building is to make the remote-sensing indices of the high spatial resolution image have the same spatial distribution as those of the low spatial resolution image, which will reduce the downscaling estimation error of different resolutions

Step 4: A-SVM Model building

Step2: SVM

$$T_H = \sum_{\substack{support\ vector\\ i=1}}^{S} W_i \cdot \exp(-\| \boxed{X_H} - X_i \|^2 / p^2) + b + \Delta T_L$$

$+$

Step3: Scaling factors spatial adjustment model

$$X_{AH} = (X_H - X_L)\sigma_L / \sigma_H + X_L$$

Step4: A-SVM

$$T_{AH} = \sum_{\substack{Support\ vector\\ i=1}}^{S} W_i \cdot \exp(-\| \boxed{X_{AH}} - X_i \|^2 / p^2) + b + \Delta T_L$$

X_H: high resolution scaling factors W: slope b: constant

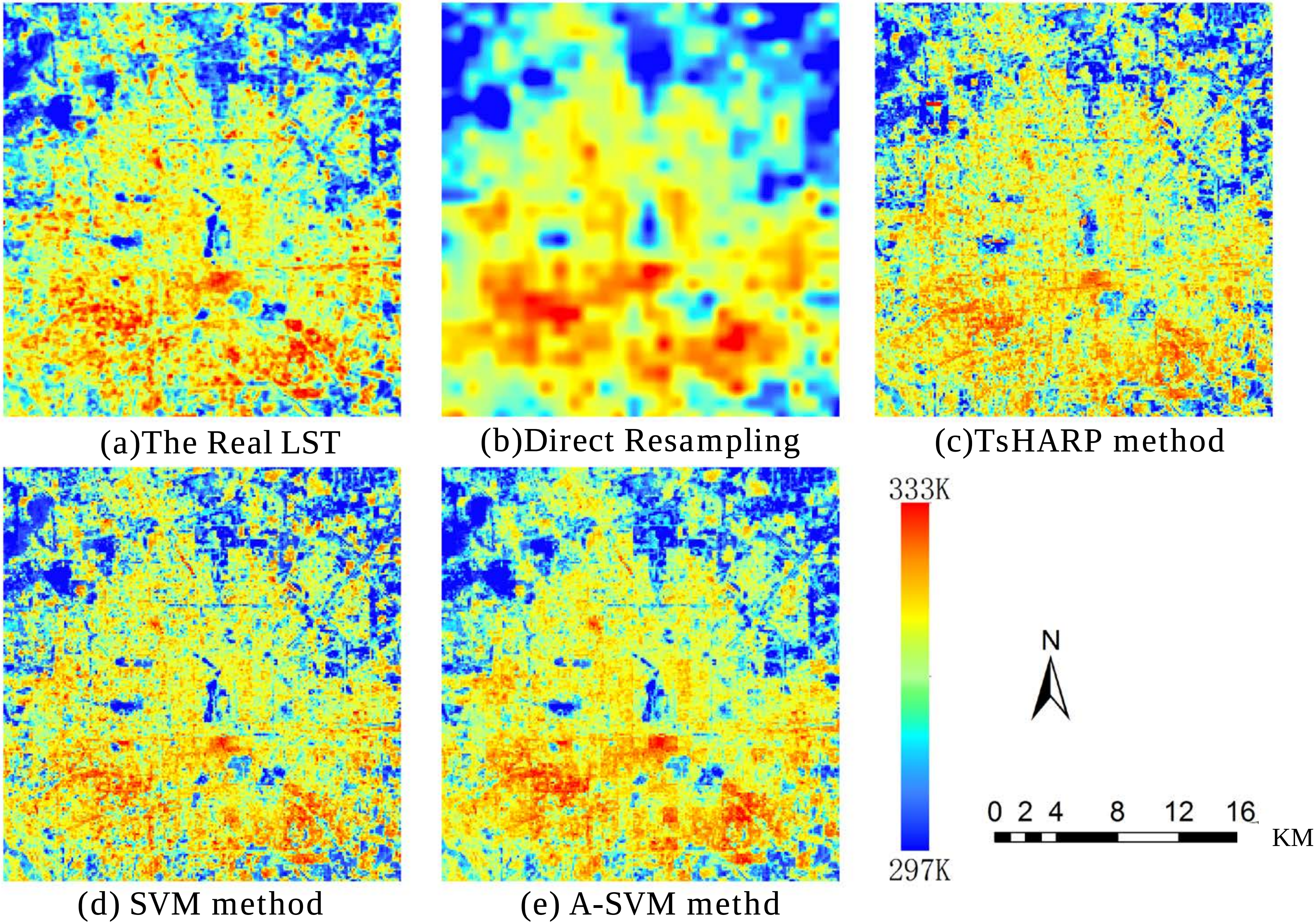
P: width of the function X_i: support vector, S groups ΔT_L: the error of estimate

σ_L/σ_H: Scaling factors standard deviation of lowand high resolution

X_{AH}: adjusted scaling factors with spatial distribution modle

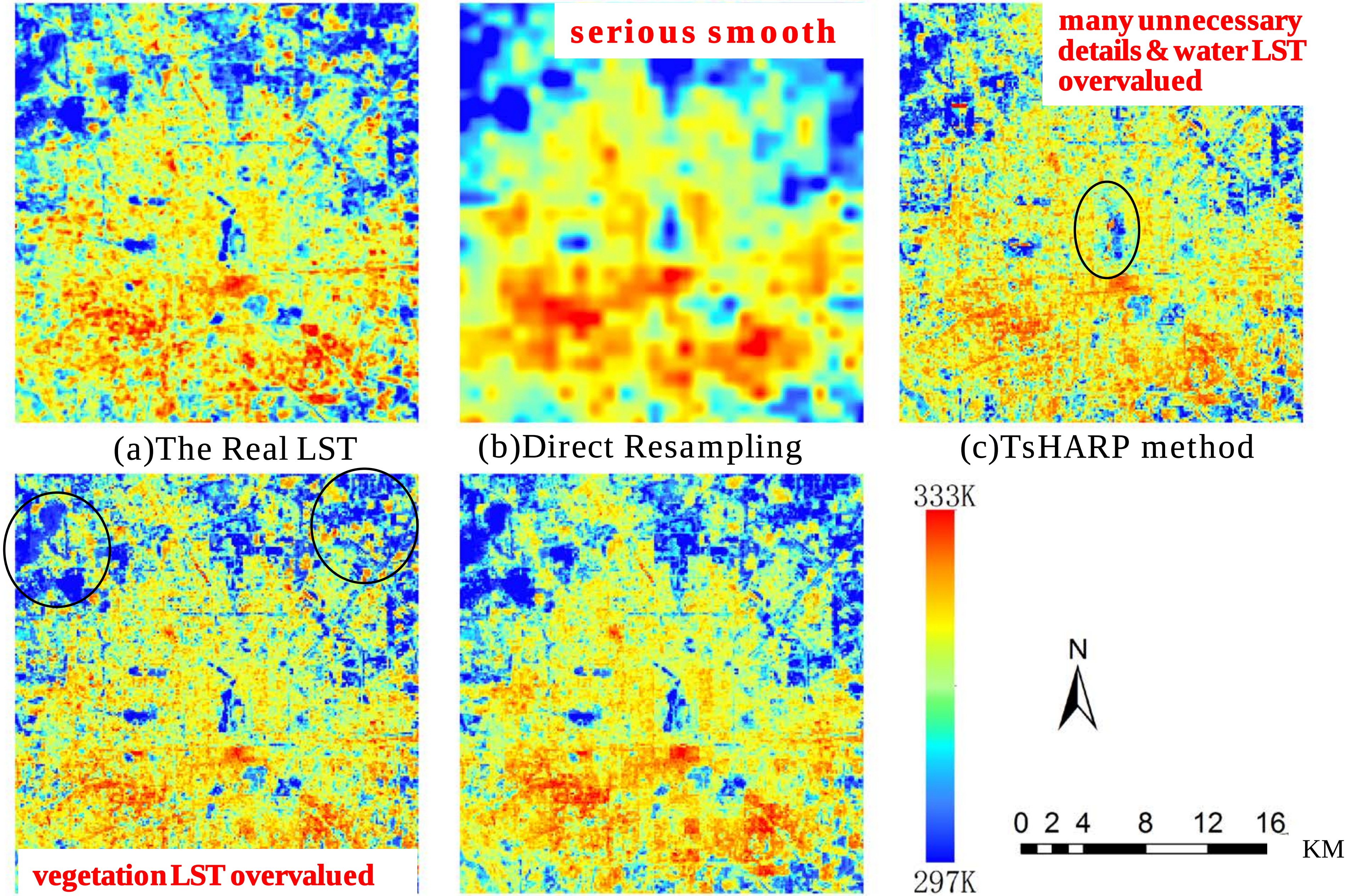
T_H/T_{AH}: fitted high resolution LST from SVM and A-SVM mothed

Results



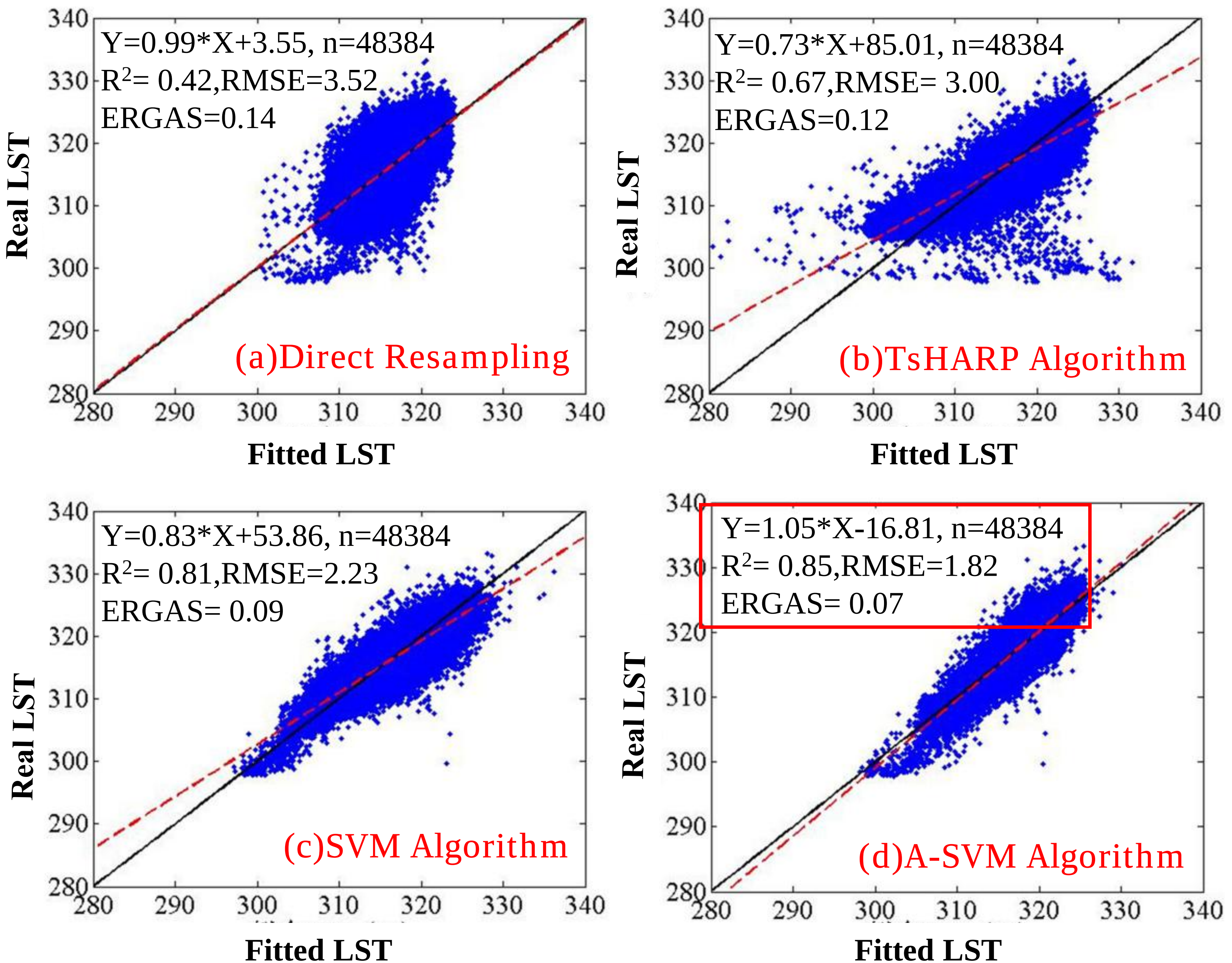
(a)The Real LST
(b)Direct Resampling
(c)TsHARP method
(d) SVM method
(e) A-SVM methd
333K
297K
N
0 2 4 8 12 16
KM

Results Validation



(a)The Real LST (b)Direct Resampling (c)TsHARP method

(d) SVM method (e) A-SVM methd



Y=0.99*X+3.55, n=48384
R2= 0.42,RMSE=3.52
ERGAS=0.14
(a)Direct Resampling
Y=0.73*X+85.01, n=48384
R2= 0.67,RMSE= 3.00
ERGAS=0.12
(b)TsHARP Algorithm
Y=0.83*X+53.86, n=48384
R2= 0.81,RMSE=2.23
ERGAS= 0.09
(c)SVM Algorithm
Y=1.05*X-16.81, n=48384
R2= 0.85,RMSE=1.82
ERGAS= 0.07
(d)A-SVM Algorithm
Real LST
Fitted LST
280
290
300
310
320
330
340

4. Summary

- Using multiple related parameters with LST including NDVI, UI, MNDWI,VAP,BAP,WAP can reflect the complex characteristics of urban surface, also can partly show the change of urban LST.
- Based on the 6 kinds of scaling factors, a new adjusted-SVM spatial downscaling method for urban land surface (A-SVM) was developed combining the SVM model with a space distribution adjustment model,which could avoid the ideal assumptions that the relation between scaling factors and LST was invariant.The validation result shows A-SVM method can get the better prediction precision.

5. Future Work

- The optimization process trainings have used all the original data, which were very large, and it made the time to rise and maybe would influence the model accuracy.Therefore, other sampling ways should be considered to select training samples to make the model more efficient and expand to more application fields.
- Adding more optical images as the assistant data to help downscaling.For example, using more accurate LUCC classification methods and high resolution data in urban area combining with object-oriented method.
- If downsacling 100m levels LST to 10m or smaller, adding some landscape indexes to represent urban detail characteristics and surface complexity, such as Patch Number, Patch Density, Interspersion and Aggregation Index, will probably further improve the downscale precision in theory.

5. Future Work

- Existing research shows that the downscaling multiple should be constrainted 3-5 times to avoid producing more superposition errores. The next step,we will use two kinds of downscaling strategies to compare the effects: downscaling step by step(for example,120m - 60m - 30m) and direct downscaling(such as,120m - 30m).
- MODIS has the temporal advantages and MODIS/ASTER have the same satellite platform. So the A-SVM should be used for MODIS data downscaling and the result also should be compared and tested by the real 90m ASTER LST data to enhance the model accuracy and resolve the contradiction of spatial & temporal resolution.

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Thank You!