SCIENCE & TECHNOLOGY RESEARCH INSTITUTE
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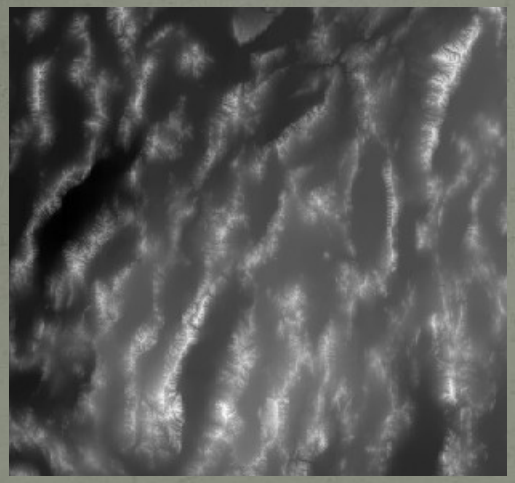
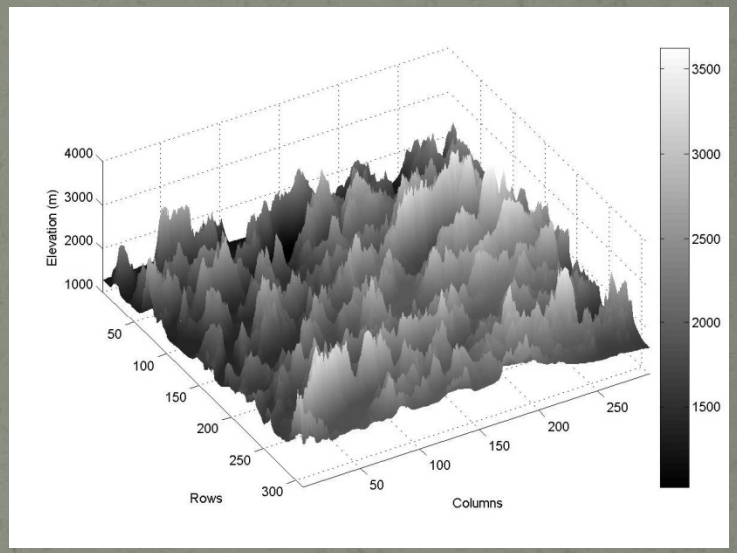
STRIDE

Comparative Analysis of Cell- and Object-Based Local Variance for Physiographic Features Extracted from Multiscale Digital Elevation Models

Digital Elevation Models (DEMs)

The Global Digital Elevation Model (GTOPO30) of Great Basin





- Location: latitude 38° 15' to 42° N, longitude 118° 30' to 115° 30' W
- Grid size: 925 m
- Elevation range: 1,005 – 3,651 m (rescaled to the interval of 0 to 255 - the brightest pixel has the highest elevation)

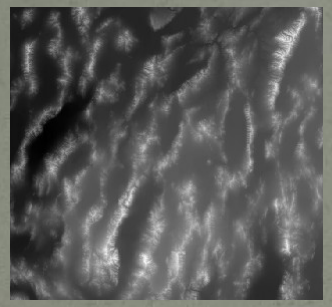
Digital Elevation Models (DEMs)

- One of the primary issues in dealing with DEMs are uncertainties caused by:
  - Data errors:
    - Data capture errors:
      - Cloud or forest cover
      - Instable remote sensing equipment
      - Atmospheric refraction
    - Analysis and visualization errors:
      - Interpolation procedures
      - The limited horizontal and vertical resolution of terrain models
  - Scale
    - Spatial resolution
    - Spatial extent
  - Lack of standardisation

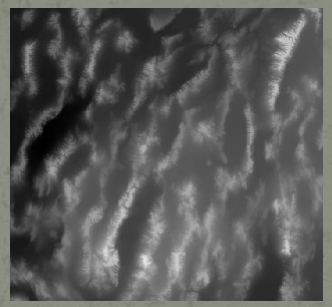
- These factors lead to uncertainties in the extracted landforms and features

Generation of Multiscale DEMs

Multiscale DEMs generated using the lifting scheme, using scales of 1to 20



Scale: 1



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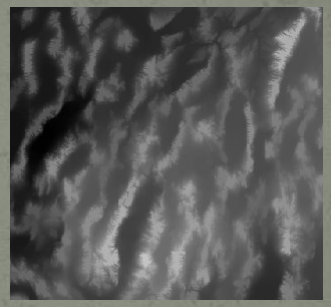
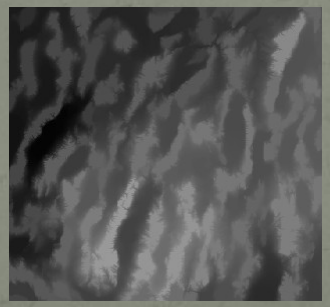
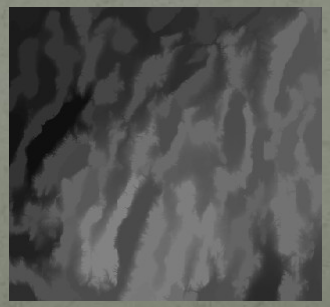


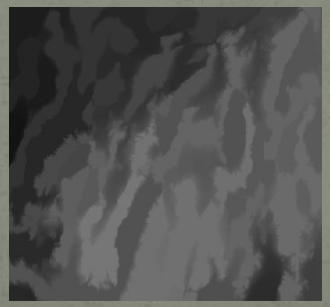
Scale: 5



Scale: 10



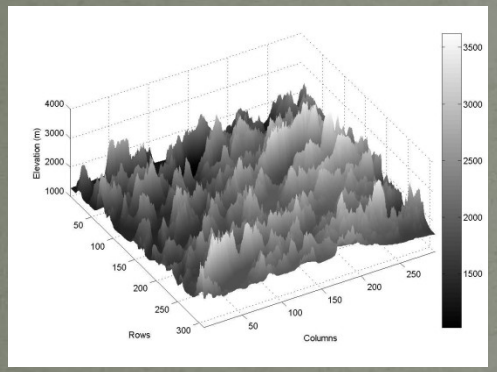
Scale: 15



Scale: 20

Generation of Multiscale DEMs

Multiscale DEMs generated using the lifting scheme, using scales of 1to 20



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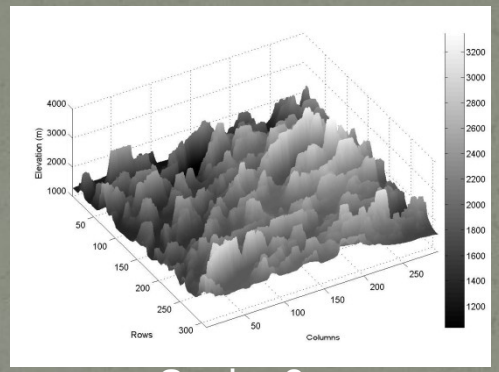

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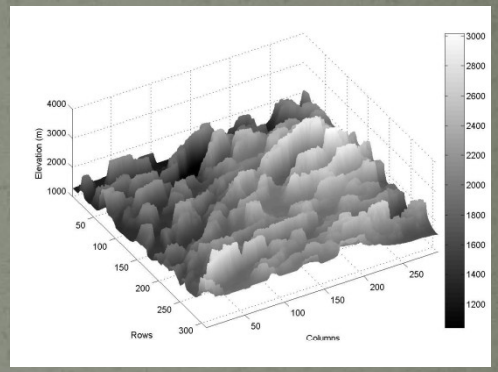

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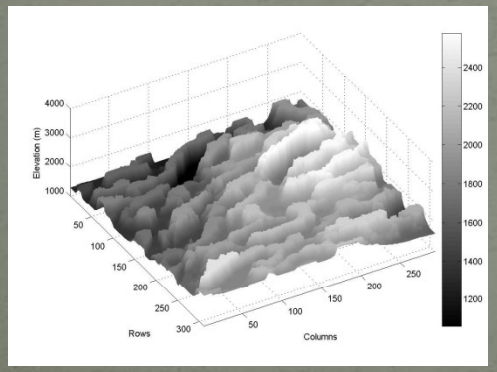

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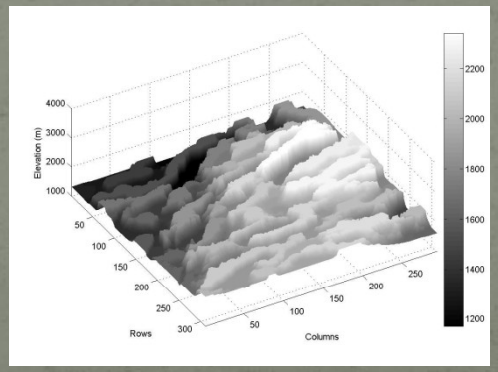

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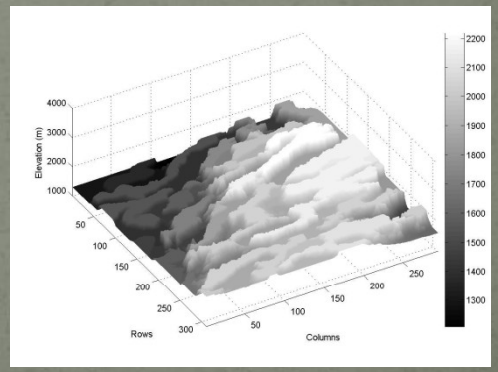


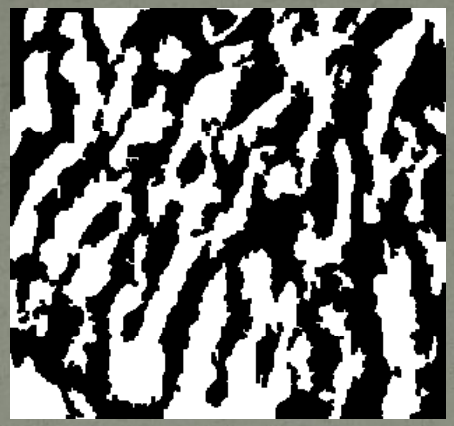
Scale: 20

Physiographic Features Extracted from of the DEM

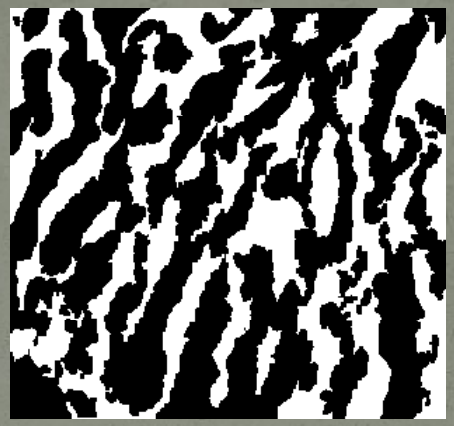
- Segmentation of the terrain of the DEM of Great Basin into the predominant physiographic features; mountains, basins and piedmont slopes

	Mountains
	Piedmont slopes
	Basins

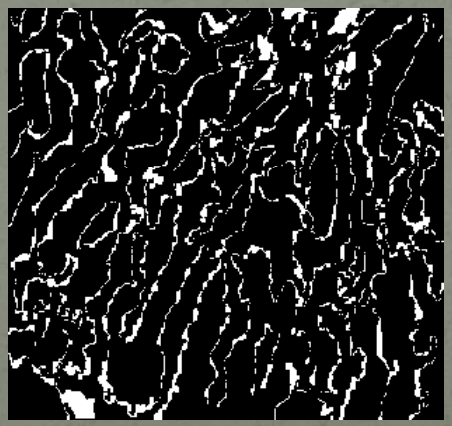
Physiographic Features Extracted from of the DEM



Mountains



Basins



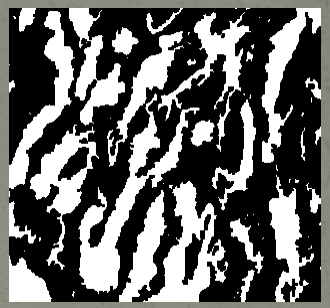
Piedmont slopes

Physiographic Features Extracted from the Generated Multiscale DEMs

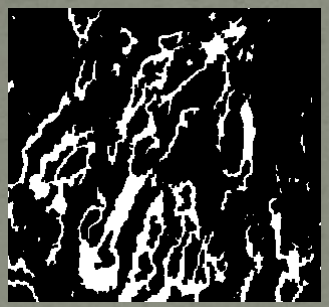
Mountains

Scale: 1

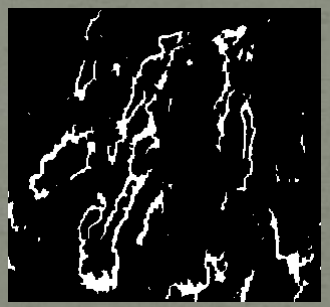
Scale: 3



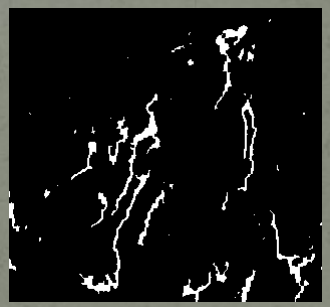
Scale: 5



Scale: 10



Scale: 15



Scale: 20

Physiographic Features Extracted from the Generated Multiscale DEMs

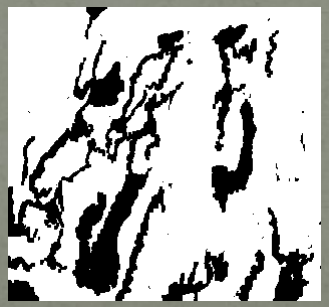
Basins

Scale:

Scale:

Scale:

Scale: 10

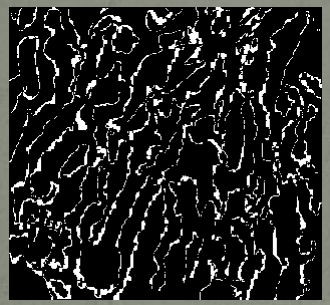


Scale: 15

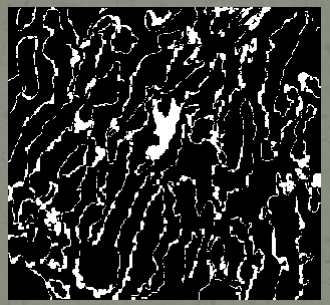
Scale: 20

Physiographic Features Extracted from the Generated Multiscale DEMs

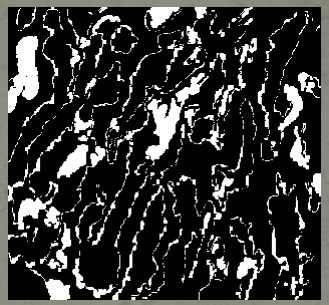
Piedmont slopes



Scale:



Scale:



Scale:

Scale: 10

Scale: 15

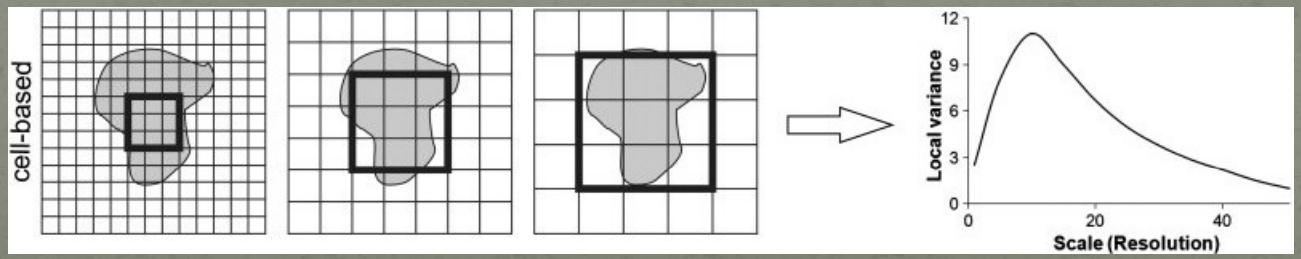
Scale: 20

Multiscale Analysis

- A number of methods have been proposed to study the effect of scale on spatial attributes of terrains, including:
  - Geographic variance
  - Local variance
  - Texture analysis
  - Fractals
- From the aspect of simplicity and performance, local variance is more widely used for geospatial analysis.

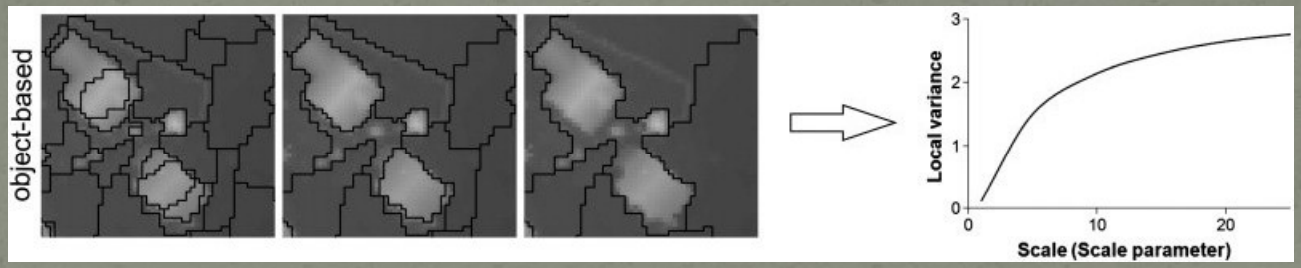
Local Variance

- Local variance *LV* is a statistical indicator that measures spatial variability in an image.
- *LV* is the mean of standard deviation *s* values in a local window moving over an entire image.
- The procedure is then applied on successively coarser scales, with the graph of *LV* values across the scales being used to measure spatial structures in the multiscale images.



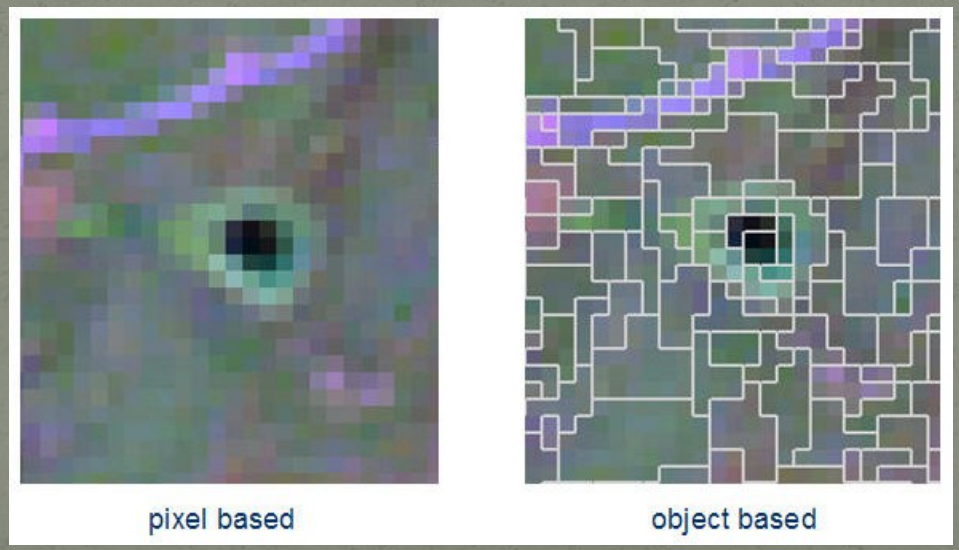
Local Variance

- For the object-based image analysis (OBIA) approach, instead of computing *s* from a moving window, it is derived from objects obtained through segmentation.
- This approach allows for more accurate evaluation of changes in spatial structures of images across scales as a function of *LV*, spatial variability and number of objects.



Objective

- To provide a comparative analysis of cell- and object-based *LV* for physiographic features extracted from multiscale DEMs.
- The results of this study will be used to highlight the advantages of object-based *LV* over cell-based *LV* in quantifying changes in spatial variabilities of physiographic features over multiples scales.



Cell-Based *LV*

- The traditional cell-based *LV* method uses fixed local window sizes (e.g. size 3 square) for computing *LV* values over varying scales.
  - Fixed local window sizes result in *LV* values being computed for variable ground areas for images with varying scales, resulting in poor comparability between the images.
- Hence, a modified *LV* technique is used:
  - Window sizes are customised to the scales, so that *LV* values are computed for constant ground areas across the scales
  - This ensures that the LV values quantify changes of variance with scale more objectively.

Cell-Based *LV*

- At each scale s, as the local window, with area of $(2s+1)^2$, moves through the entire image, the standard deviation for each cell s_{ij}, at location (i, j) with grey level of $f(i, j)$, is computed as:

$$\sigma_{ij} = \sqrt{\frac{\sum_{k=i-s}^{i+s} \sum_{l=j-s}^{j+s} \left(f(k,l) - \mu_{ij} \right)^2}{(2s+1)^2}}$$

where μ_{ij} is the mean cell value in the window:

$$\mu_{ij} = \frac{\sum_{k=i-s}^{i+s} \sum_{l=j-s}^{j+s} f(k,l)}{(2s+1)^2}$$

Cell-Based *LV*

- *LV* is then computed as the mean s_{ij} value for all the cells in the image:

$$LV = \frac{\sigma_T}{A - (2s)^2}$$

where *A* is the area of the region under investigation, and s_T is the total standard deviation of all the cells in the image:

$$\sigma_T = \sum_{i=1+s}^{x-s} \sum_{j=1+s}^{y-s} \sigma_{ij}$$

where *x* and *y* are the number of rows and columns in the image respectively.

Cell-Based *LV*

$$LV = \frac{\sigma_T}{A - (2s)^2}$$

- The variation of cell-based *LV* values over the scales depends on the total standard deviation of the cells s_T and area of the region under investigation *A* at each scale:
  - Decrease in s_T results in decrease in *LV*
  - Decrease in *A* results in increase in *LV*.
- Variation of values of s_T over the scales depends on size of the moving window and rate of removal of fine detail in the terrain during multiscaling:
  - Increase of window size causes increase of spatial variability in the window and hence, increase in s_T
  - Increase in rate of removal of fine detail results in decrease in s_T

Object-Based *LV*

- A significant, but usually ignored problem, with cell-based image analysis is that objects in images are usually made up of several cells, rather than just single cells.
- Hence, OBIA has become increasingly prevalent due to the realisation that objects, which are generated by one or more criteria of homogeneity between neighbouring cells, hold more real-world value, and provide additional spatial and contextual information than cells alone
- To this end, object-based *LV* computation techniques have been proposed.

Object-Based *LV*

- At each scale s, the standard deviation for each individual object s_n in the image is computed as:

$$\sigma_n = \sqrt{\frac{\sum_{i=1}^{x}\sum_{j=1}^{y}\left(f_n(i,j)-\mu_n\right)^2}{A_n}}$$

where $f_n(i, j)$ is the grey level of each cell at location (i, j) in the object, A_n is the area of the object, and μ_n is the mean cell value in the object:

$$\mu_n = \frac{\sum_{i=1}^{x}\sum_{j=1}^{y} f(i,j)}{A_n}$$

Object-Based *LV*

- *LV* is then computed as the mean s_n value for all the objects in the image:

$$LV = \frac{\sigma_T}{N}$$

where N is the total number of objects in the image, and s_T is the total standard deviation of all the cells in the image:

$$\sigma_T = \sum_{n=1}^{N} \sigma_n$$

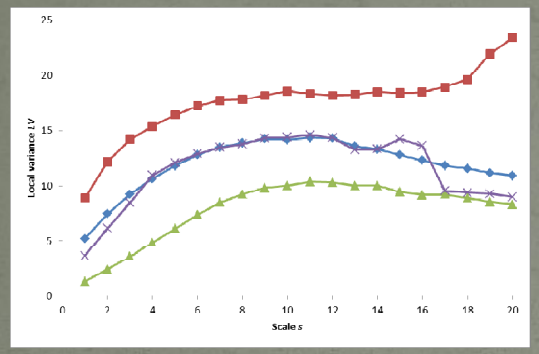
Object-Based *LV*

$$LV = \frac{\sigma_T}{N}$$

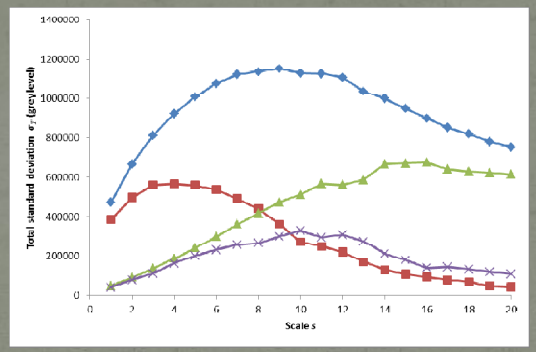
- The variation of object-based *LV* values over the scales depends on the total standard deviation of the objects s_T and number of objects N at each scale.
  - Decrease in s_T results in decrease in *LV*
  - Decrease in N results in increase in *LV*.
- Variation of values of s_T over the scales depends on sizes of the objects and rate of removal of fine detail in the terrain during multiscaling.
  - Increase of object sizes causes increase of spatial variabilities in the objects and hence, increase in s_T
  - Increase in rate of removal of fine detail results in decrease in s_T.

Results & Analysis

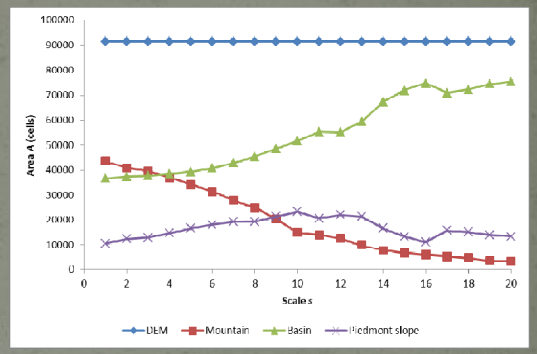
- Cell-Based *LV*



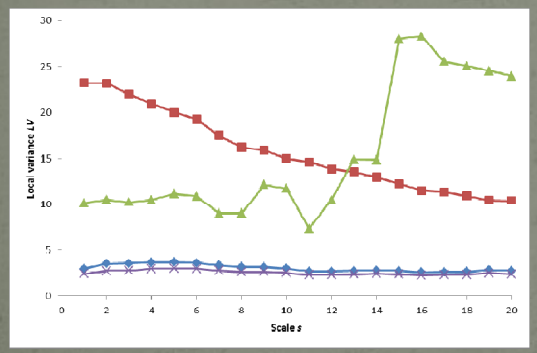
LV values

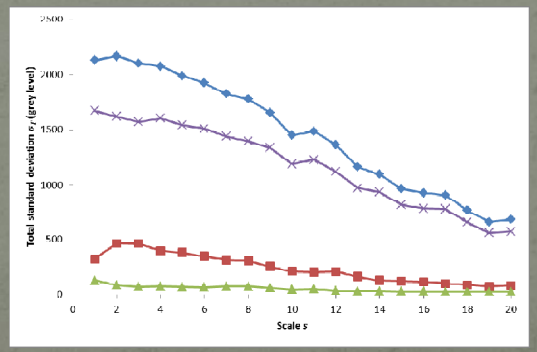


Total standard deviation s_T

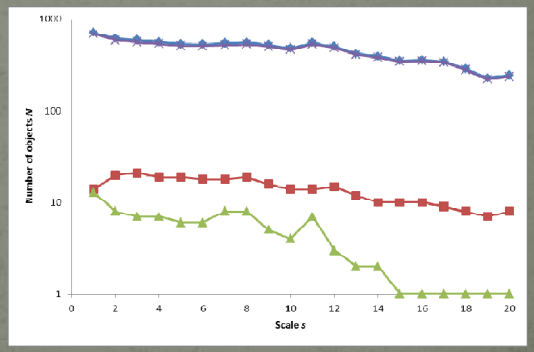


Area *A*





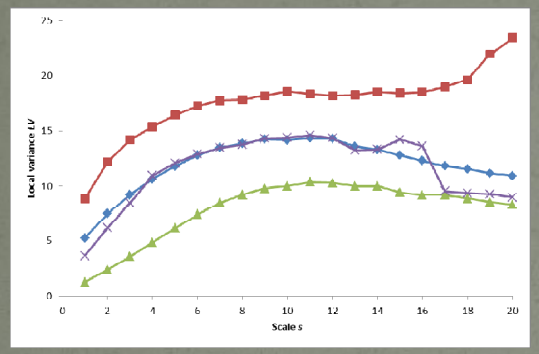
Number of objects *N*



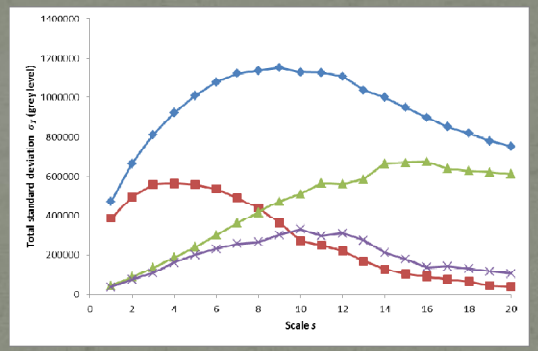
- Object-Based *LV*

Results & Analysis

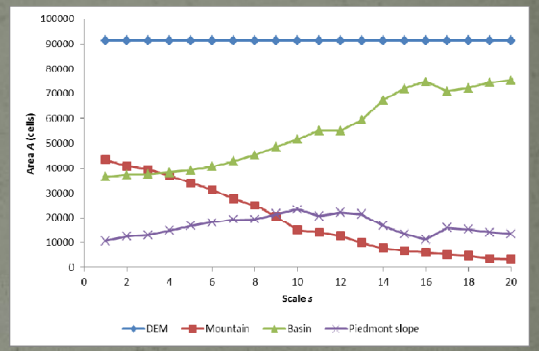
- Cell-Based *LV*



LV values



Total standard deviation s_T



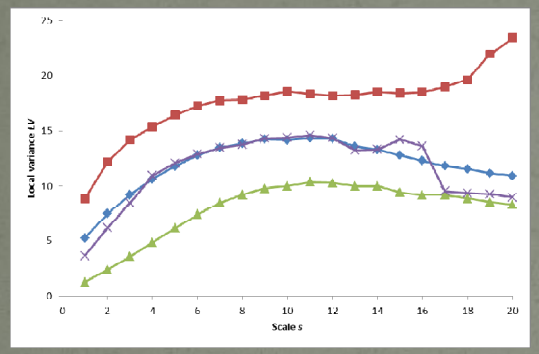
Area *A*

DEM Mountain Basin Piedmont Slope

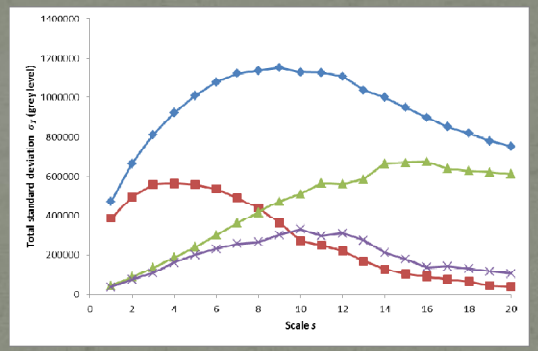
- The values of *LV* for all the regions initially increase with increasing scale.
- This occurs as, at this stage:
  - The increase of size of the moving window causes increase in spatial variability in the window
  - The rate of removal of fine detail is relatively low, resulting in increase in s_T.

Results & Analysis

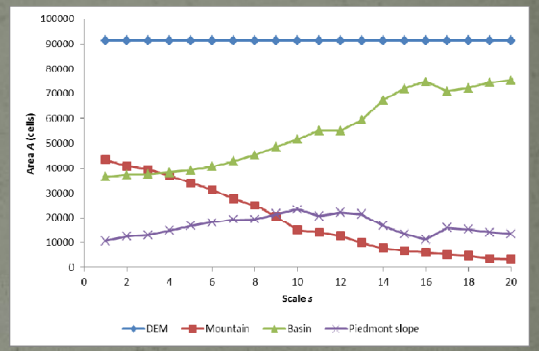
- Cell-Based *LV*



LV values



Total standard deviation s_T



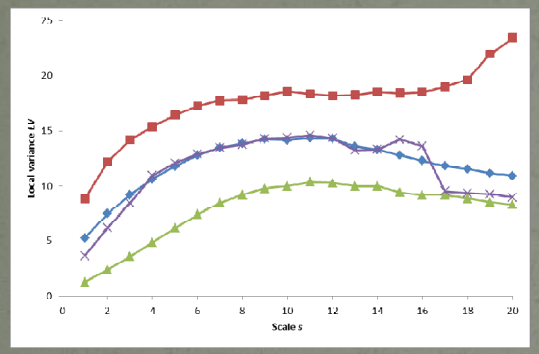
Area *A*

DEM — Mountain — Basin — Piedmont Slope

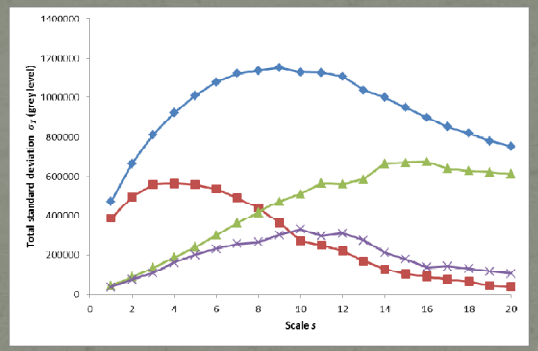
- The values of *LV* for the DEMs and piedmont slopes then decrease because of increase in rate of removal of fine detail, resulting in decrease in s_T.
- For the basins, the increase in rate of removal of fine detail is relatively lower as most of the fine detail in the region has been removed, resulting in s_T being constant.
  - The increase in area of basins over the scales causes a reduction in *LV* values.
- For the mountains, while s_T decreases over the scales, the higher rate of decrease in area results in increase of values of *LV*.

Results & Analysis

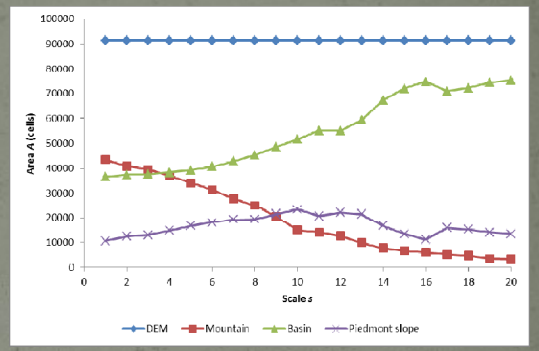
- Cell-Based *LV*



LV values



Total standard deviation s_T



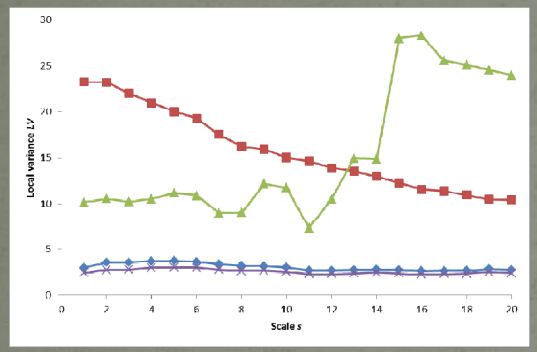
Area *A*

DEM Mountain Basin Piedmont Slope

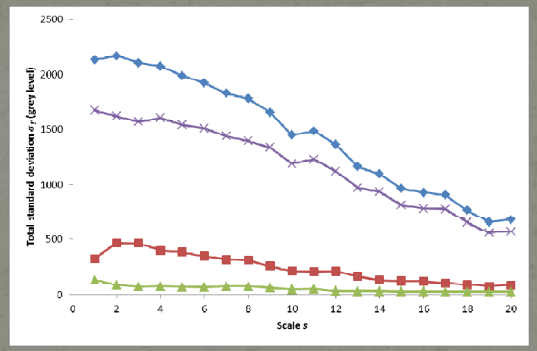
- For all the scales, mountains have the highest values of *LV* as compared to the other features, while basins have the lowest values of *LV*, indicating that mountains and basins have the highest and lowest spatial variabilities respectively.
- The DEMs and piedmont slopes exhibit similar patterns at the initial scales, as both represent the average spatial variability of the terrain.

Results & Analysis

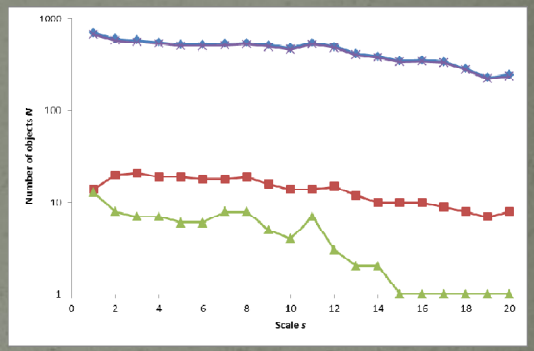
- Object-Based *LV*



LV values



Total standard deviation s_T



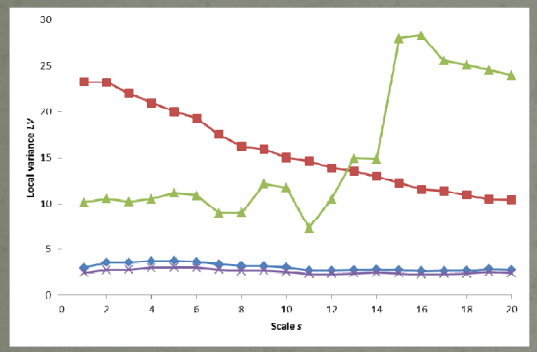
Number of objects *N*

DEM Mountain Basin Piedmont Slope

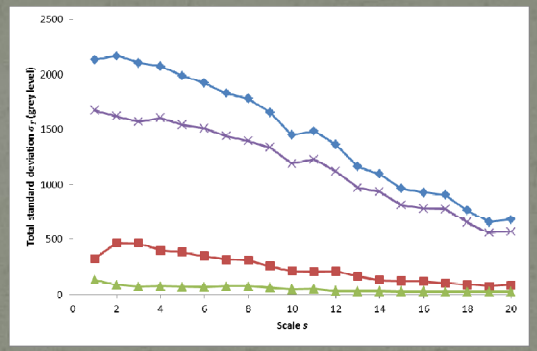
- The decrease in area of mountains with increasing scale results in decrease in *N*, and decrease in spatial variabilites of the objects, causing decrease in s_T.
- As the rate of decrease of s_T is higher as compared to *N*, the *LV* values decrease.

Results & Analysis

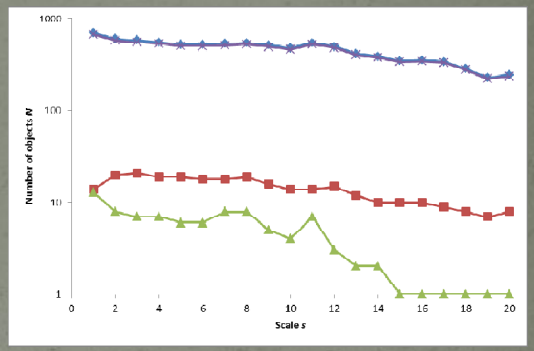
- Object-Based *LV*



LV values



Total standard deviation s_T



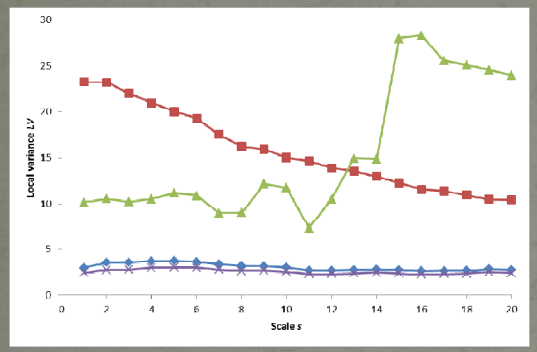
Number of objects *N*

DEM Mountain Basin Piedmont Slope

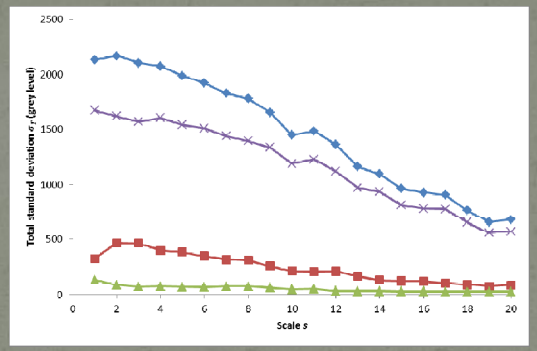
- For basins, at the initial scales, the values of s_T, *N* and *LV* remain relatively constant.
- The increase in area of basins with increasing scale results in the basin objects merging, causing decrease in *N*, and hence, increase in *LV*.
- After this point, *N* remains constant at 1, while s_T decreases due to the removal of fine detail, resulting decrease in *LV*, though at much higer values as compared to the initial scales.

Results & Analysis

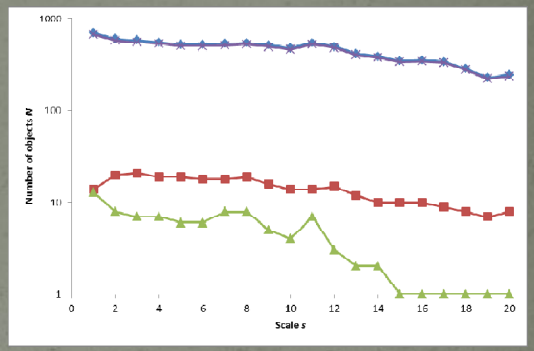
- Object-Based *LV*



LV values



Total standard deviation s_T



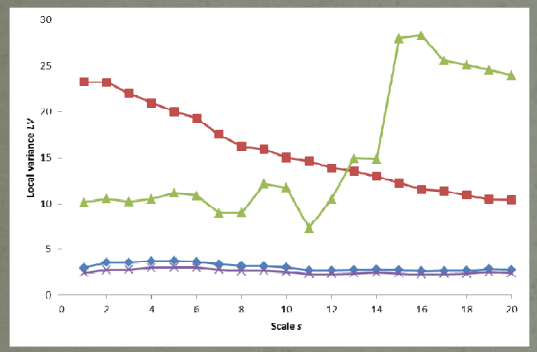
Number of objects *N*

DEM Mountain Basin Piedmont Slope

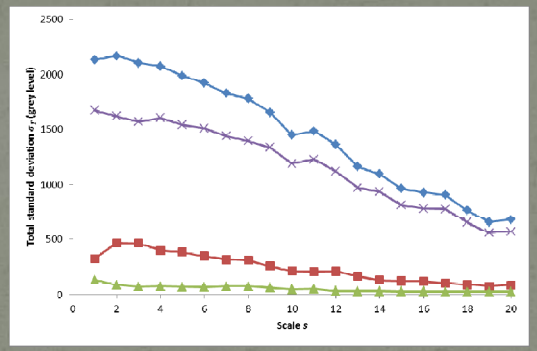
- For piedmont slopes, as the rate of decrease of values of s_T and *N* are relatively similar, the *LV* values remain fairly constant.
- Similar to the cell-based approach, the DEMs exhibit similar *LV* value patterns as the piedmont slopes, representing the average spatial variability of the terrain.

Results & Analysis

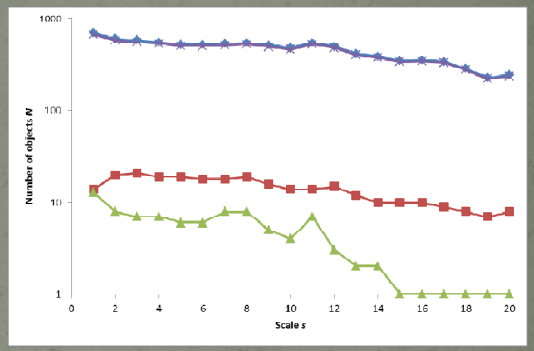
- Object-Based *LV*



LV values



Total standard deviation s_T



Number of objects *N*

DEM Mountain Basin Piedmont Slope

- At the initial scales, mountains have the higher *LV* values as compared basins, indicating that mountains have higher spatial variability.
- As the scale is further increased, the decrease in area of mountain objects result in decrease of spatial variability, while the increase in area of basin objects result in increase of spatial variability.
- Hence, the *LV* values decrease for mountains and increase for basins. As the area of basin objects become significantly larger than mountain objects, the spatial variability of basins becomes higher then mountains and hence, basins have higher *LV* values.
- Piedmonts slopes have the lowest *LV* values at all the scales, as the objects are significantly smaller in size.

Results & Analysis

- By analysing objects rather than individual cells, the object-based approach takes into account the spatial and contextual information of the cells.
  - This results in *LV* values that accurately quantify the change in spatial variabilities of the physiographic features over the scales.
- Mountains have the highest spatial variability at the initial scales, which decreases with reducing area over the scales.
  - Therefore, it has the highest *LV* values at the initial scales, which then decrease as the scale is increased.
- Basins have spatial variability that is lower than mountains at the initial scales, which increases with increasing area over the scales.
  - Hence, it has *LV* values that are lower than mountains at the initial scales, which then increase as the scale is increased.
- As piedmont slopes have the lowest spatial variability, it is has the lowest *LV* values.

Results & Analysis

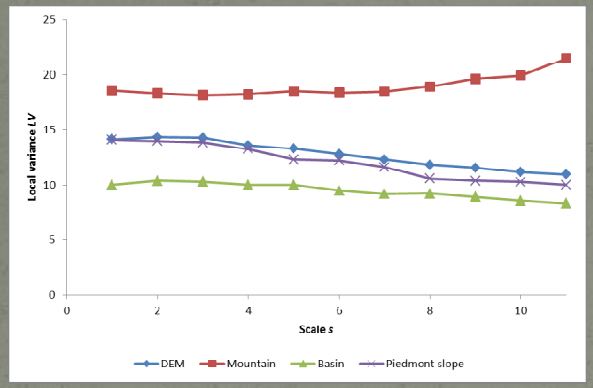
- Implementation on terrains with moderate and smooth surface profiles

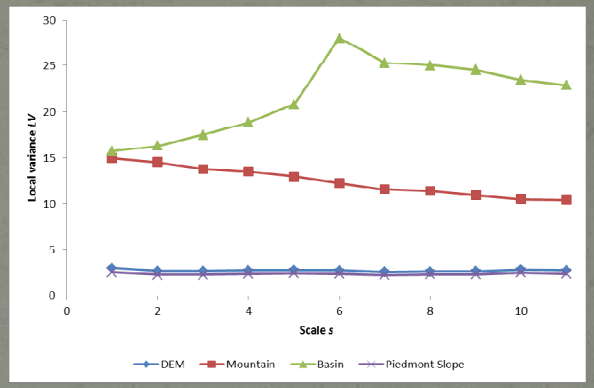
Great Plains

Great Falls

Results & Analysis

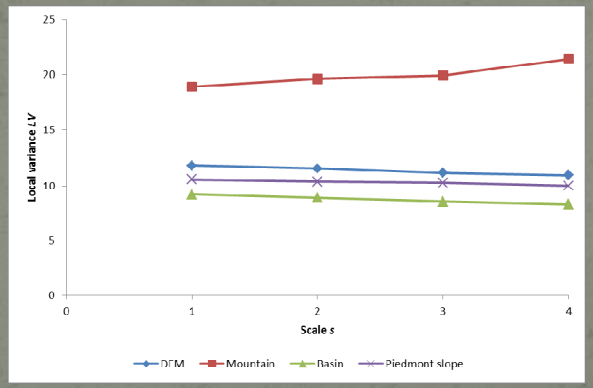
- Great Plains (Moderate surface profile)

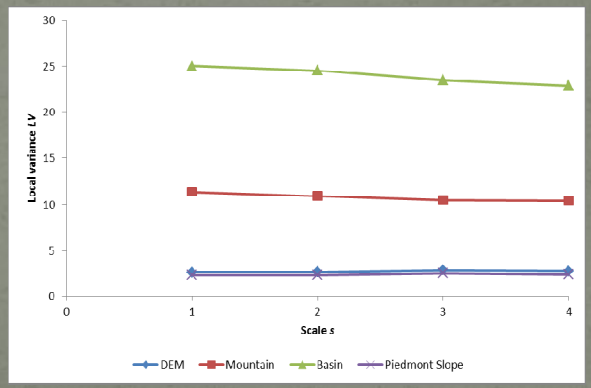




Cell-based *LV*

Object-based *LV*





- Great Falls (Smooth surface profile)

Conclusion

- The results obtained in this study highlight the advantages of object-based *LV* over cell-based *LV*.
- The cell-based approach does not take into account the spatial and contextual information of the cells analysed
  - Results in assignment of *LV* values that do not quantify the change in spatial variabilities of the multiscale DEMs and corresponding physiographic features.
- The object-based approach takes into account the spatial and contextual information of the cells
  - Results in *LV* values that accurately quantify the change in spatial variabilities of the physiographic features.