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

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)
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 1 to 20
Generation of Multiscale DEMs

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

<table>
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<th>Mountains</th>
<th>Piedmont slopes</th>
<th>Basins</th>
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Physiographic Features Extracted from 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: 1
Scale: 3
Scale: 5
Scale: 10
Scale: 15
Scale: 20
Physiographic Features Extracted from the Generated Multiscale DEMs

Piedmont slopes

Scale: 1
Scale: 3
Scale: 5
Scale: 10
Scale: 15
Scale: 20
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.
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.
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:

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

where $\mu_{ij}$ 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:

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

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 $\mu_n$ 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 $LV$

- 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 $s_T$. 
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

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.
The decrease in area of mountains with increasing scale results in decrease in $N$, and decrease in spatial variabilities 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 $LV$

- 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 higher values as compared to the initial scales.
Results & Analysis

- Object-Based LV

- 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 $LV$

- 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.
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
Results & Analysis

- **Great Plains (Moderate surface profile)**

- **Great Falls (Smooth surface profile)**
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.