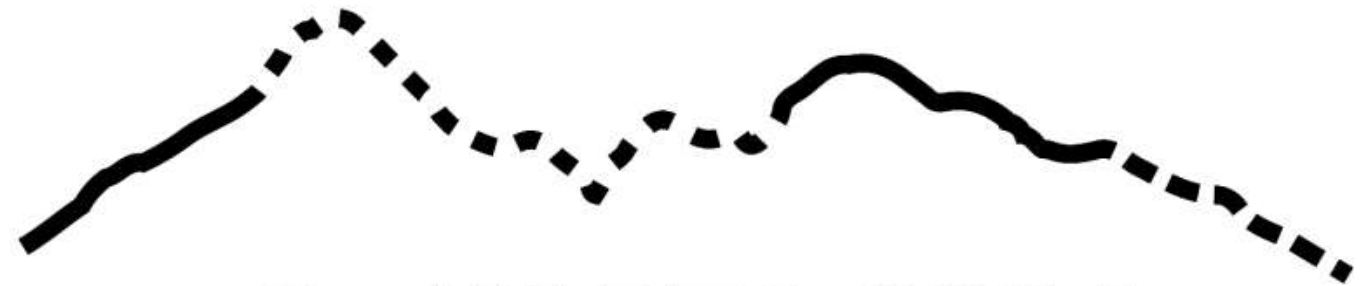


# **TEXTURE-BASED TECHNIQUES FOR VEGETATION CLASSIFICATION IN RIPARIAN ZONES USING HISTORICAL AERIAL ORTHOPHOTOS**

Afzali, Hamid, M.Sc.

Rusnák, Miloš, Mgr., PhD.

Opravil, Šimon, Mgr.



**— G<sub>Eo</sub>KARTO 2024**

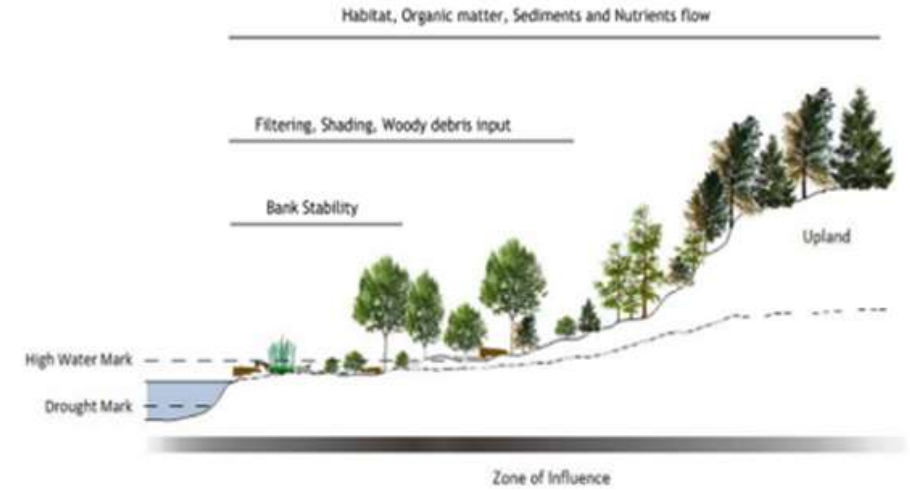
**5 - 6 SEPTEMBER**



# Introduction

## ➤ Riparian zone

- Biodiversity
- Water Resources
- Water Quality
- Soil Conservation
- Fauna and Flora
- Flood Hazards



*Clerici Nicola, et al, 2011*

## ➤ Historical Aerial Orthophotos

- Unique source of historical information
- Wide Area Coverage
- Cost-effective
- High Spatial Resolution



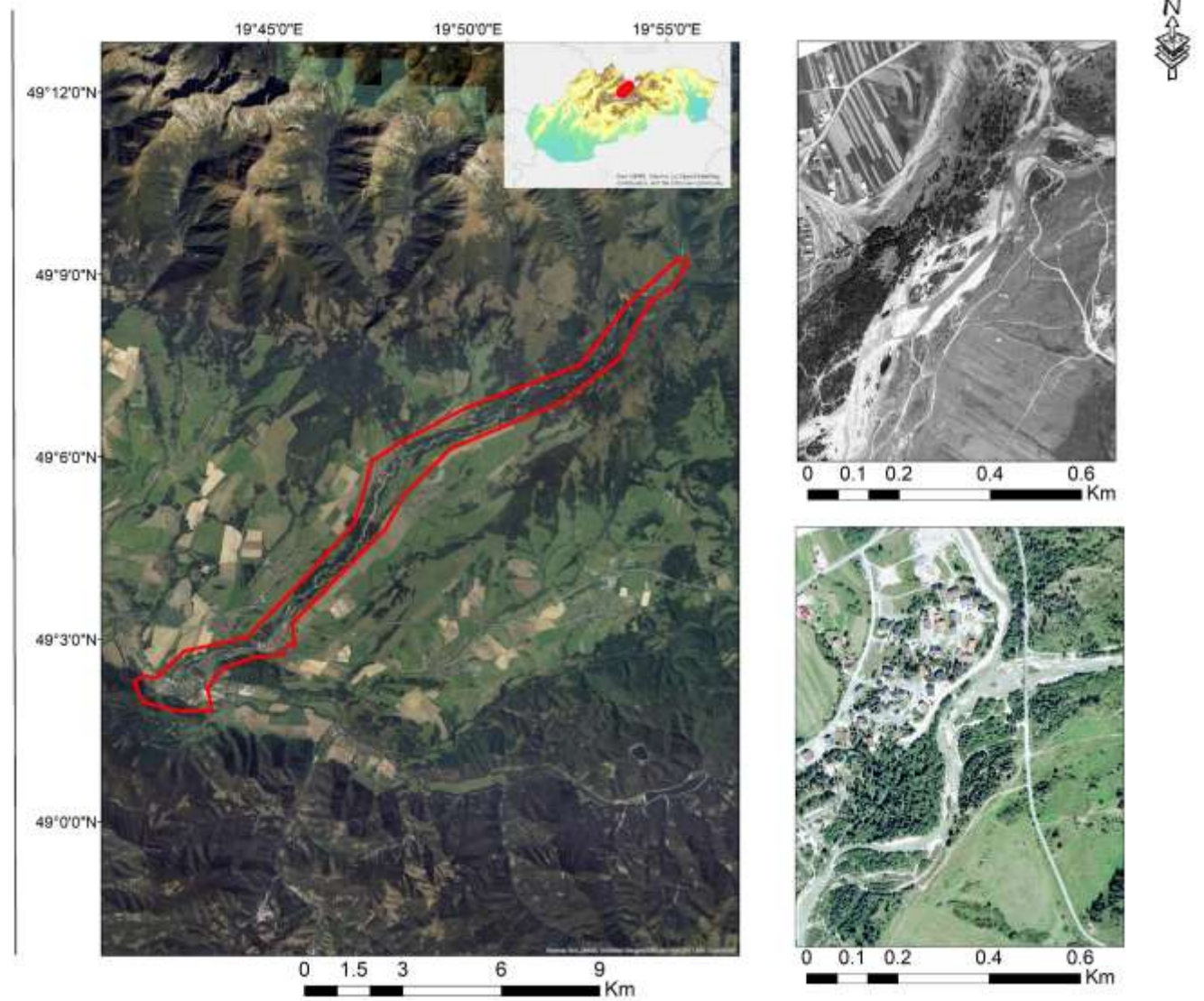
# Study Area

## Bela River

- The largest right tributary of the upper Váh River
  - 23.60Km long
  - The catchment area amounts to 244 km<sup>2</sup>
- Kidova et al, 2017*

## Dataset

Gray scale Orthophotos	RGBN
<ul style="list-style-type: none"><li>• <b>1949</b> , 0.5 m</li><li>• <b>1961</b> , 0.3 m</li><li>• <b>1973</b> , 0.3 m</li><li>• <b>1986</b> , 0.5 m</li><li>• <b>1992</b> , 0.5 m</li></ul>	<ul style="list-style-type: none"><li>• <b>2002</b> , 0.5 m</li><li>• <b>2006</b> , 0.4 m</li><li>• <b>2009</b> , 0.25 m</li><li>• <b>2012</b> , 0.25 m</li><li>• <b>2015</b> , 0.2 m</li><li>• <b>2018</b> , 0.2 m</li><li>• <b>2022</b> , 0.2 m</li></ul>



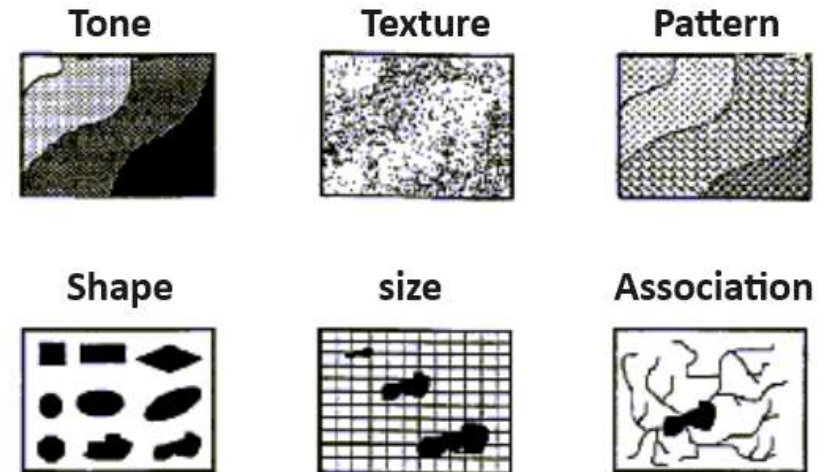
# Historical Images

## ➤ Traditional use



- **Government agencies**
- **Lawyers**
- **Land surveyor**
- **LULC Mapping and Cartography**
- **Military**
- **Archaeology**

## Visual Image Interpretation



# Historical Images

## Digital Image Processing

### ➤ Modern use



- **Gray-tone spatial dependencies**
- **Statistical properties of the intensity histogram**
- **Spatial relationship**

0	0	0	3	3	7	7
0	0	0	3	3	7	7
0	0	0	3	5	5	5
0	0	0	5	5	5	2
0	0	2	2	2	2	2
1	1	2	2	2	2	2
1	1	2	2	2	2	2

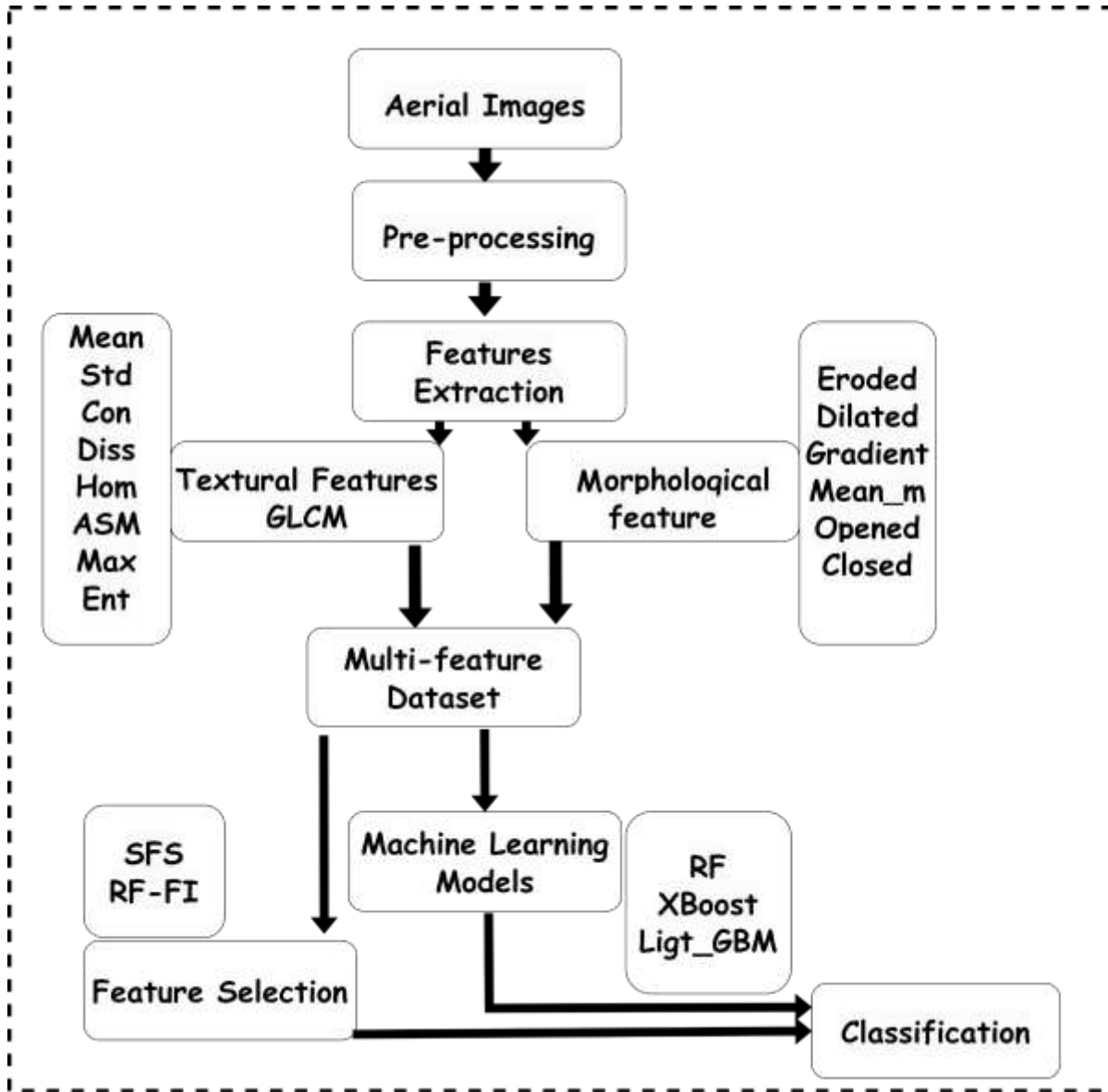
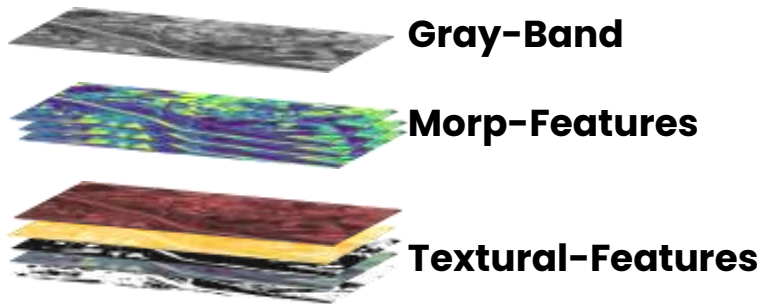
$$\text{Correlation} = \sum_i \sum_j \frac{p(i,j) [(i - \mu_i)(j - \mu_j)]}{\sigma_i \sigma_j}$$

$$\text{Energy} = \sum_i \sum_j p(i,j)^2$$

$$\text{Homogeneity} = \sum_i \sum_j \frac{p(i,j)}{1 + |i - j|}$$

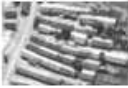

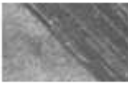









$$\text{Contrast} = \sum_i \sum_j (i - j)^2 p(i,j)$$

# Methodology

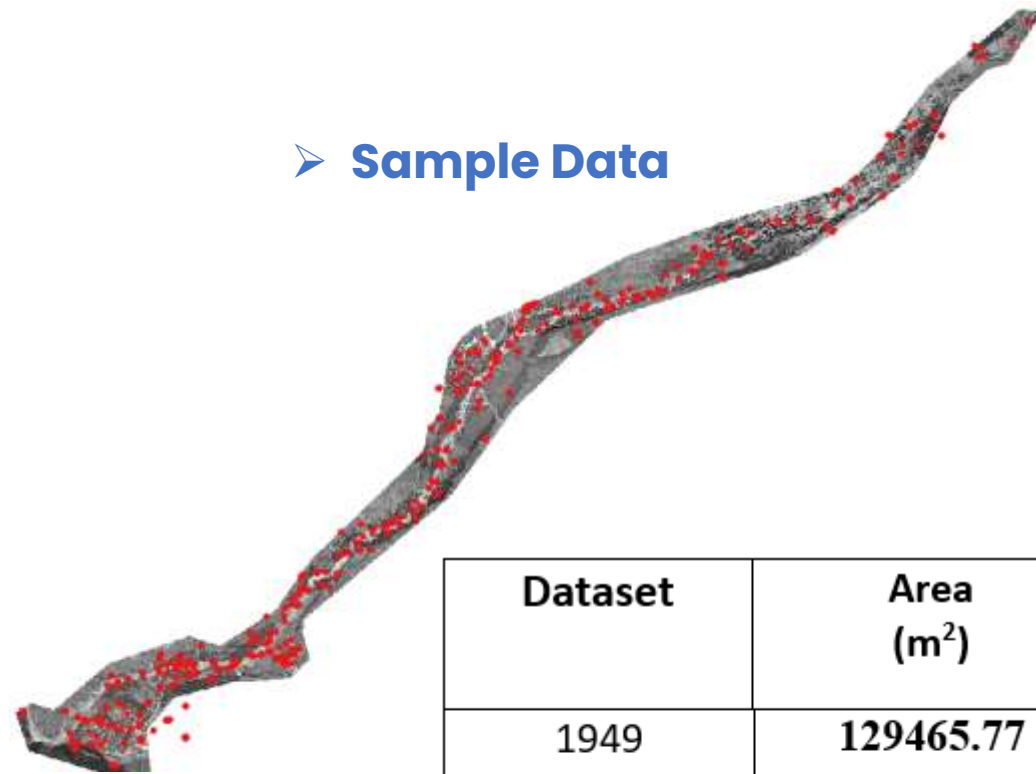


# Results

## ➤ Class definition

Class Name	Definition	B&W	RGB
Artificial	Areas that changed by human activities, such as urban developments, roads		
Cropland	Regions used for agricultural purposes, including fields where crops, cultivated		
Water	Natural or artificial bodies of water		
<u>Bare-land</u>	Exposed land surfaces with no vegetation		
<u>Grass-land</u>	Areas dominated by grasses and other low vegetation		
Forest	Regions covered by dense tree		

## ➤ Sample Data

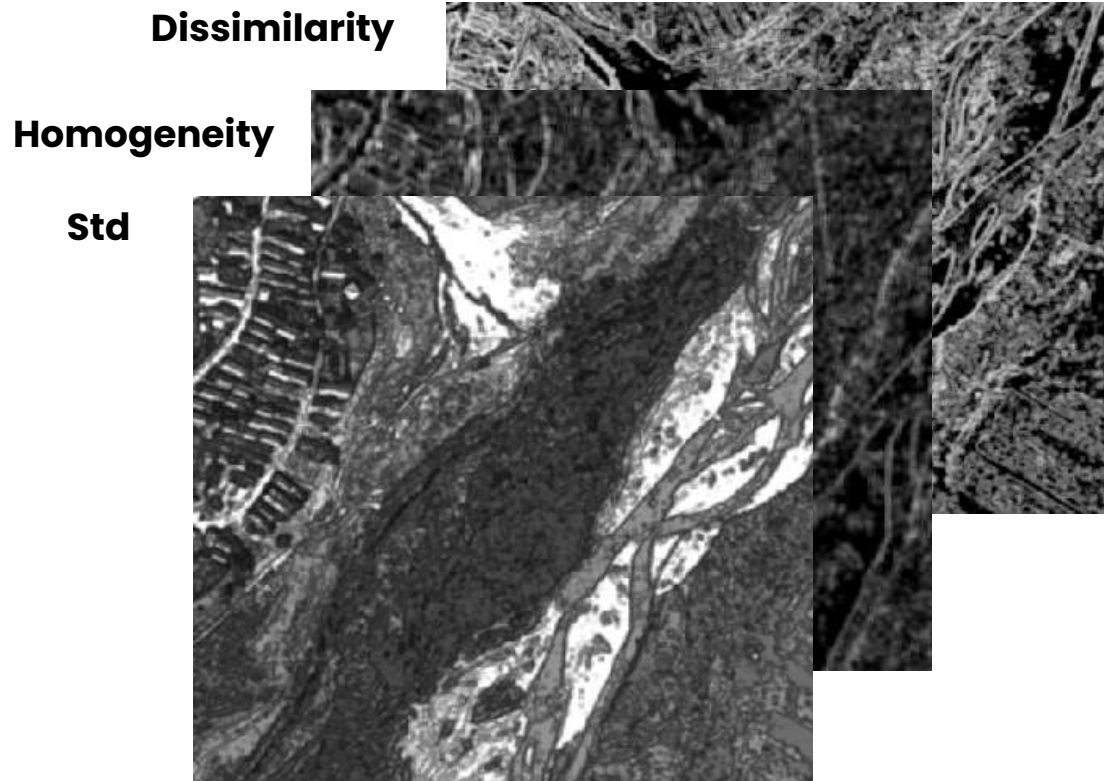


Dataset	Area (m <sup>2</sup> )
1949	<b>129465.77</b>
1961	<b>128831.95</b>
1973	<b>127969.25</b>
1986	<b>127095.02</b>
1992	<b>127944.51</b>

# Results

## ➤ Feature Extraction

### GLCM-Feature

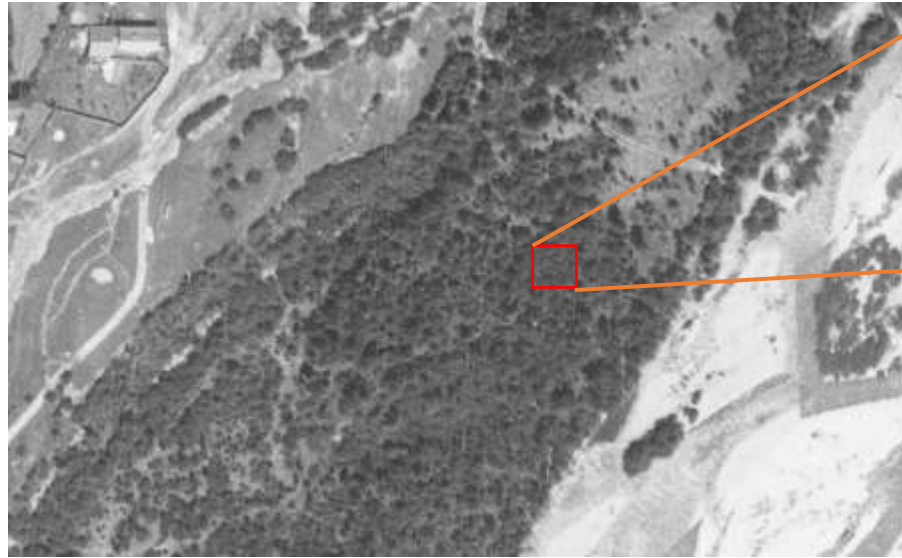


### Morphological -Feature

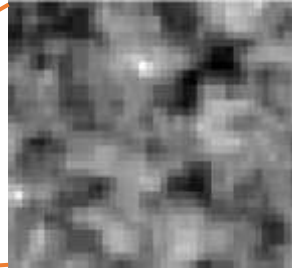




# Results



**Gray-Band**



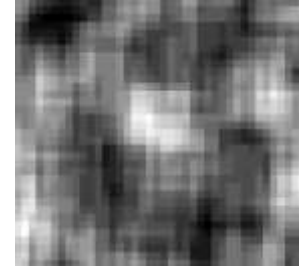
**mean\_glc**



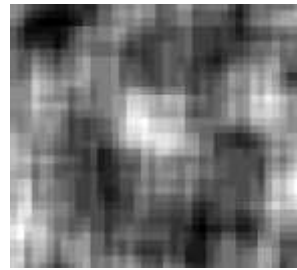
**std**



**con**



**dis**



**Hom**



**asm**



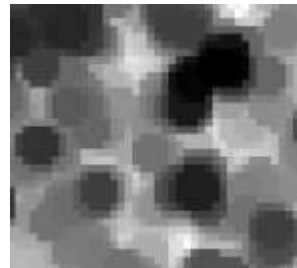
**max**



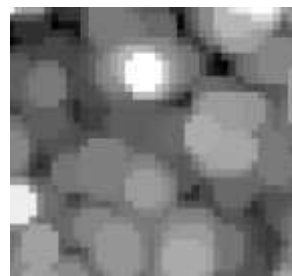
**ent**



**Eroded**



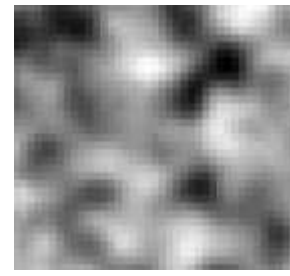
**Dilated**



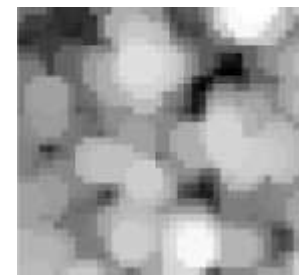
**Gradient**



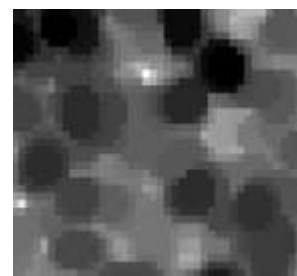
**Mean-Mor**









**Opened**



**Closed**



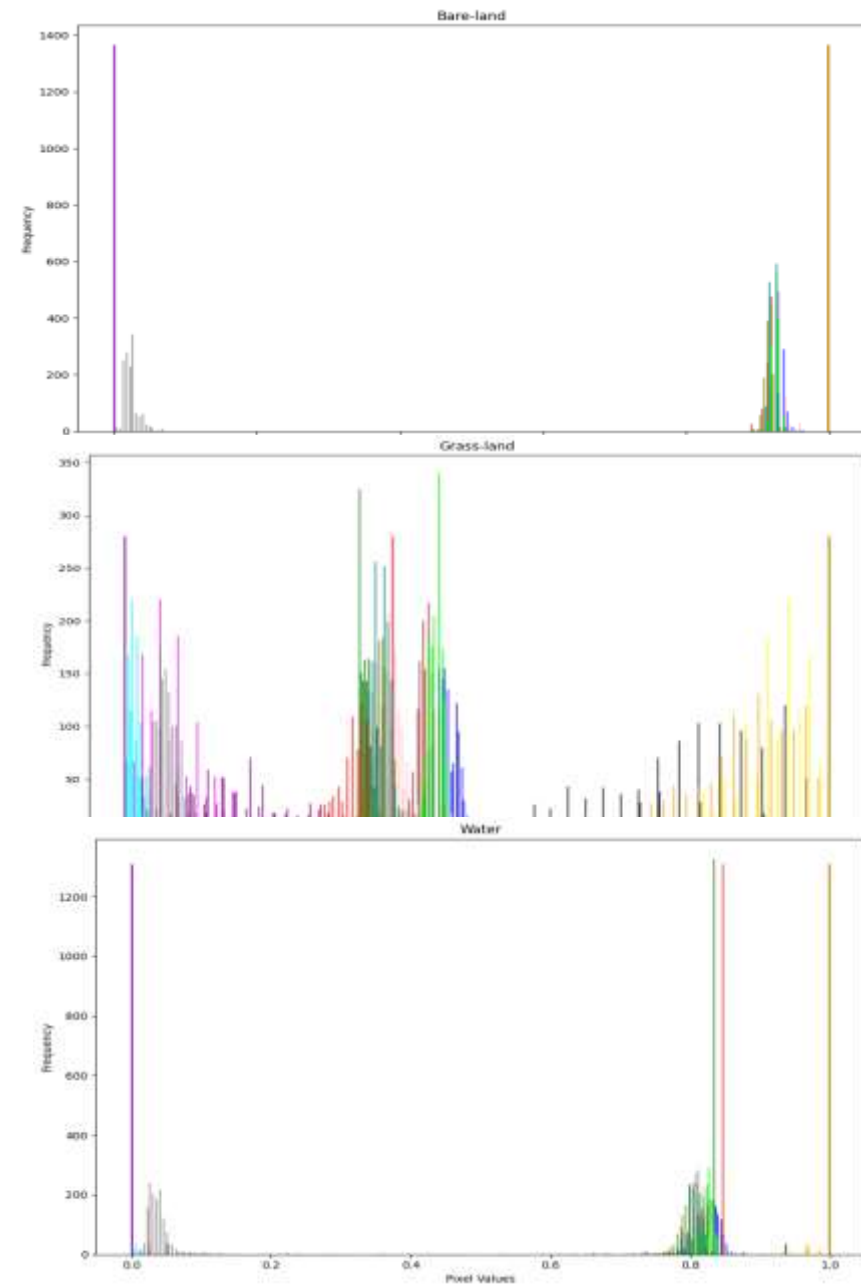
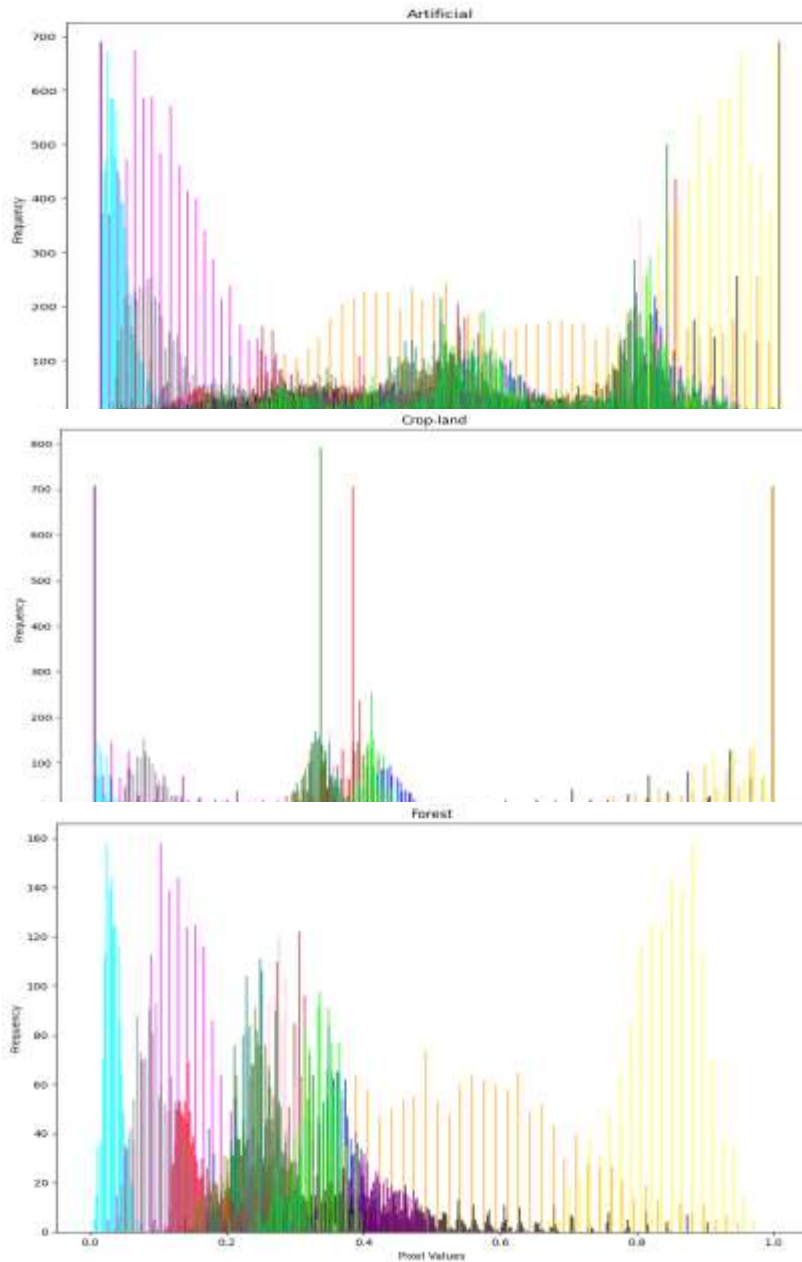
# Results

<b>GLCM</b> (40*40 Pixel Object Level=256, Horizontal)		<b>Contrast</b>	<b>Dissimilarity</b>	<b>Homogeneity</b>	<b>Correlation</b>
Artificial		<b>3022.723</b>	26.333	0.145	0.585
Cropland		2896.085	15.82	0.225	-0.04
Water		3746.689	<b>49.411</b>	<b>0.027</b>	0.132
Bare-land		2925.122	13.847	<b>0.36</b>	<b>-0.023</b>
Grass-land		2427.002	19.905	0.078	0.057
Forest		2573.538	31.037	0.084	0.445

# Results

## ➤ Histogram

- img
- mean\_glcm
- std
- con
- dis
- hom
- asm
- max
- ent
- eroded
- dilated
- gradient
- mean\_morph
- opened
- closed



# Results

## ➤ Random Forest

```
rf_params = {  
    'n_estimators': [ 500],  
    'criterion': ['entropy'],  
    'max_depth': [None, 10],  
    'min_samples_split': [ 5],  
    'min_samples_leaf': [ 4],  
}
```

## 5. GridSearchCV

```
start_time = time.time()  
grid_search = GridSearchCV(estimator=model, param_grid=rf_params, cv=5, scoring='accuracy', verbose=2, n_jobs=-1)  
grid_search.fit(X_train_smote, y_train_smote)
```

```
end_time = time.time()  
execution_time = end_time - start_time  
print("Execution time:", execution_time / 60, "Minutes")  
# Get the best model  
best_model = grid_search.best_estimator_
```

```
Fitting 5 folds for each of 2 candidates, totalling 10 fits  
Execution time: 31.626696328322094 Minutes
```

```
y_pred1 = best_model.predict(X_test)  
accuracy = accuracy_score(y_test, y_pred1)  
print(f'Best Model Accuracy: {accuracy}')
```

```
# Print best parameters  
print('Best parameters found by grid search are:', grid_search.best_params_)
```

```
Best Model Accuracy: 0.9006016847172081  
Best parameters found by grid search are: {'criterion': 'entropy', 'max_depth': None, 'min_samples_leaf': 4, 'min_samples_split': 5, 'n_estimators': 500}
```

# Results

## ➤ Model performance

### Random Forest

#### Gray-Band

```
Execution time: 6.194768865903218 Minutes
Model Accuracy: 0.5260328920978741
Classification Report:
      precision    recall  f1-score   support

     1       0.60     0.18     0.27     3112
     2       0.30     0.36     0.33     1436
     3       0.16     0.44     0.23      543
     4       0.51     0.72     0.60     1541
     5       0.38     0.41     0.39     1960
     6       0.79     0.83     0.81     3114
     7       0.98     1.00     0.99      759

 accuracy                   0.53     12465
 macro avg       0.53     0.56     0.52     12465
 weighted avg    0.57     0.53     0.51     12465
```

#### 15-Band Dataset

```
Execution time: 72.08796071211496 Minutes
Model Accuracy: 0.9006016847172081
Classification Report:
      precision    recall  f1-score   support

     1       0.92     0.88     0.90     3092
     2       0.82     0.82     0.82     1487
     3       0.78     0.90     0.84      501
     4       0.90     0.92     0.91     1530
     5       0.87     0.86     0.86     2032
     6       0.95     0.95     0.95     3102
     7       1.00     1.00     1.00      721

 accuracy                   0.90     12465
 macro avg       0.89     0.90     0.90     12465
 weighted avg    0.90     0.90     0.90     12465
```

#### SFS (7 features)

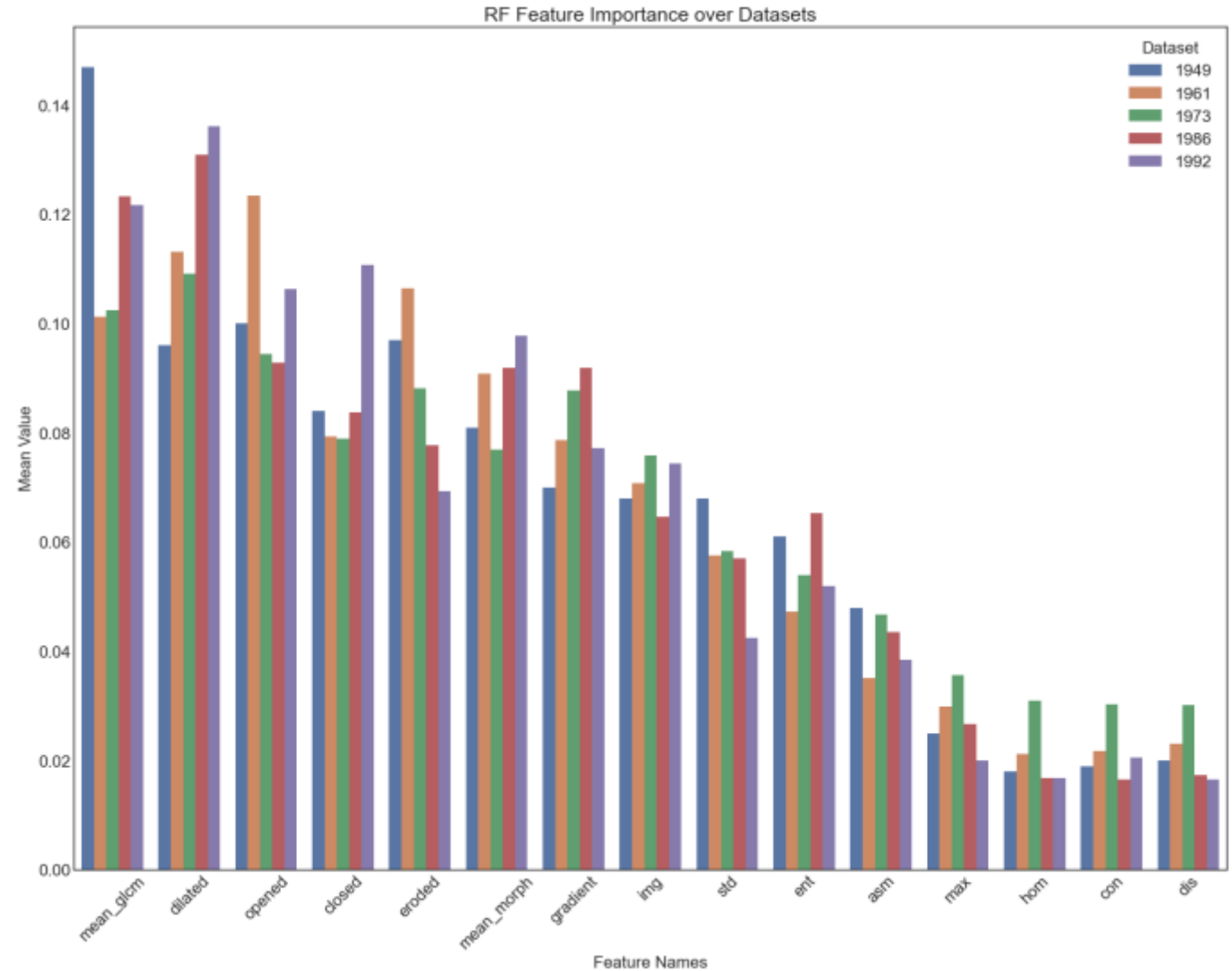
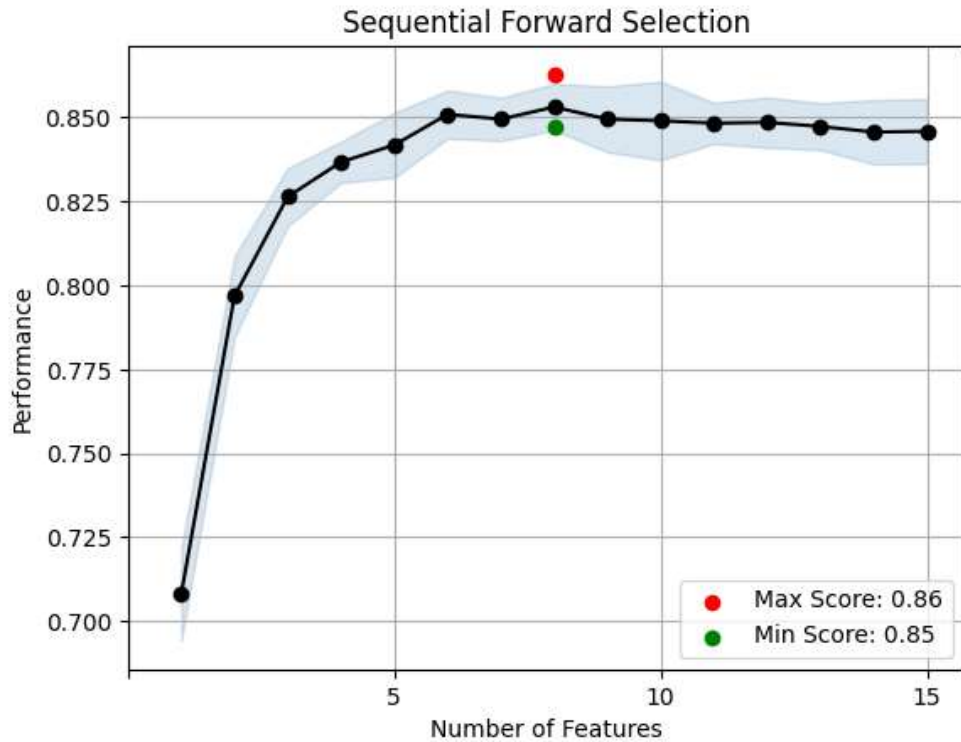
```
Execution time: 10.064293356736501 Minutes
Model Accuracy: 0.8835940633774568
Classification Report:
      precision    recall  f1-score   support

     1       0.90     0.86     0.88     3119
     2       0.78     0.81     0.79     1454
     3       0.73     0.86     0.79      533
     4       0.87     0.90     0.88     1425
     5       0.85     0.84     0.85     2028
     6       0.95     0.94     0.94     3148
     7       1.00     1.00     1.00      758

 accuracy                   0.88     12465
 macro avg       0.87     0.89     0.88     12465
 weighted avg    0.89     0.88     0.88     12465
```

# Results

## ➤ Feature Selection



# Results

## ➤ Model Performance

### OS specification:

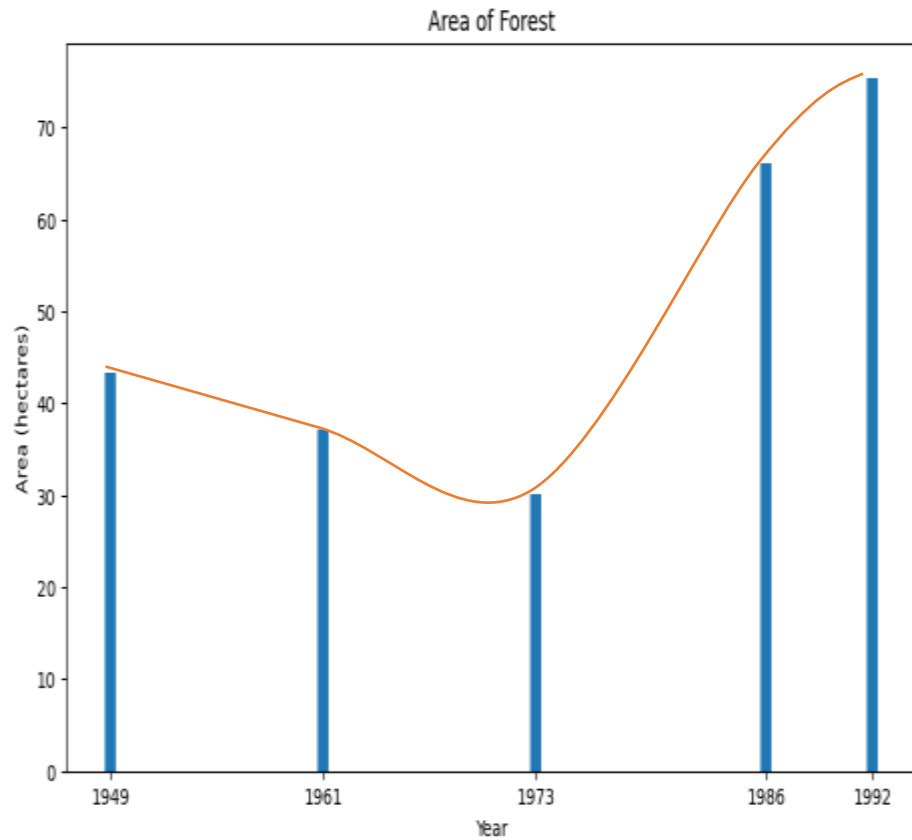
- ❑ 12th Gen Intel(R) Core(TM) i7-12700K  
3.60 GHz
- ❑ 128 GM RAM

## Model Performances on 15-Band dataset

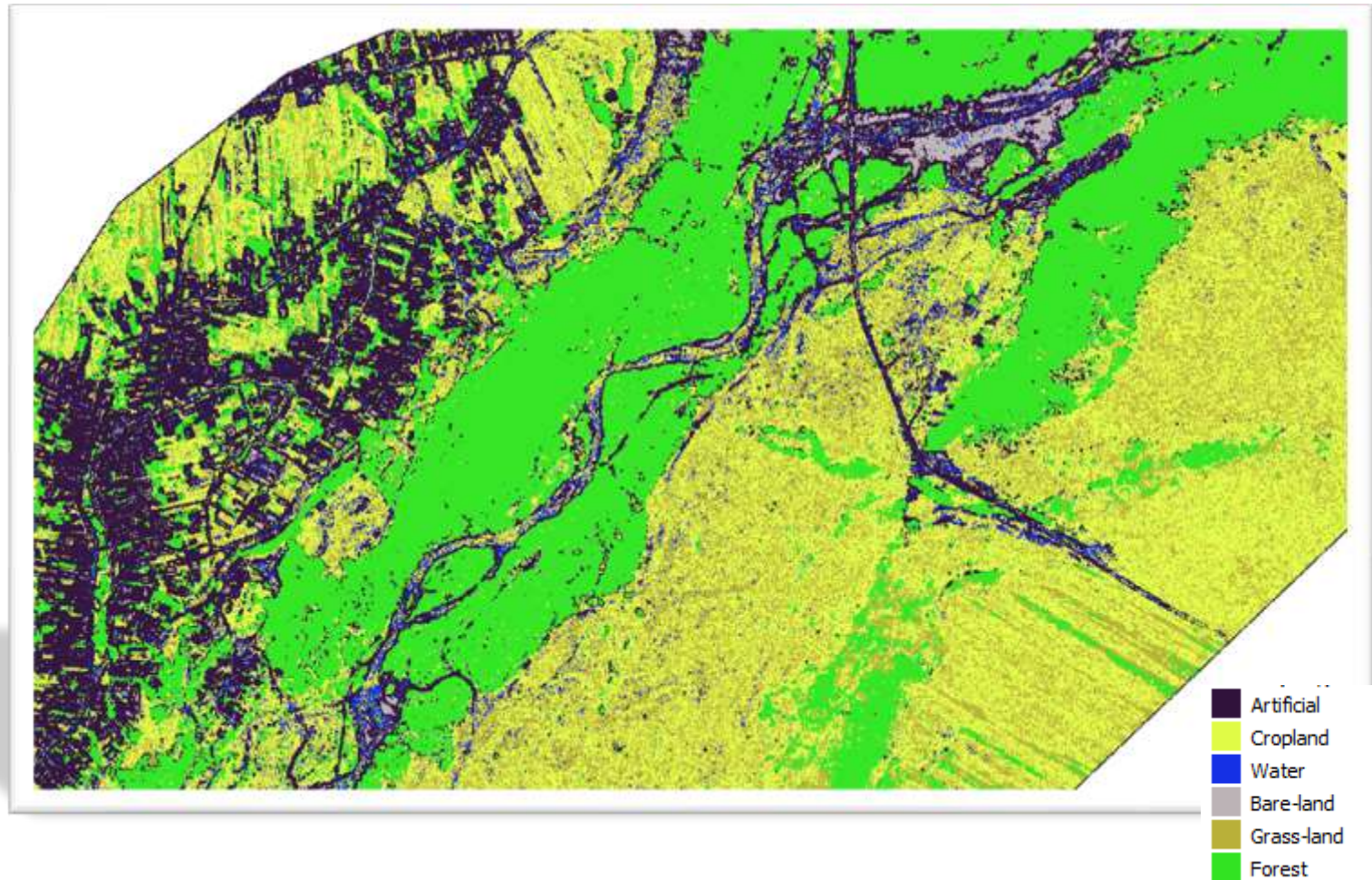
Classifier	Hyperparameters	Value	Model Performance		
			MA (%)	F1 (%)	AET(Minute)
RF	n_estimators criterion max_depth min_samples_split min_samples_leaf	500 entropy None 4 5	90.0	89.0	379
LightGBM	boosting_type learning_rate num_leaves n_estimators max_depth objective	gbdt 0.2 100 800 10 multiclass	78.0	76.0	425
XBoost	n_estimators max_depth gamma eta max_leaves subsample colsample_bytree	800 20 0.09 0.2 80 0.5 0.9	77.8	75.0	53

# Results

## ➤ RF Classification



1992





# Main Takeaways

- Incorporating GLCM and Geomorphological features significantly improves the classification accuracy
- Feature selection methods, including RF importance scores and SFS, are important in reducing data complexity and dimensionality
- We observed significant model accuracy with the RF compared to another models
- Despite advancements, issues such as shadow effects and radiometric differences in black-and-white orthophotos continue to pose challenges



**THANK YOU FOR YOUR ATTENTION**

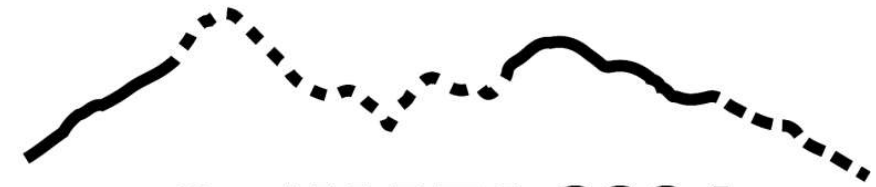
**TEXTURE-BASED TECHNIQUES FOR VEGETATION  
CLASSIFICATION IN RIPARIAN ZONES USING  
HISTORICAL AERIAL ORTHOPHOTOS**

 [github.com/hamidafzal/RF\\_aerialIMG](https://github.com/hamidafzal/RF_aerialIMG)

Afzali, Hamid,  [hamid.afzali@savba.sk](mailto:hamid.afzali@savba.sk)

Rusnák, Miloš, Mgr., PhD.

Opravil, Šimon, Mgr.



**— G<sub>Eo</sub>KARTO 2024**

**5 - 6 SEPTEMBER**