Wetland Permanence Classification Using Multi-Temporal Sentinel-2 Imagery and Coefficient of Variation Analysis Brookings County, South Dakota

Image Bhattarai

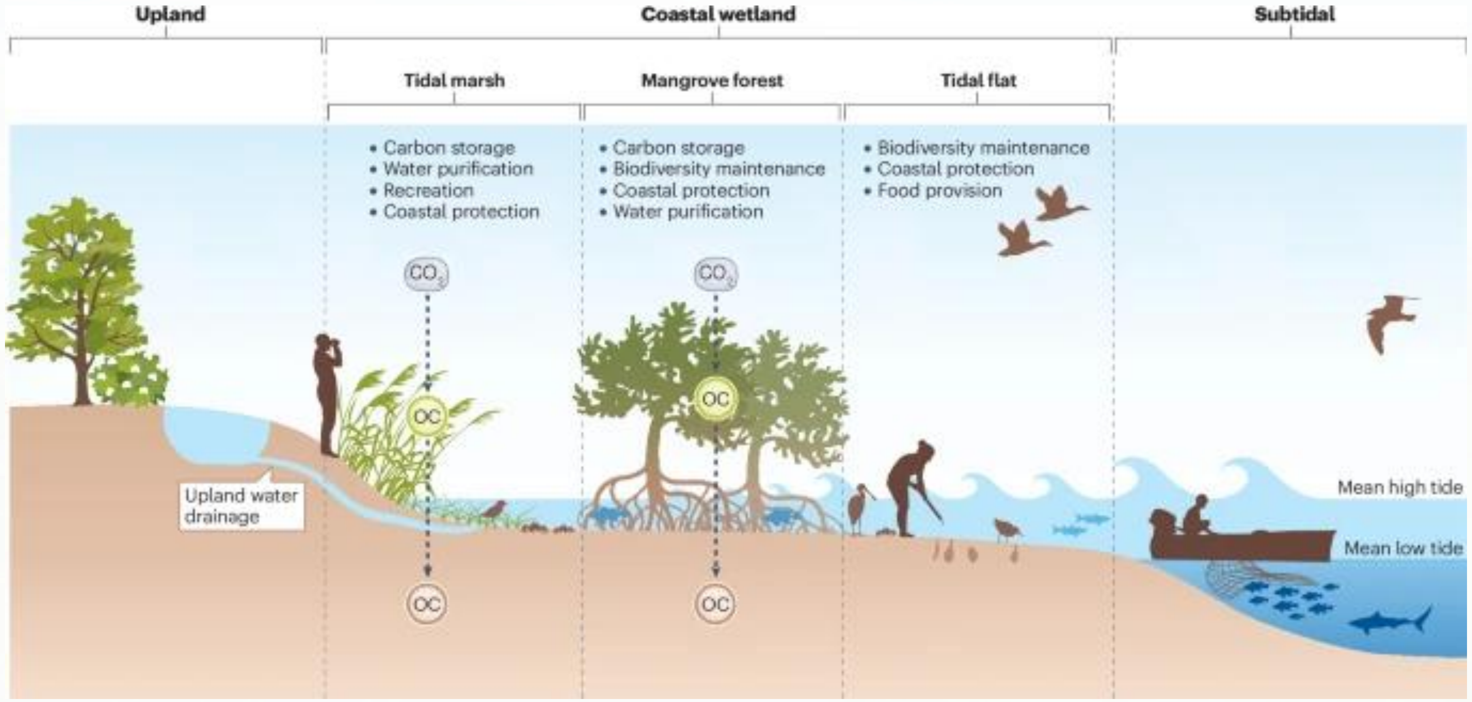
Agriculture Remote Sensing Final Project

Course Instructor: Maitiniyazi Maimaitijiang

Introduction & Problem Statement

CHALLENGES:

- Wetlands provide critical ecosystem services but face ongoing loss.
- Agricultural expansion in threatens wetland integrity
- Traditional field surveys are time-consuming and expensive
- Need for efficient, repeatable wetland classification methods



Why Hydroperiod Matters:

- Hydroperiod = duration and frequency of water presence
- Determines habitat suitability, water quality functions, and conservation value
- Permanent vs. seasonal wetlands support different species and serve different functions

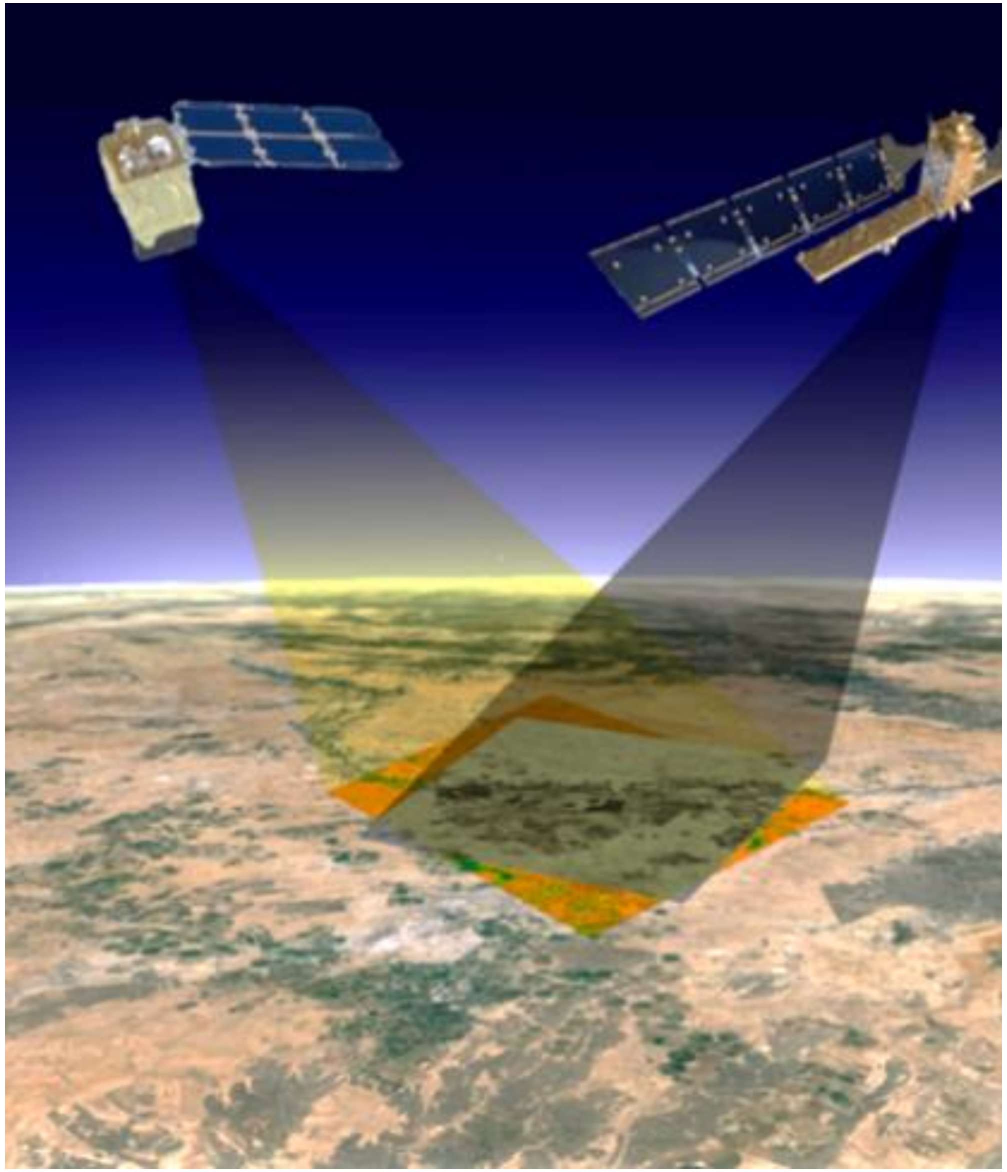
Research Objectives

➢ **Primary Research Questions:**

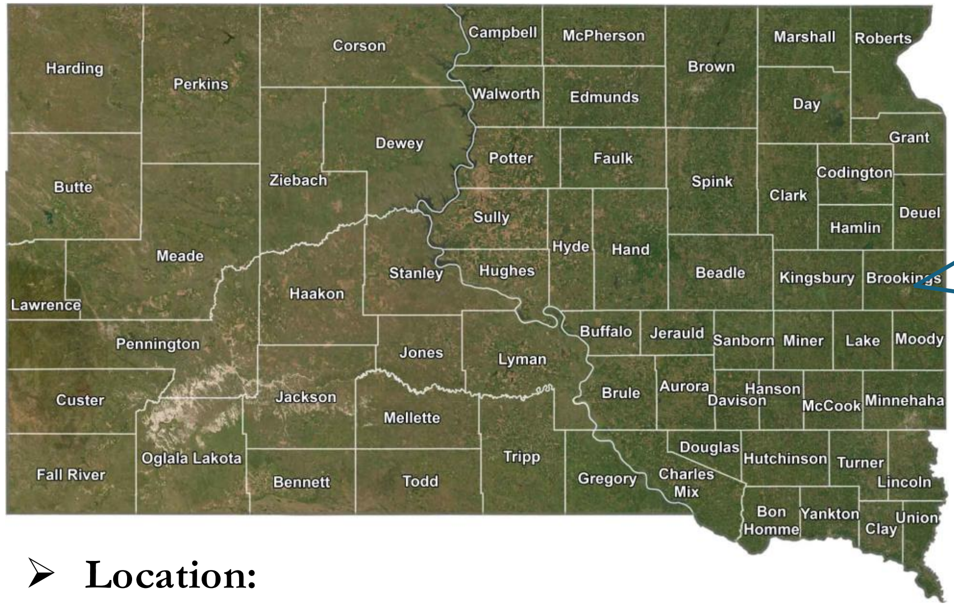
- Can temporal variability in NDWI (measured by Coefficient of Variation) effectively distinguish wetland hydroperiod types?
- What is the spatial distribution and characteristics of permanent, vegetated, and seasonal wetlands in Brookings County?
- Are wetland classifications temporally stable across multiple years (2022-2024)?

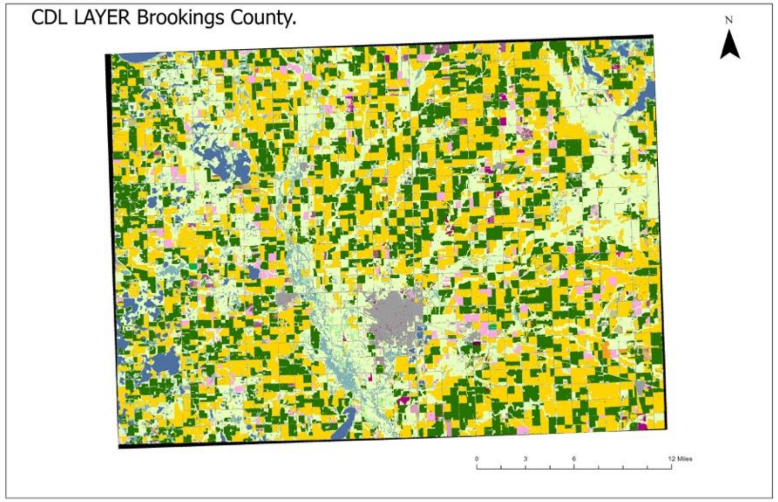
➢ **Expected Outcomes:**

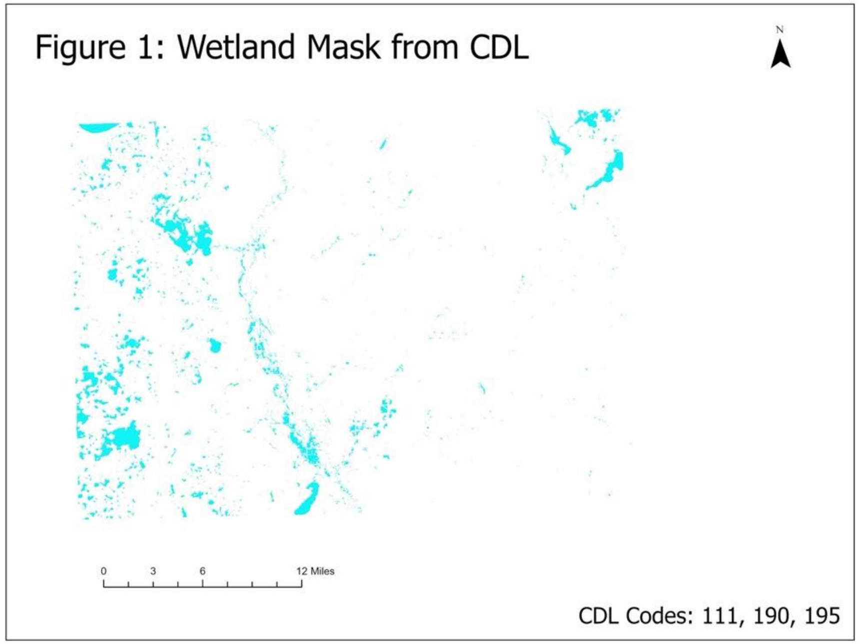
- Automated classification of wetland types based on hydroperiod
- Quantification of wetland fragmentation patterns



Study Site







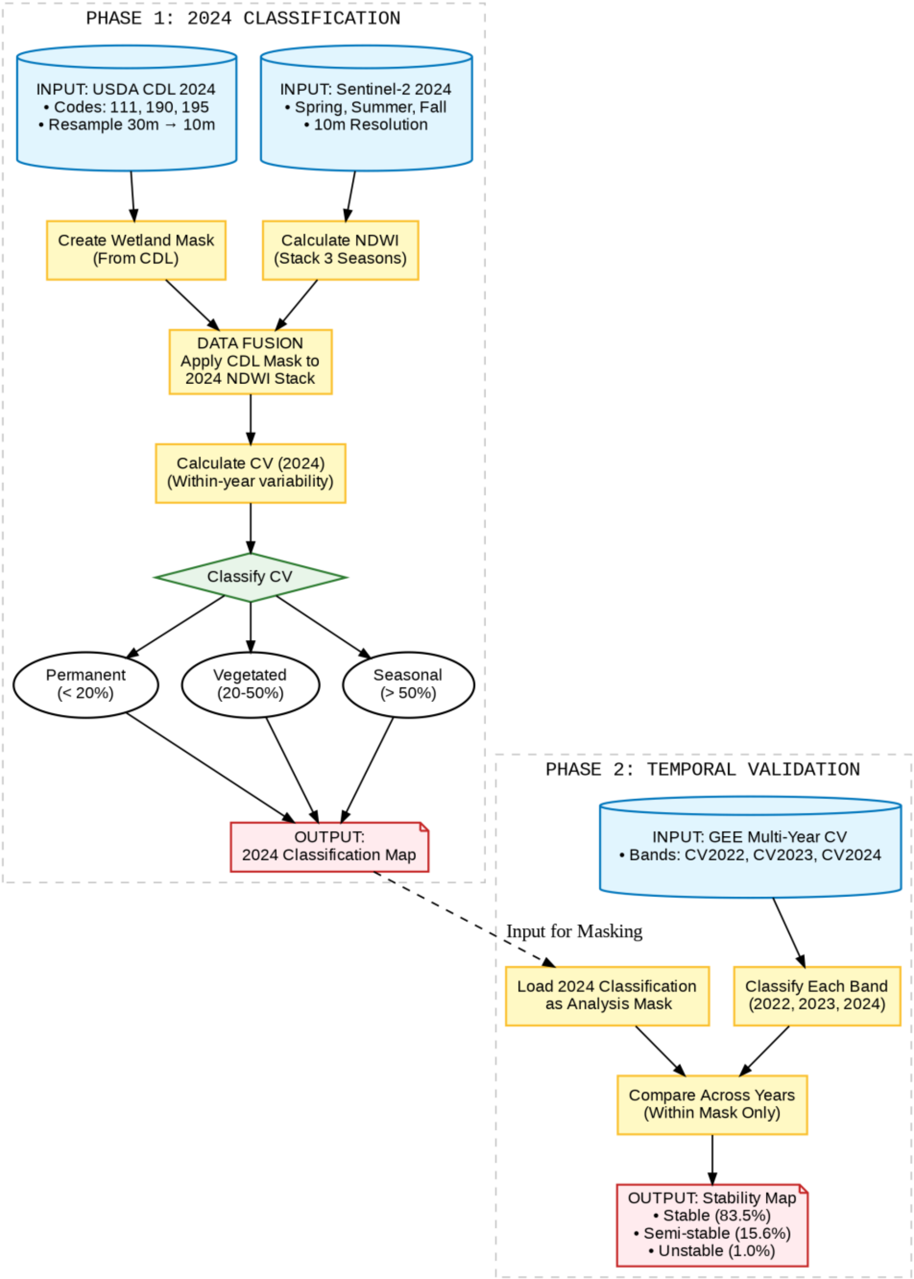
- **Location:**

•Eastern South Dakota
•Prairie Pothole Region
•Area: ~1,700 km²

- **Characteristics:**

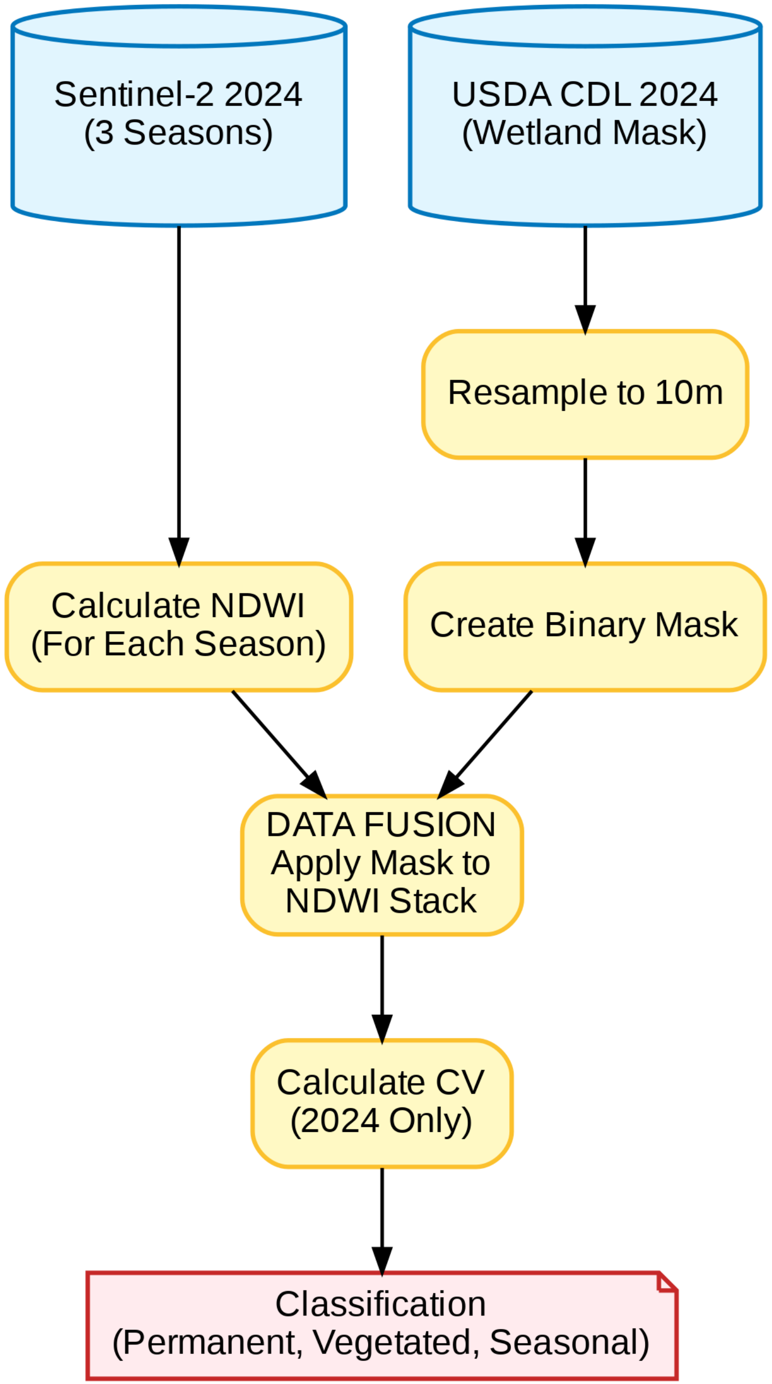
•Continental climate
•Mean annual precipitation: 610 mm
•Dominant land use: Agriculture (corn, soybeans)
•Wetland type: Glacially-formed depressions

Data Sources



Data Pre-Processing Workflow

- Pre-processing involved cloud masking and seasonal compositing using median values to remove outliers.
- Also applied a 2-pixel erosion buffer to the CDL mask to eliminate mixed pixels at wetland-upland boundaries, improving classification accuracy.



Methods –Variable Extraction

$$\text{NDWI} = \frac{\text{NIR - SWIR}}{\text{NIR + SWIR}}$$

$$\text{NDWI} = \frac{\text{B8A - B11}}{\text{B8A + B11}}$$

$$\text{CV} = \frac{\sigma}{|\mu|} \times 100$$

where:
σ = Standard deviation of NDWI (3 seasons)
μ = Mean NDWI (3 seasons)

Figure 2: NDWI Coefficient of Variation (CV) Map

Feature	NIR Band (Reflection)	SWIR Band (Absorption)	NDWI (Gao) Result
Vegetated Wetland	**High Reflection** (from healthy leaves)	**High Absorption** (from water inside leaves)	**High Positive Value** (e.g., +0.4244)
Open Water	**High Absorption** (water absorbs NIR)	**High Absorption** (water absorbs SWIR)	**Low Positive Value** (e.g., +0.0595)

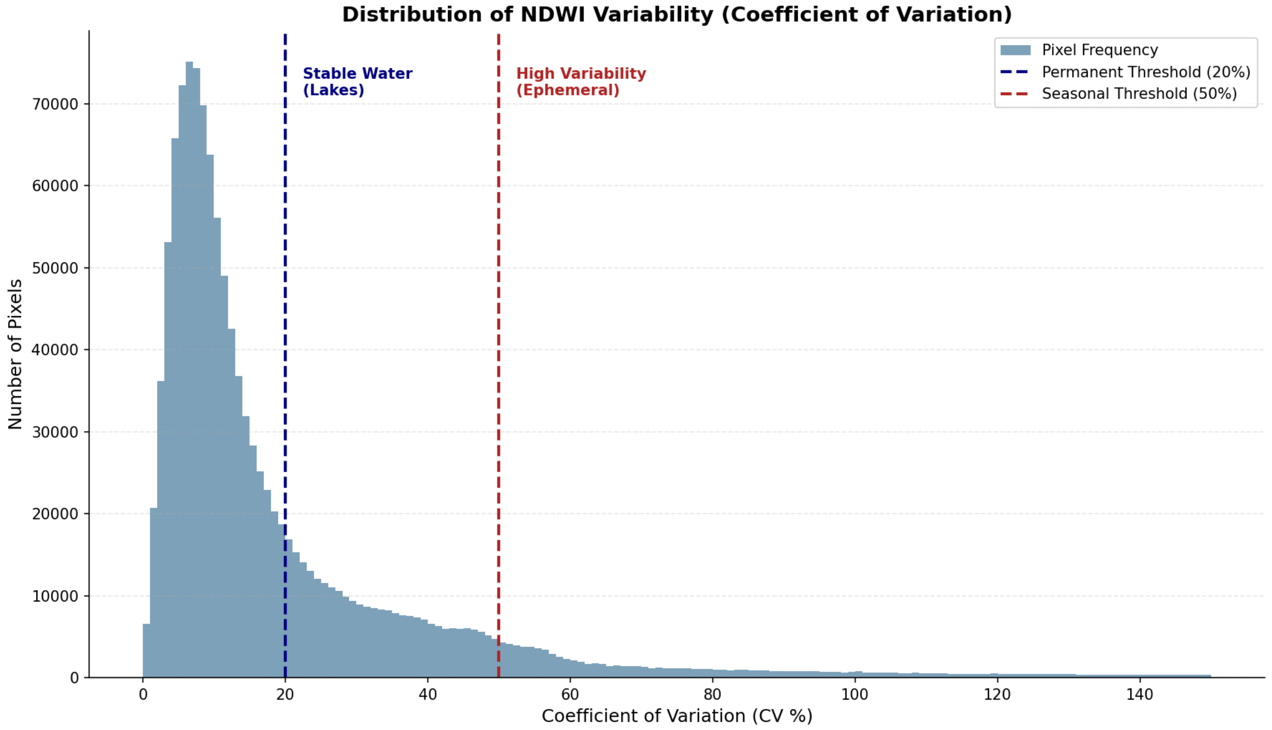
Rationale:
- •CV quantifies temporal variability
- •Low CV → Stable hydroperiod (permanent)
- •High CV → Variable hydroperiod (seasonal)

Methods – Classification Approach

- **Post-Classification Refinement:**
  - Minimum patch size > 0.01 ha (remove single-pixel noise)
  - Patch connectivity: 4-connectivity analysis
  - Edge buffer: 2-pixel erosion applied

Class	CV Threshold	Characteristics	Ecological Interpretation
Permanent	CV < 20%	Stable water presence	Lakes, ponds, perennial marshes
Vegetated	20-50%	Moderate variability	Emergent wetlands (cattails, bulrush)
Seasonal	CV > 50%	High variability	Ephemeral pools, vernal wetlands

Methods: Threshold Justification



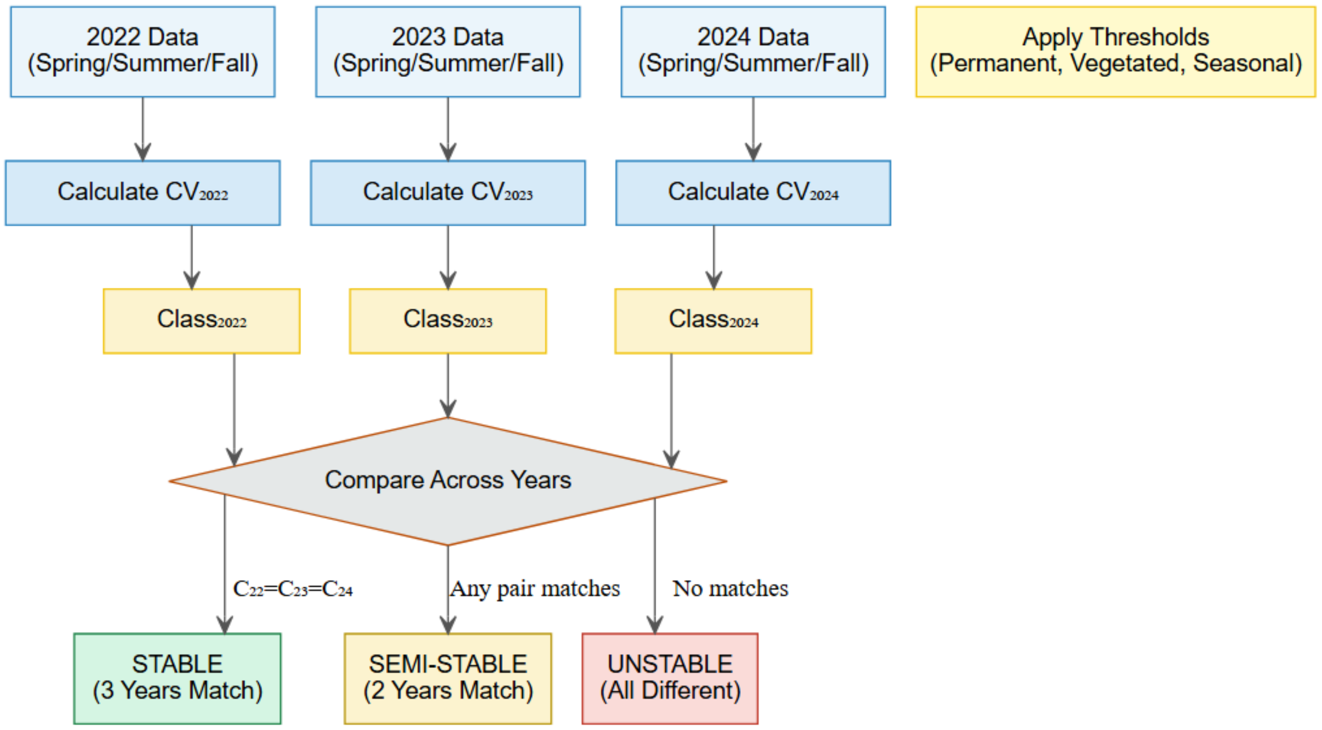
CV Distribution Statistics & Logic

Metric	Value
Median CV	11.57%
Mean CV	21.23%
25th Percentile (Q1)	6.75%
75th Percentile (Q3)	24.41%
Threshold Placement	
• 20% Threshold	Between Median and Q3
• 50% Threshold	Upper Quartile (>Q3)

Methods - Temporal Validation

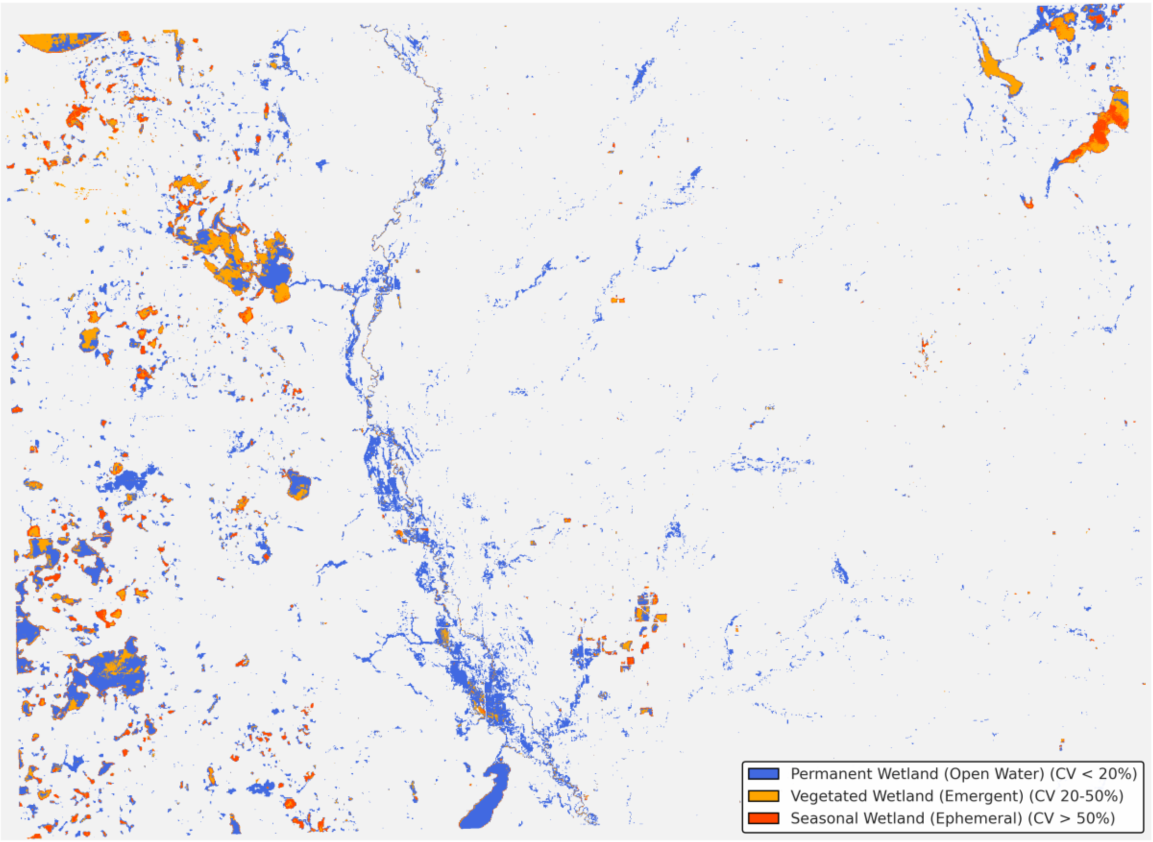
Rationale:

- Tests temporal transferability of CV thresholds
- Validates that 2024 classification captures persistent patterns
- Distinguishes genuine hydrological features from anomalies

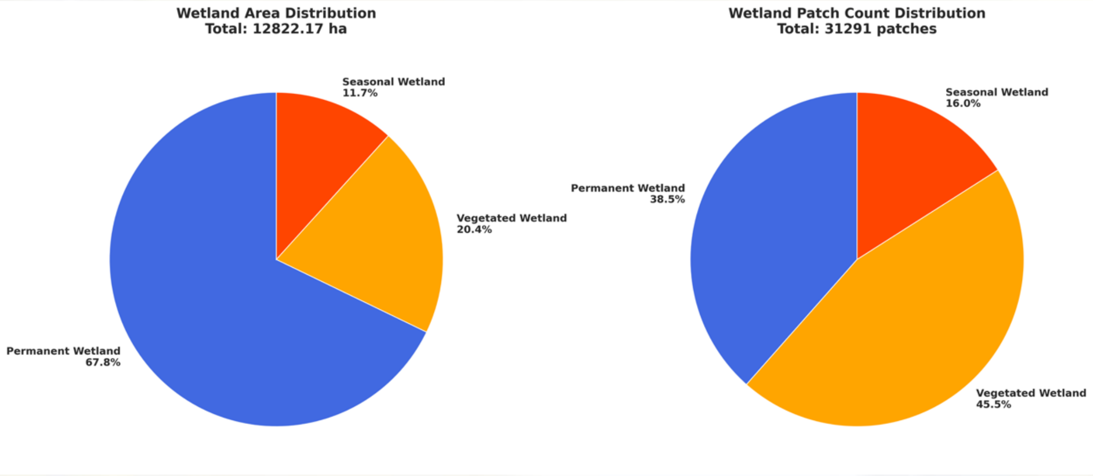


Results - Classification Overview

Figure 3: Wetland Classification Map



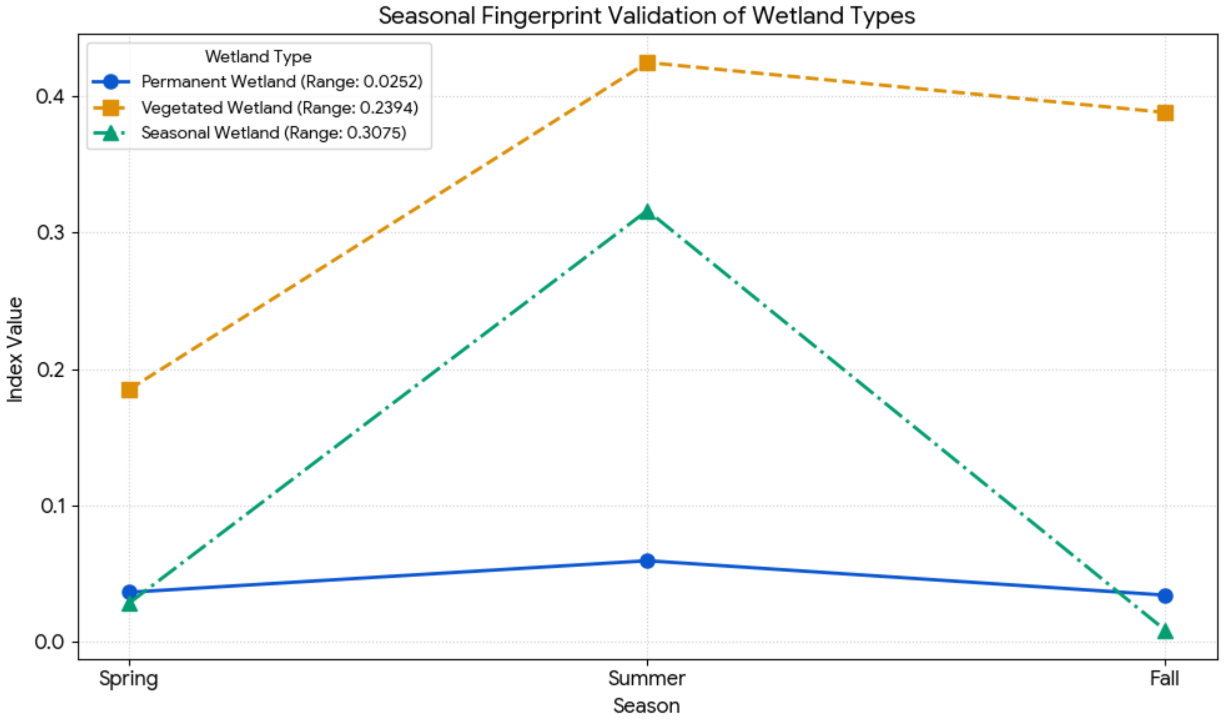
Class	CV Threshold	Area (ha)	Area (%)	Patches	Patch (%)	Mean Size (ha)	Median Size (ha)
Permanent Wetland	CV < 20%	8698.68	67.8	12036	38.5	0.7227	0.0900
Vegetated Wetland	20%-50%	2620.68	20.4	14250	45.5	0.1839	0.0200
Seasonal Wetland	CV > 50%	1502.81	11.7	5005	16.0	0.3003	0.0300

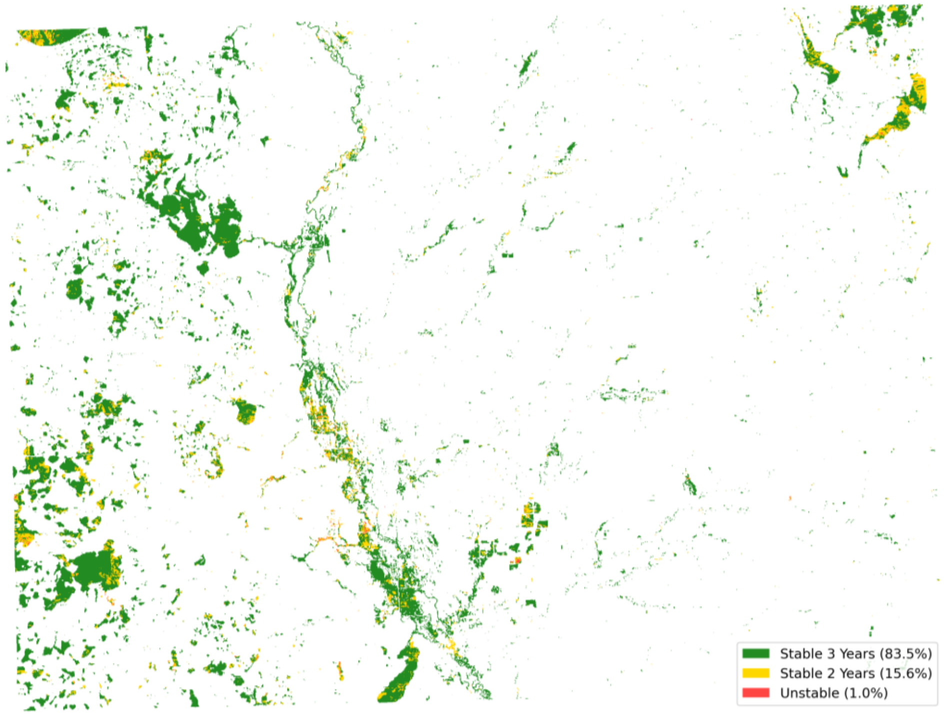


Area vs Patch Distribution
Wetland Fragmentation Patterns

- Permanent wetlands dominate landscape (67.8% of area) BUT 38.5% of patches, and Larger patches (mean 0.72 ha)
- Seasonal Wetlands cover 11.7% of area, and 16.0% of patches having Intermediate size (mean 0.30 ha)
- Extreme fragmentation (31,291 patches)

Results - Validation





Seasonal Fingerprint Validation Table

Class	Spring	Summer	Fall	Range	Interpretation
Permanent	+0.0364	+0.0595	+0.0343	0.0252	✓ Stably low (Water/Inundated)
Vegetated	+0.1850	+0.4244	+0.3878	0.2394	✓ Stably positive (Vegetation)
Seasonal	+0.0285	+0.3160	+0.0085	0.3075	✓ High variance (Ephemeral)

Stability Category	Percentage	Pixel Count	Interpretation
Stable (3 years)	83.5%	719,381	Same class all years
Semi-stable (2 years)	15.6%	134,493	Changed once
Unstable	1.0%	8,621	Highly variable

Discussion - Key Interpretations

➢ **Major Findings:**

1. Permanent Wetlands Dominate but Are Fragmented

- 67.8% of area provides stable year-round habitat
- BUT fragmented into 12,036 patches
- → Reliable water resources exist but connectivity limited

2. CV-Based Classification Is Robust

- 83.5% temporal stability validates methodology
- Seasonal fingerprints match expected behavior
- Thresholds successfully distinguish hydroperiod types

3. Landscape-Scale Fragmentation

- 31,291 patches averaging 0.41 ha
- Historical drainage evident in spatial pattern
- Low functional connectivity despite close proximity

Limitations

1. Lack of Ground Truth Data

- No field-collected validation samples
- Cannot calculate traditional accuracy metrics (overall accuracy, kappa)
- **Mitigation:** Used convergent validation (CDL, temporal stability, seasonal patterns)

2. Resolution Constraints

- 10m pixels may miss very small wetlands (<0.01 ha)
- Mixed pixels at edges (partially mitigated by 2-pixel erosion)
- **Future:** Higher resolution data from CDL

3. CDL Dependency

- Classification extent relies on CDL accuracy
- CDL errors propagate to final results

4. Threshold Generalizability

- CV thresholds (20%, 50%) are regionally calibrated
- May need adjustment for other climates or wetland types

5. Temporal Representativeness

- Analysis covers 2022-2024 (3 years)
- May not capture full climate variability (wet/dry cycles)
- **Ideal:** 5-10 year time series

Conclusion and Future Work

- **Key Contributions:**
- Demonstrated automated, repeatable wetland classification using free satellite data
- Quantified fragmentation patterns in agricultural landscape

Future Work:

- Field validation campaign for quantitative accuracy assessment
- Regional expansion across Prairie Pothole Region
- Long-term climate change impact assessment

References

- **Data Sources:**
- European Space Agency (ESA). Sentinel-2 MSI Level-2A Surface Reflectance. Accessed via Google Earth Engine, 2024.
- USDA National Agricultural Statistics Service (NASS). Cropland Data Layer, 2024. https://nassgeodata.gmu.edu/CropScape/
- **Methodology References:**
- Gao, B. C. (1996). NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sensing of Environment*, 58(3), 257-266.
- Jones, J. W. (2015). Efficient wetland surface water detection and monitoring via Landsat: Comparison with in situ data from the Everglades Depth Estimation Network. *Remote Sensing*, 7(9), 12503-12538.
- Ozesmi, S. L., & Bauer, M. E. (2002). Satellite remote sensing of wetlands. *Wetlands Ecology and Management*, 10(5), 381-402.
- Xu, H. (2006). Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. *International Journal of Remote Sensing*, 27(14), 3025-3033.
- **Software & Tools:**
- Google Earth Engine (cloud-based geospatial analysis platform)
- Python 3.9 (rasterio, numpy, scipy, matplotlib libraries)

Questions