Crop Vigorous limitation under Soil Salinity Variation Using Remote Sensing Indices in Arid Environments

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Overview

- Introduction
- Objectives
- Study area
- Methodological framework
- Findings
- Conclusions
Introduction

Remote Sensing Data

- Satellite images offer a large amount of data that could be analyzed
- Convenient source to perform several vegetation indices
- Spectral reflectance variabilities tend to differentiate between different vegetation characteristics based on crop water relationships

Spectral Vegetation Indices

- Spectral vegetation indices are mathematical combinations of different spectral bands mostly in the visible and near-infrared regions of the electromagnetic spectrum
- Vegetation activities can be measured comprehensively through semi-analytical methods of spectral band ratios
Introduction

Excessive irrigation

Poor drainage

Soil Salinization
Objectives

Soil Salinity Indices

Spectral Vegetation Indices

Regression Analysis

Find the correlation between Soil Salinity indices and Hydrological Drought Indices

Conservation of natural resources
Agriculture in Wadi Ad Dawasir area consists of technically highly developed farm enterprises that operate with modern pivot irrigation system.

All year fodder consists of alfalfa, which is cut up to 10 times a year for food.

The shallow alluvial aquifers could not sustain the high groundwater abstraction rates for a long time.

The groundwater level declined dramatically in most areas from 120 to almost 400 m deep.

The location of the study area in false color composite
Methodological framework

- Estimation of vegetation indices
- Estimation of soil salinity index
- Regression Analysis
Methodological framework

- **Estimation of vegetation indices**
  - Water Supply Vegetation Index (WSVI)
  - Soil Adjusted Vegetation Index (SAVI)
  - Moisture Stress Index (MSI)
  - Normalized Difference infrared Index (NDII)

- **Estimation of soil salinity index**
  - Brightness Index
  - Normalized Difference Salinity Index
  - Salinity Index SI-6
  - Salinity Index SI-9

- **Regression Analysis**
  - Principle Component Analysis (PCA)
  - Artificial Neural Network (ANN)
Water Supply Vegetation Index (WSVI):

\[ WSVI = \frac{NDVI}{T_s} \]

Soil Adjusted Vegetation Index (SAVI):

\[ SAVI = \frac{(NIR - R)}{(NIR + R) \times (1 + L)} \]

Moisture Stress Index (MSI):

\[ MSI = \frac{SWIR_1}{NIR} \]

Normalized Difference Infrared Index (NDII):

\[ NDII = \frac{(NIR - SWIR_1)}{(NIR + SWIR_1)} \]

Normalized Difference Salinity Index (NDSI):

\[ NDSI = \frac{R - NIR}{R + NIR} \]

Brightness Index:

\[ BI = \sqrt{R^2 + NIR^2} \]

Salinity Index SI-6:

\[ SI = \frac{(B - R)}{(B + R)} \]

Salinity Index SI-9:

\[ SI = \frac{(NIR \times R)}{G} \]
Findings

- Water Supply Vegetation Index (WSVI)
- Soil Adjusted Vegetation Index (SAVI)
- Moisture Stress Index (MSI)
- Normalized Difference infrared Index (NDII)
Findings

Normalized Difference Salinity Index

Regression analyzes of NDSI (ppm) against hydrological drought indices
Findings

**Principle Component Analysis**

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<tr>
<th></th>
<th>Training Measures</th>
<th>Validation Measures</th>
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**Neural Network Analysis**
Conclusion & Recommendations

Remote Sensing techniques were satisfactorily implemented and interpreted in term of soil salinity mapping in consort with hydrological drought indices.

Normalized Difference Infrared Index was statistically proved to be the Normalized Difference Salinity Index profound, followed by Soil Adjusted Vegetation Index and Water Shortage Vegetation Index respectively.

Principal Component Analysis and Artificial Neural Network Analysis are complementary tools to understand the regression pattern of the hydrological drought indices in the designated study area.