Index-based Approach with Remote Sensing for the Assessment of Extreme Weather Impact on Watershed Vegetation Dynamics

Kushan Bellanthudawage

University of Central Florida

Part of the Environmental Engineering Commons, and the Environmental Sciences Commons

Find similar works at: https://stars.library.ucf.edu/etd2020

This Masters Thesis (Open Access) is brought to you for free and open access by STARS. It has been accepted for inclusion in Electronic Theses and Dissertations, 2020- by an authorized administrator of STARS. For more information, please contact STARS@ucf.edu.

STARS Citation
https://stars.library.ucf.edu/etd2020/472
INDEX-BASED APPROACH WITH REMOTE SENSING FOR THE ASSESSMENT OF EXTREME WEATHER IMPACT ON WATERSHED VEGETATION DYNAMICS

by

BELLANTHUDAWAGE KUSHAN ARAVINDA BELLANTHUDAWA
B.S. Environmental Conservation and Management, University of Kelaniya, 2017

A thesis submitted in partial fulfilment of the requirements for the degree of Master of Science in the Department of Civil, Environmental, and Construction Engineering in the College of Engineering and Computer Science at the University of Central Florida Orlando, Florida

Spring Term 2021

Major Professor: Ni-Bin Chang
ABSTRACT

Spatial technologies such as satellite remote sensing can be used to identify vegetation dynamics over space and time, which play a critical role in earth observations. Biophysical and biochemical features associated with vegetation cover can then be used to elucidate climate change impact such as floods and droughts on ecosystem that may in turn affect watershed-scale water resources management. Unlike single flood or drought event, intermittent extreme weather events may exert more physiological and biological pressures on the canopy vegetation. This study aims to investigate the climate change impacts on canopy vegetation, which occurred from March 2017 to October 2017 in the Santa Fe River Watershed, Florida, the United States of America. First, this study explores the effect of Hurricane Irma on vegetation dynamics via the pre and post landfall conditions in terms of biophysical and biochemical features. The environmental system analysis compares a suite of remote sensing indices: enhanced vegetation index (EVI), leaf area index (LAI), fraction of photosynthetically active radiation (FPAR), evapotranspiration (ET), land surface temperature (LST), gross primary productivity (GPP), and global vegetation moisture index (GVMI) for a holistic assessment. The satellite images from MODIS (Moderate Resolution Imaging Spectroradiometer) were projected from the MODIS Sinusoidal projection to WGS84 geographic coordination systems to conduct the essential spatial analysis. In addition, the evolution of features associated with the vegetation was analyzed in terms of a new indicator, the functional capacity of the different land uses for grassland, evergreen forested, deciduous forested, and agricultural land uses to elevate our understanding of the ecosystem’s sustainability and possible recovery processes as a response to damage caused by the Hurricane Irma event. Urban land use and open water space showed a low level of EVI, LAI, FPAR, GVMI, whereas LST and ET were significantly higher compared to the forested and agricultural land uses. Coupling LAI and LST,
EVI and GVMI, or EVI and LST confirms the hypotheses of the study, namely that biophysical features pre and post landfall of Hurricane Irma exhibit significant spatial and temporal variations, and integration of pairwise comparisons of biophysical and biochemical features can better portray the impacts driven by the landfall of Hurricane Irma than a single biophysical feature. The functional capacity of the ecosystem can be derived in terms of EVI, LAI, GVMI, and LST analysis over grassland, evergreen forested, deciduous forested, and agricultural land to quantitively reflect the ecosystem response due to landfall of Hurricane Irma. Secondly, emphasis was placed on determining the impacts of alternating adverse flood and drought events on four vegetative land use types via remote sensing and contrasting the vegetation canopy resilience, resistance, and elasticity in intermittent extreme weather events from March to Oct. 2017 in the same subtropical watershed. Nonlinear extreme weather events in sequence discriminated the marginal resilience, resistance, and thus elasticity of four land uses showing high resilience and elasticity in transitions of dry and wet events. It is indicative that thermodynamics driven LST served as the energy source that explains the forcing of variations of these vegetation indices and sustainability indicators.
To my family and friend for all their support
ACKNOWLEDGMENTS

I would like to convey sincere gratitude to my principal thesis advisor, Dr. Ni-Bin Chang, for his support and guidance to successfully complete this thesis project. Further, I appreciate my advisor for giving the opportunity to enhance my knowledge in environmental sustainability, remote sensing, and climate change studies. In addition, my sincere thanks go to my committee members Dr. Dingbao Wang and Dr. Anwar Sadmani for their comments in the present research. I also share my thanks with my mother, brothers, sister, and friends for all their kindness, motivation, support, and encouragement during this work. I strongly believe that I would not be able to successfully finish this work without their support. Together with, I thank my lab mates and friends in the University of Central Florida: Dr. Wei Zhang, Min Ko, Andrea Valencia, Diana Ordonez, and Syed Hammad for their backup in this journey. Their encouragement, support, and guidance leveled my knowledge up in research and greatly contributed to cherish this task. Ultimately, I appreciate the assistance of the Suwannee River Water Management District and United States Geological Survey to make this thesis a success.
# TABLE OF CONTENTS

LIST OF FIGURES .................................................................................................................. ix
LIST OF TABLES ..................................................................................................................... xi
LIST OF ACRONYMS .............................................................................................................. xii

CHAPTER ONE: INTRODUCTION ......................................................................................... 1
  1.1. Climate Change and its Impacts .................................................................................... 1
  1.2. Use of Vegetation Indices for Climate Change Assessment and Water Resources Management .................................................................................................................. 2

CHAPTER TWO: LITERATURE REVIEW ............................................................................. 6

CHAPTER THREE: BIOPHYSICAL AND BIOCHEMICAL FEATURES OF CANOPY VEGETATION DUE TO HURRICANE IRMA IMPACTS ............................................................... 11
  3.1. Introduction .................................................................................................................. 11
  3.2. Methodology ............................................................................................................... 15
    3.2.1. Study Area and Study Period ............................................................................... 15
    3.2.2. Satellite Data Retrieval and Image Processing ...................................................... 20
    3.2.3. Evolution of Biophysical and Biochemical Features ............................................. 24
    3.2.4. Function Capacity (F) Analysis ............................................................................. 27
      3.2.4.1. EVI and GVMI Relationship .......................................................................... 27
      3.2.4.2. LAI and LST Relationship ............................................................................ 28
      3.2.4.3. EVI and LAI Relationship ............................................................................ 28
  3.3. Results ......................................................................................................................... 29
    3.3.1. Biophysical and Biochemical Features During the Landfall of Hurricane Irma ...... 29
    3.3.2. Co-evolution of Biophysical and Biochemical Features ........................................ 37
  3.4. Discussion .................................................................................................................... 42
    3.4.1. Variation of the Biophysical and Biochemical Features over Diverse Land Uses ...... 42
    3.4.2. Functional Capacity Fluctuations ......................................................................... 51
    3.4.3. Ecosystem Resilience Assessment ....................................................................... 55

CHAPTER FOUR: NONLINEAR PHASE SHIFTS IMPACT MARGINAL ELASTICITY OF CANOPY VEGETATION IN INTERMITTENT EXTREME WEATHER EVENTS ....................................... 59
  4.1. Introduction ................................................................................................................. 59
  4.2. Methodology .............................................................................................................. 62
LIST OF FIGURES

Figure 1. The LULC Map of the Santa Fe river watershed study area with county boundaries in Florida State, USA (Landsat, 30m spatial resolution, United States Geological Survey, 2016).. 17

Figure 2. Hurricane Irma pathway satellite imagery on September 11, 2017 (NOAA GOES-16 satellite)................................................................. 19

Figure 3. Daily total precipitation received associated with the Ichetucknee flood monitoring station during the last 5 years, indicating the landfall of Hurricane Irma................................................................. 19

Figure 4. The schematic of the image processing for identifying the relationships between biophysical and biochemical features in ecosystem resilience assessment ............................................. 23

Figure 5. The spatial and temporal variation of biophysical and biochemical features (a) pre EVI, (b) post EVI, (c) pre-LAI, (d) post LAI, (e) pre LST, (f) post LST, (g) pre GVMI, (h) post GVMI, (i) pre ET, (j) post ET, (k) pre FPAR, and (l) post FPAR of the landfall of Hurricane Irma ........... 35

Figure 6. Evolution of biophysical and biochemical features over space in 2D representation (a) P1 (b) P2 (c) P3 (d) P4 (e) P5 (f) P6 (g) P7 (h) P8.............................................................. 41

Figure 7. The relationship of variation of EVI and GVMI before (October 07, 2017) the landfall of Hurricane Irma in (a) grassland land uses, (b) evergreen forested land uses, (c) agricultural land uses, and (d) deciduous forested land uses in the Santa Fe River Watershed ................................................... 45

Figure 8. The relationship of variation of LAI (m²/m²) and LST (°C) before (October 07, 2017) the landfall of Hurricane Irma in (a) grassland land uses, (b) evergreen forested land uses, (c) agricultural land uses, and (d) deciduous forested land uses in the Santa Fe River Watershed ....... 47

Figure 9. The relationship of variation of EVI and LAI (m²/m²) before (October 07, 2017) the landfall of Hurricane Irma in (a) grassland land uses, (b) evergreen forested land uses, (c) agricultural land uses and (d) deciduous forested land uses in the Santa Fe River Watershed .... 50

Figure 10. Resilience, Resistance, and Ecosystem elasticity values of main four selected vegetative land use patterns (agricultural, deciduous forested, evergreen forested, and grassland) in the Santa Fe watershed over the study period (March 2017 – October 2017). a, Resilience in terms of LAI (m²/m²). b, Resilience in terms of GPP (kg C/m²). c, Resistance in terms of LAI (m²/m²). d, Resistance in terms of GPP (kg C/m²). e, Ecosystem elasticity in terms of LAI (m²/m²). f, Ecosystem elasticity in terms of GPP (kg C/m²). .............................................................. 75

Figure 11. Correlation of biophysical and biochemical features. a), Dry event in agricultural land use. b, Wet event in agricultural land use. c, Dry event in deciduous forested land use. d, Wet event in deciduous forested land use. e. Dry event in evergreen land use. f, Wet event in evergreen land use. g, Dry event in a grassland land use. h, Wet event in grassland land use. The correlation of the features was significant at 0.01 (2-tailed, Spearman’s correlation analysis)......................... 79

Figure 12. The non-linear phase shifts of biophysical and biochemical parameters in terms of change percentage of the four main vegetative land uses over the period (March 2017 – October 2017). a, agricultural (ΔEVI %). b, agricultural (ΔLAI %). c, agricultural (ΔGPP %). d,
agricultural (ΔFPAR %). e, agricultural (ΔLST %). f, deciduous forested (ΔEVI %). g, deciduous forested (ΔLAI %). h, deciduous forested (ΔGPP %). i, deciduous forested (ΔFPAR %). j, deciduous forested (ΔLST %). k, evergreen forested (ΔEVI %). l, evergreen forested (ΔLAI %). m, evergreen forested (ΔGPP %). n, evergreen forested (ΔFPAR %). o, evergreen forested (ΔLST %). p, grassland (ΔEVI %). q, grassland (ΔLAI %). r, grassland (ΔGPP %). s, grassland (ΔFPAR %). t, grassland (ΔLST %).
**LIST OF TABLES**

Table 1. Common Indices Used in Drought Assessment .................................................. 7
Table 2. Commonly Used Vegetation Indices ...................................................................... 8
Table 3. Literature Review of Applications of Visible and Microwave Bands in Single Event Climate Change Assessment Approaches with Indices ......................................................... 9
Table 4. Literature Review of Applications of Visible and Microwave Bands in Multiple Events Climate Change Assessment Approaches with Indices .................................................... 10
Table 5. The specifications of the selected MODIS image products ................................ 10
Table 6. Pairwise comparison of biophysical and biochemical features ............................ 21
Table 7. Descriptive statistics of the biophysical and biochemical features observed pre (August 04, 2017) and post (October 07, 2017) landfall of Hurricane Irma ........................................ 36
Table 8. Ecosystem Functional Capacity (F) Analysis of EVI and GVMI ........................... 52
Table 9. Ecosystem Functional Capacity (F) Analysis of LAI and LST ............................... 53
Table 10. Ecosystem Functional Capacity (F) Analysis of EVI and LAI ............................... 54
Table 11. Calculated SPI Values Using Meteorological Drought Monitor Software (Belayneh and Adamowski, 2012) Using the Ichetucknee Flood Monitoring Precipitation Information Located in the Santa Fe River Watershed from 2016 to 2019. The Categorization of SPI Value Classes is Expressed as Follows; SPI > 2 = extremely wet, 1.99 > SPI > 1.5 = very wet, 1.49 > SPI > 1.0 = moderately wet, 0.99 > SPI > -0.99 = near normal, -1 > SPI > -1.49 = moderately dry, -1.5 > SPI > -1.99 = very dry, SPI < -2 = extremely dry ........................................................................................................ 64
Table 12. Sensitivity Analysis of Marginal Resilience, Marginal Resistance, and Marginal Elasticity Based on the LAI and GPP as the Main Two Biophysical and Biochemical Features Triggered by the LST (°C) of Deciduous Forested and Evergreen Forested Land Uses in the Santa Fe River Watershed in March 2017 to Oct, 2017 (DF stands for the deciduous forested land uses and EF stands for the evergreen forested land uses) ......................................................................................... 89
<table>
<thead>
<tr>
<th>Acronym</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>ET</td>
<td>Evapotranspiration</td>
</tr>
<tr>
<td>EVI</td>
<td>Enhanced Vegetation Index</td>
</tr>
<tr>
<td>FPAR</td>
<td>Fraction of Photosynthetically Active Radiation</td>
</tr>
<tr>
<td>GPP</td>
<td>Gross Primary Productivity</td>
</tr>
<tr>
<td>GVMI</td>
<td>Global Vegetation Moisture Index</td>
</tr>
<tr>
<td>LAI</td>
<td>Leaf Area Index</td>
</tr>
<tr>
<td>LST</td>
<td>Land Surface Temperature</td>
</tr>
<tr>
<td>SPI</td>
<td>Standard Precipitation Index</td>
</tr>
</tbody>
</table>
CHAPTER ONE: INTRODUCTION

1.1. Climate Change and its Impacts

Climate change stems from temperature fluctuations due to greenhouse gases emissions (Montzka et al., 2011), and extreme events in rainfall patterns and snow falls cause numerous negative impacts on marine waters (Doney et al., 2012; Poloczanska et al., 2013), forested areas (Lindner et al., 2010; Hisano et al., 2018), freshwater wetlands and groundwaters (Whitehead et al., 2009; Kløve et al., 2014) coral reefs (Ateweberhan et al., 2013; Cinner et al., 2016), and mangroves (Uddin et al., 2013; Ward et al., 2016) ecosystems. From an ecological perspective, loss of biodiversity, changes in land use patterns, and influence on climate-vegetation interactions are major causes of extreme climatic events (London Climate Change Program, 2002). These negative impacts significantly alter the energy and water balance in natural system. Hence, understanding ecosystem resilience, defined as the capability of an ecosystem to cope with an external disturbance while maintaining the balance and services of an ecosystem, is vital for climate change adaptation (Ives et al., 2007). To address climate change impacts on an ecosystem over a short time period, quantification of ecosystem resilience via a sensitive evaluation of regime shifts is vital. However, measuring ecosystem resilience while addressing resistance and recovery processes toward sustainability is a global challenge due to the lack of appropriate indicators (Côté and Darling, 2010).

Many nations worldwide have been attempting to mitigate natural and anthropogenic stressors to enhance ecosystem resilience to global climate change and develop some benchmarks to abate global climate change impacts. For example, 1.5°C of global warming decline can be achieved by an increase in forest cover of 1 billion ha by 2050 (Intergovernmental Panel on
Climate Change, 2013). The net primary productivity of the vegetation, which is the carbohydrate accumulation rate and the base of matter and energy for secondary production of an ecosystem (Gao et al., 2009), maintains the balance of the ecosystem and provides details on ecological regulation and carbon sequestration. Geophysical technologies such as remote sensing play a significant role in the assessment of regional and global climate variations and their effect on the net primary productivity, focusing on climate change adaptation and dynamics of carbon sequestration (Wu et al., 2014; Gang et al., 2017). Hence, remote sensing can be employed as a key tool to assess and monitor the resilience of an ecosystem and better understand the impacts of climate change (Cui et al., 2013; Harris et al., 2014; Maina et al., 2015; Levine et al., 2016).

1.2. Use of Vegetation Indices for Climate Change Assessment and Water Resources Management

Identification of biophysical and biochemical features to elucidate climate change resilience over space and time with the aid of remote sensing is important. Vegetation dynamics play a major role in ecological systems’ functioning by changing their coverage, density, and productivity in response to natural impacts such as excessive rainfall and runoff, desertification, and changes in soil fertility and land use patterns (Sun et al., 2015). Further, depending on the duration, magnitude, and intensity of drought and precipitation conditions, vegetation cover and productivity exhibit variations in seasonal patterns of phenology, growth, photosynthetic capacity, and soil, water, and plant interaction (Abera et al., 2018). Thus, monitoring vegetation cover dynamics can aid in understanding the resilience of ecological systems in response to climate change. Normalized Difference Vegetation Index (NDVI), introduced by Tucker and Sellers (1986), is a vegetation index widely used to monitor vegetation health. With the aid of the visible red and near-infrared bands in the electromagnetic spectrum, NDVI provides a measurement of
chlorophyll via the reflected red bands, and spongy mesophyll concentration via the reflected near-infrared bands. When the reflected near-infrared band wavelength is higher than that of the red band in visible wavelengths, it indicates a dense vegetation with high NDVI pixels. Even though NDVI is widely utilized, atmospheric and soil interferences to the calculation of NDVI measurement can be exacerbated by water vapors in the atmosphere (Huete et al., 2002). However, by avoiding the shortcomings associated with NDVI, Enhanced Vegetation Index (EVI) enables more effective spatial and temporal comparisons of vegetation conditions across the world (Waring et al., 2006). Further, due to its high sensitivity to changing biomass, canopy background signals corrections, and reduced atmospheric influences (Rocha and Shaver, 2009), EVI is an ideal candidate to portray the resilience in an ecological system toward extreme climate variations.

Among the biophysical indicators of climate change assessment, Leaf Area Index (LAI) (m²/m²) can be regarded as a key indicator, as it correlates with water, energy, and CO₂ exchange potentials of a vegetative ecosystem and atmosphere (Korhonen et al., 2011). LAI showcases the ratio of the green surface area to the soil or ground surface area (Cutini et al., 1998). With this said, LAI effectively displays the change of vegetative surfaces with regards to wet and dry environmental conditions (Mafi-Gholami et al., 2019). Therefore, LAI based satellite images can be employed as parameters for quantifying vegetation changes with respect to climatic factors. Houborg et al. (2015) reported that foliar biochemistry strongly correlates with the productivity of plants and is vital to the primary productivity of ecosystems. The plant pigments, such as cellulose, chlorophylls, plant phenolics, and proteins with nitrogen are considered biochemical features of the vegetation (Kokaly and Skidmore, 2015). In plant leaves, barks, and stems, photosynthetically active pigments called chlorophylls absorb the solar radiation and enhance the storing of starch in parts of plants for survival. Through these phenomena, the concentration of healthy chlorophyll
serves as a proxy for the production ability of plants, and it is sensitive to climatological variations in the environment. The fraction of absorbed photosynthetically active radiation (FPAR) is an indicator of vegetation productivity, as it provides the photosynthetic capability in the 0.4 to 0.7μm electromagnetic spectral range. FPAR serves as a proxy variable featuring mass, energy, and exchange of momentum in between the atmosphere and vegetative surfaces (Dong et al., 2016). Hence, remote sensing can be applied to extract the FPAR or the direct chlorophyll-a concentration in vegetative surfaces to address the impacts of climate variation (Gitelson et al., 2014; Dong et al., 2015).

In addition, some parameters in the water cycle work in concert with this endeavor. The Global Vegetation Moisture Index (GVMI), which is another significant vegetation indicator, expresses vegetation water content from the local to the global scale. The GVMI is widely used to comprehend the status of vegetation in different climatic conditions (Ceccato et al., 2002). Land surface temperature (LST) (°C) is a key tool for predicting vegetation health, including the gross primary productivity of an ecosystem, as the temperature exhibits a relationship with variations in vegetation moisture content. Phompila et al. (2015) described the relationship of EVI with LST over various terrestrial ecosystems. Further, a study conducted by Bendib et al. (2017) demonstrates the applications of LST in hydrology, land use changes, urban climate change, and evapotranspiration (ET). Moreover, LST is widely employed in energy and water budget assessment. Katul et al. (2012) claimed that LST provides a better indication of the level of photosynthesis rather than the air temperature due to the linkage between the regulation of water and CO₂ exchange via the stomata of plants. Hence, LST is a vital biophysical feature for monitoring variations in soil moisture, vegetation stress of water, and ET. In addition, some studies have demonstrated the suitability of total ET (kg/m²/day) for monitoring seasonal and climatic
variations, as it includes parameters such as plant transpiration and direct evaporation from soil, surface waters, and wet canopies and precipitation (Glenn et al., 2011). Even though techniques such as the eddy covariance method or catchment water balance exist, measurements of ET using remote sensing ensure more accuracy and precision in climate change assessment applications (Nagler et al., 2007).
CHAPTER TWO: LITERATURE REVIEW

Many remote sensing indices were used to elucidate drought conditions in terms of severity and magnitude and the health and greenness of vegetation cover in response to climate variation. The following tables (Table 1 and Table 2) illustrate the most common indices used for drought assessment and vegetation dynamics, respectively. Some of those indices are calculated using remote sensing. Further, some studies applied visible bands and microwave bands in the electromagnetic spectrum to assess the climate change, as illustrated in Table 3 for a single event and Table 4 for multiple events.
Table 1. Common Indices Used in Drought Assessment

<table>
<thead>
<tr>
<th>Drought assessment index</th>
<th>Acronym</th>
<th>Equation</th>
<th>Spectral bands</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relative soil moisture</td>
<td>RSM</td>
<td>( \frac{SMD_{\text{max}} - SMD}{SMD_{\text{max}}} )</td>
<td></td>
<td>(Legates and Willmott, 1995)</td>
</tr>
<tr>
<td>Palmer drought severity index</td>
<td>PDSI</td>
<td>( \frac{(W - DW)}{(TW - DW)} \times 100 )</td>
<td></td>
<td>(Palmer, 1965)</td>
</tr>
<tr>
<td>Relative water content</td>
<td>RWC</td>
<td>( \left( \frac{FW - DW}{DW} \right) \times 100 )</td>
<td></td>
<td>(Barrs and Weatherley, 1962;)</td>
</tr>
<tr>
<td>Fuel moisture content</td>
<td>FMC</td>
<td>( 10 - 2.5(T - H) )</td>
<td></td>
<td>Simard, 1968; Danson and Bowyer, 2004</td>
</tr>
<tr>
<td>Fuel moisture index</td>
<td>FMI</td>
<td></td>
<td></td>
<td>Sharples et al., 2009</td>
</tr>
<tr>
<td>Equivalent water thickness (canopy)</td>
<td>EWTcanopy</td>
<td>( \frac{ad + c - d(GVMI + 0.13)}{2cd} + \sqrt{(ad + c - d(GVMI + 0.13)^2 - 4cd(a + b - \lambda)} )</td>
<td></td>
<td>Dawson et al., 1998</td>
</tr>
<tr>
<td>Vegetation health index</td>
<td>VHI</td>
<td>( a \times VCI - (1 - a) \times TCI )</td>
<td></td>
<td>Kogan, 1990</td>
</tr>
<tr>
<td>Vegetation supply water index</td>
<td>VSWI</td>
<td>( B \times \frac{NDVI}{LSI} )</td>
<td>Red and NIR</td>
<td>Carlson et al., 1990</td>
</tr>
<tr>
<td>Normalized Multi-band Drought Index</td>
<td>NMDI</td>
<td>( \frac{R_{860} - (R_{1640} - R_{2130})}{R_{860} + (R_{1640} - R_{2130})} )</td>
<td></td>
<td>Wang and Qu, 2007</td>
</tr>
<tr>
<td>Integrated drought index</td>
<td>IDI</td>
<td>( \phi^{-1}(p) )</td>
<td></td>
<td>Shah and Mishra, 2019</td>
</tr>
<tr>
<td>Standard precipitation index</td>
<td>SPI</td>
<td></td>
<td></td>
<td>McKee et al., 1993</td>
</tr>
<tr>
<td>US Drought Monitor</td>
<td>USDM</td>
<td></td>
<td></td>
<td>Svoboda et al., 2002</td>
</tr>
<tr>
<td>Crop water stress index</td>
<td>CWSI</td>
<td>( \frac{T_{\text{canopy}} - T_{\text{wets}}}{T_{\text{dry}} - T_{\text{wets}}} )</td>
<td></td>
<td>Idso et al., 1980</td>
</tr>
<tr>
<td>Regional water stress index</td>
<td>RWSI</td>
<td>( 1 - \frac{\lambda ET}{\lambda ET_{\text{wet}}} )</td>
<td></td>
<td>Bastiaanssen et al., 1998</td>
</tr>
<tr>
<td>Temperature condition index</td>
<td>TCI</td>
<td>( 100 \times \frac{T_{\text{max}} - T}{T_{\text{max}} - T_{\text{min}}} )</td>
<td></td>
<td>Kogan, 1995</td>
</tr>
<tr>
<td>Water deficit index</td>
<td>WDI</td>
<td>( 1 - \frac{\lambda ET}{\lambda ET_{\text{wet}}} )</td>
<td></td>
<td>Moran et al., 1994</td>
</tr>
<tr>
<td>Temperature Vegetation Dryness Index</td>
<td>TVDI</td>
<td>( \frac{Ts - T_{\text{min}}}{a + bNDVI - T_{\text{min}}} )</td>
<td>Red and NIR</td>
<td>Sandholt et al., 2002</td>
</tr>
<tr>
<td>Vegetation index</td>
<td>Acronym</td>
<td>Equation</td>
<td>Spectral bands</td>
<td>Reference</td>
</tr>
<tr>
<td>----------------------------------------</td>
<td>---------</td>
<td>---------------------------------------------------------------------------</td>
<td>----------------</td>
<td>----------------------------------</td>
</tr>
<tr>
<td>Soil adjusted vegetation index</td>
<td>SAVI</td>
<td>(\frac{(\rho_{NIR} - \rho_b)}{(\rho_{NIR} + \rho_b + L)} + (1 + L))</td>
<td>Red and NIR</td>
<td>(Huete, 1988)</td>
</tr>
<tr>
<td>Modified soil adjusted vegetation index</td>
<td>MSAVI</td>
<td>(0.5 \times \left[ (2\rho_{NIR} + 1) \right.)( - \sqrt{(2\rho_{NIR} + 1)^2 - 8(\rho_{NIR} - \rho_R)} \left.])</td>
<td>Red and NIR</td>
<td>(Qi et al., 1994)</td>
</tr>
<tr>
<td>Normalized difference vegetation index</td>
<td>NDVI</td>
<td>(\frac{(\rho_{NIR} - \rho_R)}{(\rho_{NIR} + \rho_R)})</td>
<td>Red and NIR</td>
<td>(Tucker and Sellers, 1986)</td>
</tr>
<tr>
<td>Transformed difference vegetation index</td>
<td>TDVI</td>
<td>(\sqrt{0.5 + \frac{(\rho_{NIR} - \rho_R)}{(\rho_{NIR} + \rho_R)}})</td>
<td>Red and NIR</td>
<td>(Bannari et al., 2002)</td>
</tr>
<tr>
<td>Transformed soil adjusted vegetation index</td>
<td>TSAVI</td>
<td>(\frac{(a(NIR - aR - B))}{(R + aNIR - aB)})</td>
<td>Red, Blue, and NIR</td>
<td>(Baret et al., 1989)</td>
</tr>
<tr>
<td>Visible-band difference vegetation index</td>
<td>VDVI</td>
<td>(\frac{(2 \cdot \rho_G - \rho_R - \rho_B)}{(2 \cdot \rho_G + \rho_R + \rho_B)})</td>
<td>Green, Blue, Red</td>
<td>(Du and Noguchi, 2017)</td>
</tr>
<tr>
<td>Renormalized difference vegetation index</td>
<td>RDVI</td>
<td>(\frac{(R_{800} - R_{670})}{\sqrt{(R_{800} + R_{670})}})</td>
<td>VNIR</td>
<td>(Roujean and Breon, 1995)</td>
</tr>
<tr>
<td>Enhanced vegetation index</td>
<td>EVI</td>
<td>(G \times \frac{(\rho_{NIR} - \rho_R)}{(\rho_{NIR} + C_1\rho_R - C_2\rho_R + L)})</td>
<td>Red, Blue, and NIR</td>
<td>(Huete et al., 1997)</td>
</tr>
<tr>
<td>Leaf area index</td>
<td>LAI</td>
<td>(\frac{\text{projected leaf area}}{\text{ground area}})</td>
<td></td>
<td>(Cutini et al., 1998)</td>
</tr>
<tr>
<td>Global vegetation moisture index</td>
<td>GVMI</td>
<td>((\text{NIR} + 0.1) - (\text{SWIR} + 0.02))</td>
<td>NIR and SWIR</td>
<td>(Ceccato et al., 2002)</td>
</tr>
<tr>
<td>Optimized Soil-Adjusted Vegetation Index</td>
<td>OSAVI</td>
<td>(\frac{(\text{NIR} - R)}{(\text{NIR} + R + 0.16)})</td>
<td>Red and NIR</td>
<td>(Steven, 1998)</td>
</tr>
<tr>
<td>Normalized difference water index</td>
<td>NDWI</td>
<td>(\frac{(\text{Green} - \text{NIR})}{(\text{Green} + \text{NIR})})</td>
<td>Green and NIR</td>
<td>(Mcfeeters, 1996)</td>
</tr>
<tr>
<td>Ratio vegetation index</td>
<td>RVI</td>
<td>(\frac{R}{\text{NIR}})</td>
<td>Red and NIR</td>
<td>(Gupta, 1993)</td>
</tr>
<tr>
<td>Perpendicular Vegetation Index</td>
<td>PVI</td>
<td>(\sin(a) \cdot \text{NIR} - \cos(a) \cdot R)</td>
<td>Red and NIR</td>
<td>(Richardson and Wiegand, 1977)</td>
</tr>
</tbody>
</table>
### Table 3. Literature Review of Applications of Visible and Microwave Bands in Single Event Climate Change Assessment Approaches with Indices

<table>
<thead>
<tr>
<th>Title</th>
<th>Indices used</th>
<th>bands used</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single event</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Applications of Radarsat-1 synthetic aperture radar imagery to assess hurricane-related flooding of coastal Louisiana</td>
<td>-</td>
<td>Radarsat-1 image</td>
<td>(Kiage et al., 2005)</td>
</tr>
<tr>
<td>Geoinformatics in mangrove monitoring: damage and recovery after the 2004 Indian Ocean tsunami in Phang Nga, Thailand</td>
<td>NDVI, VFC</td>
<td>Red and NIR (Advanced Spaceborne Thermal Emission and Reflection radiometer and SPOT 5)</td>
<td>(Kamthonkiat et al., 2011)</td>
</tr>
<tr>
<td>Mapping paddy rice agriculture in southern China using multi-temporal MODIS images</td>
<td>NDVI, EVI, LWSI, NDSI</td>
<td>Green, red, NIR (MODIS)</td>
<td>(Xiao et al., 2005)</td>
</tr>
<tr>
<td>The Impact of Hurricane Katrina on the Coastal Vegetation of the Weeks Bay Reserve, Alabama from NDVI Data</td>
<td>NDVI</td>
<td>Red and NIR (Landsat)</td>
<td>(Rodgers et al., 2009)</td>
</tr>
<tr>
<td>Ecological Impacts of Hurricane Ivan on the Gulf Coast of Alabama: A Remote Sensing Study</td>
<td>NDVI</td>
<td>Red and NIR (Landsat 5)</td>
<td>(Bianchettef et al., 2009)</td>
</tr>
<tr>
<td>The Impact of Hurricane Maria on the Vegetation of Dominica and Puerto Rico Using Multispectral Remote Sensing</td>
<td>NDVI</td>
<td>Red and NIR (Landsat 8)</td>
<td>(Hu and Smith, 2018)</td>
</tr>
<tr>
<td>NMDI: A normalized multi-band drought index for monitoring soil and vegetation moisture with satellite remote sensing</td>
<td>NMDI, LAI, NDVI</td>
<td>860nm, 1640nm, and 2130nm (MODIS)</td>
<td>(Wang and Qu, 2007)</td>
</tr>
</tbody>
</table>
Table 4. Literature Review of Applications of Visible and Microwave Bands in Multiple Events Climate Change Assessment Approaches with Indices

<table>
<thead>
<tr>
<th>Title</th>
<th>Indices used</th>
<th>bands used</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Multiple events</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mapping paddy rice planting area in wheat-rice double-cropped areas through integration of Landsat-8 OLI, MODIS and PALSAR images</td>
<td>NDVI, EVI</td>
<td>Red, Blue, NIR (Landsat-8 OLI, MODIS and PALSAR images)</td>
<td>(Wang et al., 2015)</td>
</tr>
<tr>
<td>Vegetation index suites as indicators of vegetation state in grassland and savanna: An analysis with simulated Sentinel 2 data for a North American transect</td>
<td>NDVI, CRI, NDII, SATVI</td>
<td>(490–2190 nm: Sentinel-2)</td>
<td>(Hill, 2013)</td>
</tr>
<tr>
<td>Multi-scale sensitivity of Landsat and MODIS to forest disturbance associated with tropical cyclones</td>
<td>GV (green vegetation), NPV (non photosynthetic vegetation)</td>
<td>MODIS band 1-7</td>
<td>(Negrón-Juárez et al., 2014)</td>
</tr>
<tr>
<td>Potential of MODIS EVI in Identifying Hurricane Disturbance to Coastal Vegetation in the Northern Gulf of Mexico</td>
<td>EVI</td>
<td>MODIS</td>
<td>(Wang and D’Sa, 2010)</td>
</tr>
<tr>
<td>A five-year analysis of MODIS NDVI and NDWI for grassland drought assessment over the central Great Plains of the United States</td>
<td>NDVI, NDWI</td>
<td>MODIS</td>
<td>(Gu et al., 2007)</td>
</tr>
<tr>
<td>The Vegetation Drought Response Index (VegDRI): A new integrated approach for monitoring drought stress in vegetation</td>
<td>Vegetation Drought Response Index, NDVI</td>
<td>Red and NIR (AVHRR)</td>
<td>(Brown et al., 2008)</td>
</tr>
<tr>
<td>The use of remote sensing and GIS for spatio-temporal analysis of the physiological state of a semi-arid forest with respect to drought years</td>
<td>NDVI</td>
<td>Red and NIR (Landsat TM and ETM+)</td>
<td>(Volcani et al., 2005)</td>
</tr>
<tr>
<td>SAR polarimetric change detection for flooded vegetation</td>
<td>-</td>
<td>Synthetic Aperture Radar</td>
<td>(Brisco et al., 2013)</td>
</tr>
<tr>
<td>Modelling the vegetation–climate relationship in a boreal mixed wood forest of Alberta using normalized difference and enhanced vegetation indices</td>
<td>NDVI, EVI</td>
<td>Red, Blue, and NIR (AVHRR and MODIS)</td>
<td>(Jahan and Gan, 2011)</td>
</tr>
<tr>
<td>Integrating temperature vegetation dryness index (TVDI) and regional water stress index (RWSI) for drought assessment with the aid of LANDSAT TM/ETM+ images</td>
<td>TVDI, RWSI, LST, NDVI, SAVI, MSAVI, ANDVI</td>
<td>Red and NIR (Landsat TM and ETM+)</td>
<td>(Gao et al., 2011)</td>
</tr>
<tr>
<td>Spatio-temporal Soil Moisture Estimation Using Neural Network with Wavelet Preprocessing</td>
<td>NDVI, EVI, MSAVI, LST, TVDI</td>
<td>Red and NIR (Landsat 7 and 8)</td>
<td>(Kulaglic and Ustundag, 2017)</td>
</tr>
<tr>
<td>Detection of vegetation changes associated with extensive flooding in a forested ecosystem</td>
<td>NDVI</td>
<td>Red and NIR (SPOT satellite)</td>
<td>(Michener and Houhoulis, 1997)</td>
</tr>
</tbody>
</table>
CHAPTER THREE: BIOPHYSICAL AND BIOCHEMICAL FEATURES OF CANOPY VEGETATION DUE TO HURRICANE IRMA IMPACTS

3.1. Introduction

Hurricanes are considered as one of the natural disturbances of vegetative ecosystems, especially forests in the North and Central America (McNab et al., 2004). Based on the duration and magnitude of the hurricane, physical damages on plants fluctuate critically, for instance, defoliation, branches loss, uprooting of stems or trunks, etc. (Lugo, 2008). The ability to withstand disturbance driven by the wind speed of hurricane influence the plant type, stand characteristics, and tree species, stem density, and collateral effects (Negrón-Juárez et al., 2014). Hence, the susceptibility to hurricane-based stresses and their recovery pathways depends on species level (Canham et al., 2010). Hence, understanding ecosystem resilience, defined as the capability of an ecosystem to cope with an external disturbance while maintaining the balance and services of an ecosystem, is vital for climate change adaptation (Ives et al., 2007). Moreover, as hurricanes causes the alterations of plants functions, it exceeds the threshold or the tipping point of the plant-based ecosystem equilibrium. The “functional capacity (F)” is a criterium that is defined as the ability to maintain the functions of plants against external disturbances. The value of F of a given ecosystem can be expressed as the potential of an ecosystem to continue its natural processes and components to maintain goods ecosystem services capacity. The F of an ecosystem is subject to a drastic reduction in natural hazard events normally (Smith et al., 2009; Craine et al., 2012). Changes in the F of an ecosystem, especially in vegetation, help illustrate the resilience of vegetation to climate change drivers such as hurricanes. However, measuring ecosystem resilience and functional capacity while addressing resistance and recovery processes caused by climate change drivers like hurricanes is a global challenge due to the lack of accurate and reliable indicators (Côté and Darling, 2010). Even though field surveys and ground-based measurements are available, time,
labor, and cost constrain the disturbance assessment studies at higher spatial scale. To overcome this issue, spatial technologies such as remote sensing can be employed to assess impacts of hurricanes on plants using vegetation indices-based approaches. This is a breakthrough effort to explore whether ecosystems can help adapt to extreme events caused by climate change.

Among the vegetation indices, Enhanced Vegetation Index (EVI) enables more effective spatial and temporal comparisons of vegetation conditions across the world (Waring et al., 2006). EVI is calculated using the NIR, red, and blue bands of the electromagnetic spectrum along with the adjustment for canopy background, coefficients for atmospheric resistance, and gain factor (Rocha and Shaver, 2009a). Further, due to its high sensitivity to changing biomass, canopy background signals corrections, and reduced atmospheric influences (Rocha and Shaver, 2009b), EVI is an ideal candidate to portray the resilience in an ecological system toward extreme climate variations. In addition, Leaf Area Index (LAI) ($m^2/m^2$) can be regarded as a key indicator, as it correlates with water, energy, and CO$_2$ exchange potentials of a vegetative ecosystem and atmosphere (Korhonen et al., 2011). LAI showcases the ratio of the green surface area to the soil or ground surface area (Cutini et al., 1998). Thus, LAI can effectively display the change of vegetative surfaces with regards to wet and dry environmental conditions (Mafi-Gholami et al., 2019). LAI based satellite images can be employed as parameters for quantifying vegetation changes with respect to hurricane scenarios. The fraction of absorbed photosynthetically active radiation (FPAR) is a biochemical indicator of vegetation productivity, as it provides the photosynthetic capability in the 0.4 to 0.7$\mu$m electromagnetic spectral range. FPAR serves as a proxy variable featuring mass, energy, and exchange of momentum in between the atmosphere and vegetative surfaces (Dong et al., 2016). Hence, remote sensing can be applied to extract the
FPAR or the direct chlorophyll-a concentration in vegetative surfaces to address the impacts of climate variation driven by hurricanes (Gitelson et al., 2014; Dong et al., 2015).

Global Vegetation Moisture Index (GVMI), which is another significant vegetation indicator, expresses vegetation water content from the local to the global scale. The GVMI is widely used to comprehend the status of vegetation in different climatic conditions (Ceccato et al., 2002). Land surface temperature (LST) (℃) is a key tool for predicting vegetation health, including the gross primary productivity of an ecosystem, as the temperature exhibits a relationship with variations in vegetation moisture content. In addition, some studies have demonstrated the suitability of total ET (kg/m²/day) for monitoring seasonal and climatic variations, as it includes parameters such as plant transpiration and direct evaporation from soil, surface waters, and wet canopies and precipitation (Glenn et al., 2011). Even though techniques such as the eddy covariance method or catchment water balance exist, measurements of ET using remote sensing ensure more accuracy and precision in climate change assessment applications (Nagler et al., 2007).

Feng et al. (2020) studied the relationship between the biophysical and biochemical features of forests in response to the hurricane Maria, in Puerto Rico. In addition, Hu and Smit (2019) attempted to understand the vegetation dynamic changes fueled by hurricane impacts. Senkbeli et al. (2019) explored the evacuee perception of geophysical hazards for hurricane Irma to understand the influences of hurricane Irma of ecosystems. Further, Zhang et al. (2019) modelled the risk of Hurricane Irma on the mangrove-based ecosystems. Rodgers et al. (2009) analyzed the impacts of hurricane Katrina on the coastal vegetation of Alabama. However, the study on the vegetation damages in large watersheds caused by hurricanes are yet to be discovered. There exists a research gap of the remote sensing-based vegetation canopy assessment associated
with the extreme weather events such as hurricane, based on multiple indices for functional capacity derivation. The Tables S1 and S2 in Supplementary file 1 depict the commonly used indices used for vegetation analysis and the literature review of the related scientific attempts.

The present study incorporates the Moderate Resolution Imaging Spectroradiometer (MODIS) onboard Terra and Aqua satellites, which provides the platform with more shortwave infrared (SWIR) bands that are sensitive to soil waters and vegetation. Therefore, with the aid of the MODIS sensor, the present study highlights the importance of biophysical and biochemical feature extraction over space and time from remote sensing images to elucidate the ecosystem responses and adaptability to extreme weather events. As the vegetation dynamics depend on variations in temperature and rainfall, the present study demonstrates a synergetic remote sensing approach for integrating several biophysical and biochemical features before and after one single climatic event associated with the landfall of Hurricane Irma in the Santa Fe River Watershed, north Florida, the United States. Thereby, this integrative approach can strengthen the comparison of spatial and temporal variations of biophysical and biochemical features by grouping or pairing some of these indices, enabling the exploration of more comprehensive insights in earth observations.

Hence, the scientific research questions to be answered in this unique study are as follows: (1) How did the biophysical and biochemical indices vary over different land use patterns before and after the landfall of Hurricane Irma? (2) Can the new concept of function capacity be derived for canopy vegetation to address the pathways of hurricane impact? The objectives of the present study are to: (1) demonstrate the spatial and temporal impact of the landfall of Hurricane Irma using remote sensing feature extraction pre and post the Hurricane Irma landfall event, and (2) compare the biophysical and biochemical features, namely EVI, LAI, FPAR, ET, LST, and GVMI
by grouping or pairing to extract the functional capacity of the canopy vegetation for resilience assessment. We hypothesize that: (1) there exists a significant spatial and temporal variation of biophysical and biochemical features pre and post landfall of Hurricane Irma, and (2) grouping or pairing these remote sensing indices for comparison is more effective than a single biophysical or biochemical feature for understanding the functional capacity.

3.2. Methodology

3.2.1. Study Area and Study Period

The Santa Fe River Watershed is in north-east Florida, with a total area of 3,585 km². The Santa Fe River Watershed is one of the tributaries of the Suwannee River watershed, and Santa Fe’s major tributaries include the Ichetucknee River, New River, Olustee Creek, and Cow Creek. The Santa Fe River Watershed is composed of parts of Alachua, Baker, Bradford, Columbia, Gilchrist, Suwannee, and Union counties in Florida. Land use and land cover (LULC) classes representing the Santa Fe River Watershed area are shown in (Fig. 1). The dominant types of natural land uses are (34.3%) evergreen forest, (19.5%) hay or pasture lands, and (17.3%) woody wetlands and urbanized type land uses such as (5.8%) developed open spaces, (1.7%) developed low intensity, (0.3%) developed medium intensity, and (0.1%) developed high intensity (Fig.1). Further, (3.2%) of the Santa Fe River Watershed is used to cultivate crops, namely cultivated corn, peanuts, tobacco, vegetables, blueberries, watermelons, and strawberries. The elevation of the Santa Fe River Watershed varies from 3 m to over 91 m above mean sea level. In addition, the slope of the areas varies from gentle slopes, undulating slopes, and moderate to higher slopes. Northern highlands and Gulf Coastal lowlands, which are distinct by the Cody Scarp, are the major physiographic regions in the Santa Fe River Watershed. In terms of geology, the area is composed
of Eocene limestone, Miocene sediments with clayey and phosphatic and Pliocene and Pleistocene Holocene sediments, which shows more sandy soil properties at the surface (Lamsal et al., 2006). The average rainfall and temperature of the study area are 61.47mm and 27(°C) respectively (Florida Climate Center, 2017).
Figure 1. The LULC Map of the Santa Fe river watershed study area with county boundaries in Florida State, USA (Landsat, 30m spatial resolution, United States Geological Survey, 2016)
A massive catastrophic disaster was caused in the Caribbean region due to Hurricane Irma, which was accounted as a category 5 level (Seraphin, 2019). Later, Hurricane Irma hit Florida, Georgia, and North Carolina in the USA during the period from August 30th to September 10th in 2017 as a category 4, resulting in 129 deaths in Florida. Hurricane Irma’s pathway through the Santa Fe River Watershed area is illustrated by the satellite image (Fig. 2) and the daily total precipitation received was documented by the Ichetucknee flood monitoring station over the last 20 years, which indicates the flood event triggered by the landfall of Hurricane Irma (Fig. 3). Hence, based on these observations and incidents associated with Hurricane Irma, the study period from August 2017 to October 2017 was selected, focusing on the landfall of Hurricane Irma in September 2017.
Figure 2. Hurricane Irma pathway satellite imagery on September 11, 2017 (NOAA GOES-16 satellite)

Figure 3. Daily total precipitation received associated with the Ichetucknee flood monitoring station during the last 5 years, indicating the landfall of Hurricane Irma
3.2.2. Satellite Data Retrieval and Image Processing

The MODIS sensor is composed of 36 spectral bands, and seven of those bands are specifically designed to study vegetation and land surfaces, for instance, blue (459–479 nm), green (545–565 nm), red (620–670 nm), near infrared (NIR1: 841–875 nm; NIR2: 1230–1250 nm), and shortwave infrared (SWIR1: 1628–1652 nm, SWIR2: 2105–2155 nm) (Xiao et al., 2005). In addition, the MODIS sensor provides imageries with red and NIR1 with spatial resolutions of 250-m, and blue, green, NIR2, SWIR1, SWIR2 bands with 500-m. Therefore, the present study combined the advantages of having a range of spectral bands within the MODIS platform. The flow chart of the satellite image processing is illustrated in (Fig. 4) to aid in assessment. The MODIS images for the biophysical features such as EVI, LAI, ET, LST, and surface reflectance and biochemical features, namely FPAR, were retrieved from the Land Processes Distributed Active Archive Center (LP DAAC, http://lpdaac.usgs.gov) during the period from June 04 to June 11, 2020. Initially, all images were projected from the MODIS Sinusoidal projection to WGS84 geographic coordination systems, and images were downloaded in Geotiff format. The specifications of the selected MODIS image products, including the image processing level, and spatial and temporal resolution are tabulated in (Table 3).
Table 5. The specifications of the selected MODIS image products

<table>
<thead>
<tr>
<th>Biophysical and biochemical features</th>
<th>Product</th>
<th>Spatial resolution (m)</th>
<th>Temporal resolution (days)</th>
</tr>
</thead>
<tbody>
<tr>
<td>EVI</td>
<td>MYD13A1</td>
<td>500</td>
<td>16</td>
</tr>
<tr>
<td>LAI</td>
<td>MCD15A2H</td>
<td>500</td>
<td>8</td>
</tr>
<tr>
<td>FPAR</td>
<td>MCD15A2H</td>
<td>500</td>
<td>8</td>
</tr>
<tr>
<td>ET</td>
<td>MYD16A2</td>
<td>500</td>
<td>8</td>
</tr>
<tr>
<td>Near infra-red and short wave infra-red</td>
<td>MYD09A1</td>
<td>500</td>
<td>8</td>
</tr>
<tr>
<td>LST</td>
<td>MYD21A1N</td>
<td>1000</td>
<td>1</td>
</tr>
</tbody>
</table>
By considering the maximum value of the available temporal resolution of the array of images from MODIS (Table 1), 16 temporal resolution was selected for this study. Therefore, the LAI, FPAR, ET, and surface reflectance (NIR and SWIR) images were processed to obtain the average of the 8-day composites by raster calculator technique in ArcGIS 10.3 software to align with a 16-day temporal resolution. Conversely, the LST images were subjected to processing to obtain the average of consecutive daily images to align with a 16-day temporal resolution. Then, the LST images were resampled to unify the 500-m spatial resolution using the nearest neighborhood method resampling technique in the ArcGIS 10.3 software. The GVMI (Ceccato et al., 2002) was calculated with the aid of the obtained surface reflectance values.

To address the attributes of spatial changes in this study, the selected biophysical and biochemical features of EVI, LAI, FPAR, ET, LST, and GVMI were presented using maps via ArcGIS version 10.3, and the spatial variations of those maps were analyzed in terms of land use and land cover changes (Fig. 1) in the Santa Fe River Watershed. Simultaneously, the temporal variations of those maps were interpreted with regards to the identified climatic change extremes (Table 3) in the study area.
Figure 4. The schematic of the image processing for identifying the relationships between biophysical and biochemical features in ecosystem resilience assessment.
3.2.3. Evolution of Biophysical and Biochemical Features

The selection of biophysical and biochemical features can be grouped to address the systematic changes in temperatures and soil moisture contents which can influence vegetation dynamics and structure in canopy (Table 2). LST serves as an ideal candidate for governing LULC processes such as water and energy flows during the land-atmosphere interactions, and the relationship with varying canopy covers among the different land use patterns (Phompila et al., 2015). Further, soil moisture level acts as a variable of LST, as sub-surface temperature affects soil moisture transfer among soil layers (Huang et al., 2008). LST also correlates with vegetation canopy structure and shows lower values at nighttime. Remotely sensed GVMI provides information on vegetation water content. As fewer atmospheric noises can impact its physical implications, it is suitable for determining numerous arrays of canopy water content for different rates of vegetation cover changes (Ceccato et al., 2002). Further, GVMI can effectively discriminate the vegetation water content from other dry matters in the environment (Liu et al., 2009). Thus, GVMI enables us to distinguish the soil and surface waters in low EVI conditions while differentiating vegetative surfaces in high EVI conditions (Phompila et al., 2015). As a consequence, coupling EVI with LST and GVMI alternately may account for changing biomass via canopy background signals corrections and reduced atmospheric influences, which enables us to explore the greenness variation with temperature and moisture dynamics (Huete et al., 2002; Rocha and Shaver, 2009b).

Further, LAI is considered a key driver for determining the productivity of canopy, and remotely sensed EVI has been used to estimate LAI over multiple land uses (Chen et al., 2006; le Maire et al., 2008; Thenkabail et al., 2016). Biochemical composition of the canopy relies on the spectral and optical features of leaf and canopy structure. FPAR is known as a biochemical feature
of the vegetation, along with leaf nitrogen content and carotenoids. In parallel with the LAI, FPAR absorbed by plant leaves is a vital tool for determining the dynamics of global vegetation trends. Further, the stress and physiologically induced changes of vegetation are measured by the dynamics of chlorophyll a, xanthophylls, and moisture of leaf (Horler et al., 1983; Gamon et al., 1997). Thus, coupling the LST and GVMI with LAI and FPAR separately facilitates an enhanced understanding and helps visualize the impact on vegetation due to changes in temperature and moisture levels caused by the landfall of Hurricane Irma. Thus, based on these spatial and temporal variations and the correlation analysis in this study, the first two scientific research questions can be answered regarding the climate change impacts on biophysical and biochemical features of the vegetation canopy in the watershed during the hurricane landfall event.
Table 6. Pairwise comparison of biophysical and biochemical features

<table>
<thead>
<tr>
<th>Pair number</th>
<th>feature 1</th>
<th>feature 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>P₁</td>
<td>EVI</td>
<td>LST</td>
</tr>
<tr>
<td>P₂</td>
<td>GVMI</td>
<td>LST</td>
</tr>
<tr>
<td>P₃</td>
<td>LAI</td>
<td>LST</td>
</tr>
<tr>
<td>P₄</td>
<td>EVI</td>
<td>GVMI</td>
</tr>
<tr>
<td>P₅</td>
<td>LAI</td>
<td>GVMI</td>
</tr>
<tr>
<td>P₆</td>
<td>EVI</td>
<td>LAI</td>
</tr>
<tr>
<td>P₇</td>
<td>FPAR</td>
<td>EVI</td>
</tr>
<tr>
<td>P₈</td>
<td>FPAR</td>
<td>LAI</td>
</tr>
</tbody>
</table>
In terms of the evolution of features over the space in 2D representation, we extract each data layer from the MODIS satellite images. Then in each layer the pixel value of each pixel was extracted separately, for example, in LAI, EVI, LST, etc. Later, the respective pixel value of EVI, LST, and LAI for each pixel was arranged and then the plots were created getting the dependent and independent variables in different scenarios.

3.2.4. Function Capacity (F) Analysis

Understanding the role of climate change driven stresses such as hurricane landfall Irma is significant in comprehending the structuring and functioning of dynamic ecosystems. However, the tolerance level or threshold of plant species can be heavily impacted by natural hazards such as hurricane landfall. The ecological functions of the plants could then be altered by lowering the F of the ecosystem (Craine et al., 2012). Thus, the present study explored such an impact on the F of the ecosystem in relation to the biophysical and biochemical features of the vegetation dynamics pre and post landfall of Hurricane Irma. Equations 1 to 4 illustrate the calculation of the F factor in different combinations of these features, as shown below.

3.2.4.1. EVI and GVMI Relationship

The relationship of EVI and GVMI can be expresses using Equations 1 and 2.

\[
\ln \left( \frac{EVI_{GVMI}}{1 - EVI_{GVMI}} \right) = \alpha (GVMI - GVMI_{min}) + \beta 
\]

\[
EVI_{GVMI} = \frac{C1e^{rt}}{1 + C1e^{rt}} 
\]

where,

\(EVI_{GVMI} = \) EVI at a given GVMI
\(GVMI_{min} = \) Minimum value of GVMI
\(\alpha = \) gradient of the graph
\( \beta = \text{Interception of the graph} \)

\( C_i = e^\beta \)

\( r = \alpha \)

\( t = \text{GVMI} - \text{GVMI}_{\text{min}} \)

\( F = \text{Functional capacity} \)

### 3.2.4.2. LAI and LST Relationship

The relationship of EVI and LST can be expresses using Equations 3 and 4.

\[
\ln \left( \frac{\text{LAI}_{\text{LST}}}{1-\text{LAI}_{\text{LST}}} \right) = \alpha (\text{LST} - \text{LST}_{\text{min}}) + \beta \tag{3}
\]

\[
\text{LAI}_{\text{LST}} = \frac{C_i F e^rt}{1 + C_i e^rt} \tag{4}
\]

where,

\( \text{LAI}_{\text{LST}} = \text{LAI} \text{ at a given LST} \)

\( \text{LST}_{\text{min}} = \text{Minimum value of LST} \)

\( \alpha = \text{gradient of the graph} \)

\( \beta = \text{Interception of the graph} \)

\( C_i = e^\beta \)

\( r = \alpha \)

\( t = \text{LST} - \text{LST}_{\text{min}} \)

\( F = \text{Functional capacity} \)

### 3.2.4.3. EVI and LAI Relationship

The relationship of EVI and LAI can be expresses using Equations 5 and 6.

\[
\ln \left( \frac{\text{EVI}_{\text{LAI}}}{1-\text{EVI}_{\text{LAI}}} \right) = \alpha (\text{LAI} - \text{LAI}_{\text{min}}) + \beta \tag{5}
\]

\[
\text{EVI}_{\text{LAI}} = \frac{C_i F e^rt}{1 + C_i e^rt} \tag{6}
\]
where
\[ \text{EVI}_{\text{LAI}} = \text{EVI at a given LAI} \]
\[ \text{LAI}_{\text{min}} = \text{Minimum value of LAI} \]
\[ \alpha = \text{gradient of the graph} \]
\[ \beta = \text{Interception of the graph} \]
\[ C_i = e^\beta \]
\[ r = \alpha \]
\[ t = \text{LAI} - \text{LAI}_{\text{min}} \]
\[ F = \text{Functional capacity} \]

3.3. Results

3.3.1. Biophysical and Biochemical Features During the Landfall of Hurricane Irma

The summary of the descriptive statistics of the vegetation indices observed during the landfall of Hurricane Irma is depicted in Table 7. The variation of EVI over spatial attributes is shown in Fig. 5a and Fig. 5b. The findings show that, in terms of temporal variation (Table 7), a decline in EVI (mean ± standard deviation) can be observed following the landfall of Hurricane Irma from \((0.47 \pm 0.08)\) to \((0.43 \pm 0.07)\). Open water land uses such as Sampson Lake, Crossby Lake, and Rowell Lake are located toward the central part of Bradford County, while Santa Fe Swamp Conservation Park, which is an emergent herbaceous wetland, is the main type of land use in the southwestern part of Bradford County (Fig. 1). The findings of this study demonstrated a significant decline of EVI in the southwest and central parts of Bradford County on both August 04 and October 07, 2017 (Fig. 5a and Fig. 5b) indicating a very low level of EVI. In addition, the west part of Bradford County showed a growth of EVI from medium level to high level after the landfall due to a flood event in some deciduous and evergreen forest patches in that area induced by Hurricane Irma. Interestingly, towards the southwest and south parts of Gilchrist County, an
increment of EVI was observed from a very low to low level of EVI before the Hurricane Irma event to a medium level EVI after the Hurricane Irma event (Fig. 4).

This variation is evidenced by the aggregated patches of deciduous forests along the region in Gilchrist County (Fig. 1). EVI increased comparatively from a medium level to a high level during the period from August 04 to October 07 in the north and northwest areas of Union County, where the center bay forested area and vegetative covers along the Swift Creek are present. In addition, EVI increased gradually in the northeastern and southwestern areas of Columbia County on October 07, 2017. When referring to the LULC (Fig. 1), the Olustee Creek Conservation Area and Osceola National Forest can be identified as vegetative land uses in the northeastern region of Columbia County. Comparatively, EVI increased from a medium to a high level of EVI in the west part of Alachua County (Fig. 5a and Fig. 5b). However, the developed medium to high density land uses in Alachua County, including Alachua and High Springs, exhibited no significant difference in EVI with regards to the flood occasion generated by heavy precipitation in September 2017. Likewise, Fort White in central Columbia County, Lake City in the north part of Columbia County, and Starke in Bradford County (Fig. 1), all of which have medium to high density, demonstrated similar EVI levels according to LULC.

The results of the variation of LAI (m²/m²) in the pre and post Hurricane Irma induced event are illustrated in Fig. 5c and Fig. 5d, respectively. In comparison to the LAI variation over time, LAI (mean ± standard deviation) reduced from (3.6 ± 1.4) (m²/m²) to (2.8 ± 1.5) (m²/m²) post landfall of Hurricane Irma (Table 7). LAI also reduced from pre to post Hurricane Irma in Suwannee County belonging to the study area. LAI remained consistent in Clay County, which is included in the Santa Fe River Watershed. North, central, and south parts of Bradford County experienced a significant depression of LAI from August 04 to October 07, 2017. Similarly, from
the LAI distribution in Union County, Alachua County, Gilchrist County, and Bradford County, it is clear that there exists an alleviation of LAI following the Hurricane Irma-generated flood event. Hence, a remarkable reduction in the LAI can be observed on October 07, 2017 following the Hurricane Irma event. In other words, in comparison to August 04, the ratio of greener area to area of soil surface diminished on October 07, 2017.

The comparison of the LST (°C) pre and post the Hurricane Irma-induced climate change event is presented in Fig. 5e and Fig. 5f. The LST (mean ± standard deviation) has reduced from (22.83 ± 0.84) (°C) to (21.49 ± 1.01) (°C) post landfall of Hurricane Irma (Table 7). Prior to the landfall event, LST was categorized into five classes, ranging from (18.35 °C - 30.3 °C) (Fig. 5e), whereas, in the post Hurricane Irma event scenario, LST was grouped into five classes from (18.37 °C - 28.07 °C) (Fig. 5f). The findings demonstrate that, while LST declined post landfall of Hurricane Irma in the Bradford County area, toward the center and the southeastern parts the LST remained at a very high level, symbolized by the red color. A progressive reduction of LST was observed from west to east areas of Bradford County during the post Hurricane Irma period. Moreover, regions belonging to Baker County and the northeastern region of Bradford County displayed very low LST on October 07, 2017 in comparison to August 04, 2017 (Fig. 5f). In the part of Suwannee County which belongs to the Santa Fe River Watershed, a decline of LST can be observed from a high level to a low level. Conversely, in Gilchrist County, LST decreased from high to medium to very low. In the north and northwest of Columbia County, which belongs to the Santa Fe River Watershed, LST significantly decreased from high and medium levels to a low level from August 04 to October 07, 2017. After Hurricane Irma, the western part of Union County showed a decline of LST (Fig. 5f). Further, the central part of Alachua County owned by the Santa Fe River Watershed exhibited a significant rise of LST post Hurricane Irma, while north to
northeast and west areas of Alachua indicated a drop of LST to a very low-level post Hurricane Irma. Overall, the present study findings reveal a significant reduction of LST in the study area due to the climate change event.

Evidence of the change of GVMI pre and post the Hurricane Irma-induced flood event is portrayed in Fig. 5g and Fig. 5h. GVMI (mean ± standard deviation) declined from (0.52 ±0.02) to (0.47 ± 0.03) post landfall of Hurricane Irma (Table 7). The findings of the two maps demonstrate that areas of Suwannee and Clay counties located in the Santa Fe River Watershed show a comparative decrease in GVMI after the landfall event in the study area. In addition, a diminished level of GVMI can be detected in the west and northwest parts of Gilchrist County after the flood event. A remarkable increment in GVMI in the south part of the Alachua County was observed following the Hurricane Irma event. With regards to the central and southern parts of Columbia county located in study area, a GVMI declined due to the flood event induced by Hurricane Irma. On the contrary, a growth of GVMI can be seen in the west and northeastern regions of Union County. Correspondingly, the majority of Bradford County experienced an advance in terms of GVMI distribution spatially, while the southwest part of Bradford county showed diminished GVMI in October 07, 2017. These results regarding GVMI support the idea that a significant variation exists along the Santa Fe River Watershed area in response to the climate change event in September 2017.

ET fluctuations that occurred during the flood event induced by Hurricane Irma are illustrated in Fig. 5i and Fig. 5j. In the context of temporal variation, ET (mean ± standard deviation) declined from (13156 ± 11313) (kg/m²/8day) to (8731 ± 9961) (kg/m²/8day) post landfall of Hurricane Irma (Table 7). The southern part of the Gilchrist region in the Santa Fe River Watershed displayed a decrease in ET from very high to very low, and the portion of Suwannee
County located in the study area showed similar variation. In comparison with the August 04, 2017 map, the Columbia County area shows an overall reduction in ET from very high and high levels to a very low level on October 07, 2017. In the southern part of Union County, ET declined after the flood event. Further, ET reduced significantly in central and eastern parts of Bradford County and the majority of Alachua County.
Figure 5. The spatial and temporal variation of biophysical and biochemical features (a) pre EVI, (b) post EVI, (c) pre-LAI, (d) post LAI, (e) pre LST, (f) post LST, (g) pre GVMI, (h) post GVMI, (i) pre ET, (j) post ET, (k) pre FPAR, and (l) post FPAR of the landfall of Hurricane Irma.
Table 7. Descriptive statistics of the biophysical and biochemical features observed pre (August 04, 2017) and post (October 07, 2017) landfall of Hurricane Irma.

<table>
<thead>
<tr>
<th>Biophysical and biochemical features</th>
<th>pre/post</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>EVI</td>
<td>pre</td>
<td>0.47</td>
<td>0.08</td>
<td>(-0.01 – 0.95)</td>
</tr>
<tr>
<td></td>
<td>post</td>
<td>0.43</td>
<td>0.07</td>
<td>(-0.06 – 0.65)</td>
</tr>
<tr>
<td>LAI (m²/m²)</td>
<td>pre</td>
<td>3.6</td>
<td>1.4</td>
<td>(0 – 7)</td>
</tr>
<tr>
<td></td>
<td>post</td>
<td>2.8</td>
<td>1.5</td>
<td>(0 – 7)</td>
</tr>
<tr>
<td>FPAR</td>
<td>pre</td>
<td>0.716</td>
<td>0.228</td>
<td>(0.135 – 1.00)</td>
</tr>
<tr>
<td></td>
<td>post</td>
<td>0.707</td>
<td>0.225</td>
<td>(0.255 – 1.00)</td>
</tr>
<tr>
<td>LST (°C)</td>
<td>pre</td>
<td>22.83</td>
<td>0.84</td>
<td>(18.35 – 30.03)</td>
</tr>
<tr>
<td></td>
<td>post</td>
<td>21.49</td>
<td>1.01</td>
<td>(18.36 – 28.08)</td>
</tr>
<tr>
<td>ET (kg/m²/day) *</td>
<td>pre</td>
<td>13156</td>
<td>11313</td>
<td>(148 – 32766)</td>
</tr>
<tr>
<td></td>
<td>post</td>
<td>8731</td>
<td>9961</td>
<td>(136 – 32766)</td>
</tr>
<tr>
<td>GVMRI</td>
<td>pre</td>
<td>0.52</td>
<td>0.02</td>
<td>(0.42 – 0.63)</td>
</tr>
<tr>
<td></td>
<td>post</td>
<td>0.47</td>
<td>0.03</td>
<td>(0.31 – 0.61)</td>
</tr>
</tbody>
</table>

*Note: * symbol indicates the average of 8day information
3.3.2. Co-evolution of Biophysical and Biochemical Features

The variation of pairwise comparisons of EVI vs. LST (℃) pre (August 04, 2017) and post (October 07, 2017) landfall of Hurricane Irma is illustrated in Fig. 6a. Comparatively, the variations of EVI vs. LST (℃) in both pre and post landfall events follow the logistic function relationship (Pearl and Reed, 1920; Szparaga and Kocira, 2018), as shown below in Equation 7.

\[ f(x) = \frac{L}{1 + e^{-k(x-x_o)}} \]  

(7)

where \(x_o\) = x value of midpoint, \(L\) = maximum value, and \(k\) = growth value. The logistic function has been frequently applied in population ecology, geosciences, geography, social sciences, statistics, and many other fields (Zimmerer, 1994; Hui, 2006; Sayre, 2008; Martire et al., 2015). In a logistic function, there exists both a slower growth or change and a rapid growth or change with respect to the X variable. The initial variation shows a steady change of the Y variable from the beginning to the midpoint of the X variable, while the next variation shows a rapid change of the Y variable from the midpoint of the X variable to the latter part. In this study, the change of gradients of these two stages or the shifting of logistic curves toward an end implies the impacts caused by the climate change driven by the landfall of Hurricane Irma.

EVI tended to increase with LST rapidly following the landfall of Hurricane Irma, while EVI increased slowly following the landfall of Hurricane Irma (Fig. 6a). The leftward shift of EVI variation along the LST axis after the landfall of Hurricane Irma compared to the pre landfall of Hurricane Irma scenario demonstrates the impact of the event on the greenness of vegetation with changing LST. However, when EVI reaches 0.49 at the 23.39 (℃) LST, the two curves exhibit the same rate of EVI increases with LST. This point represents the incident where the ecosystem reached its previous status pre landfall of Hurricane Irma. Interestingly, when the EVI reaches 0.78
and 0.56 of pre and post Hurricane Irma landfall, a rapid increase of EVI with increasing LST reveals the ability of the solar radiation to enhance the greenness of the vegetation. When the solar radiation is at the optimum level, it supports the plant growth, causing the plants to show more lust and green surfaces. The evidence of a wavy type of variation can be observed in the LAI \( \text{m}^2/\text{m}^2 \) vs. LST \(^\circ\text{C}\) curves (Fig. 6c), which may be due to the higher data density within a narrow range of data, as LAI ranged from 0 to 7 \( \text{m}^2/\text{m}^2 \) with one decimal point. Further, both pre and post landfall of Hurricane Irma LAI and LST curves follow a logistic relationship. Later, LAI reaches 5.7 \( \text{m}^2/\text{m}^2 \) at 23.9 \(^\circ\text{C}\), at which point both curves show an increasing trend, denoting the equilibrium of the ecosystem with these two biophysical parameters. After the ecosystem equilibrium point, both curves follow a slower increment of LAI with LST because, even though the LST is available for plant growth, the other factors that contribute to plant growth and enhance the greenness of the vegetation might be limited.

Moreover, the post landfall period shows a logistic relationship of EVI with GVMI, whereas the pre landfall period illustrates a rapid increment of EVI with increasing GVMI (Fig. 6d). In relation to the variation of EVI and GVMI, EVI increases up to 0.51 steadily, whereas the rate of change of EVI with GVMI presents a similar relationship between vegetation moisture and the greenness of the vegetation. Conversely, there existed a rapid growth of EVI with GVMI pre landfall of Hurricane Irma while there was only a slight increment of EVI with GVMI post landfall of Hurricane Irma. When moisture status is in the optimal condition, it favors plant growth and enhances the greenness of the vegetation. The shifting of the EVI variation curve with GVMI toward the left of the graph following the event driven by Hurricane Irma highlights the ecosystem regeneration in terms of biophysical features. This signifies the fact that, following the landfall of Hurricane Irma, the rise of EVI was affected by the GVMI, causing a lower enhancement of the
greenness of vegetation due to the impact of landfall. Interestingly, the pairwise comparisons of EVI vs. LAI (m²/m²) pre and post landfall of Hurricane Irma shows the logistic relationship (Fig. 6f). Until EVI reaches 0.49, EVI rises rapidly with LAI. When the plant nutrients are available, along with the optimal temperature and available water, plants grow rapidly. Thereby, it causes the LAI of the vegetation to rise while enhancing the health of vegetation. This leads to naturally increasing the greenness of the vegetation. The change of EVI with LAI both pre and post landfall of Hurricane Irma is limited after EVI passes 0.49, which is the equivalent point for both pre and post landfall of Hurricane Irma. Ultimately, the EVI sharply increases with the LAI, supporting the fact that the maximum contribution of the available chlorophylls in plants shows an increase in the primary productivity, causing a greener environment.

The FPAR does not show a regular logistic relationship with EVI (Fig. 6g) and LAI (Fig. 6h); however, it shows an exponential growth of FPAR with EVI and LAI. This illustrates that activity of photosynthetic pigments effectively contributes to primary production. The combination of GVMI with LST (Fig. 6b) also does not show any relationship like a logistic function. In addition, LAI and GVMI (Fig. 6e) displays a reduction of the LAI and GVMI curve post landfall of Hurricane Irma.
Figure 6. Evolution of biophysical and biochemical features over space in 2D representation (a) $P_1$ (b) $P_2$ (c) $P_3$ (d) $P_4$ (e) $P_5$ (f) $P_6$ (g) $P_7$ (h) $P_8$
3.4. Discussion

3.4.1. Variation of the Biophysical and Biochemical Features over Diverse Land Uses

According to ecosystem surface classifications in the International Geosphere-Biosphere Program, evergreen forests are defined as vegetation cover of more than 60% with a height greater than 2m from ground level and that are green year-round, while deciduous forests are described as vegetation cover of more than 60% with a height greater than 2m from ground level and with annual leaf on and off cycle (Friedl et al., 2002). *Pinus spp.* (Pinus) and *Tsuga canadensis* (Canadian hemlock) are some of common evergreen forest species present in the study region. In addition, *Quercus spp.* (Oaks), *Carya spp.* (Hickories), and *Acer spp.* (Mapels) are some of abundant plant species belonging to deciduous forested plants. With regards to the common grass species, *Stenotaphrum secundatum*, *Cynodon dactylon*, and *Eremochloa ophiuroides* are some of abundant species in the area (Institute of Food and Agricultural Sciences, 2020a). Hence, elucidating impacts on those vegetation-based land use patterns is vital, as they govern the primary production of the terrestrial ecosystem. Highlighting the significant variations of biophysical and biochemical properties in these specific land uses pre and post landfall of Hurricane Irma helps pinpoint the answers for the research question. The variation of grassland and evergreen forested uses exhibited a logistic relationship of EVI and GVMI curves pre and post landfall of Hurricane Irma, as shown in Fig. 7a and Fig. 7b, respectively. However, pre landfall of Hurricane Irma, the change of EVI with GVMI was more rapid comparatively. In both grassland and evergreen forested land uses, the EVI changes from 1.5 to 5, whereas GVMI ranges from 0.4 to 0.5 (Fig. 7a and Fig. 7b). The explanation behind this variation might be that when the availability of the soil water content increases, the ability of plants to absorb the water for their metabolism increases. Along with the transpiration process, roots can take water into the plants and distribute it among
the vegetative parts of plants for their growth. As a result of that, vegetation health increases. Glenn et al. (2007) explained that vegetation indices estimate the transpiration and provide information about the transpiration processes in forested areas. Thus, findings in the present study are reasoned via the concept of EVI, which represents the lust of vegetation rising naturally with an effective vegetation moisture factor. However, when GVMI ranges from 0.5 to 0.6, the increment of EVI reduces slightly. Herbert et al. (1999) mentioned that, even if the soil water content is higher, the growth of the vegetation in forests is determined by numerous factors such as CO$_2$, nutrient concentrations such as available N, P, K, and solar energy. In addition, they found that a hurricane influences the cycling of minerals and microbial activities, altering plant nutrient intake. Hence, this hurricane-induced stress may be a limitation for the process of photosynthesis. Consequently, the primary productivity and EVI, which indicates the vegetation greenness can be affected in forested land uses due to Hurricane Irma.

Moreover, cultivated agricultural land uses (Fig. 7c), and deciduous land uses (Fig. 7d) show a slight rise of EVI in advance of GVMI in the post landfall Hurricane Irma scenario. This Hurricane Irma impact can be generated due to alteration of main biochemical features, including circulation of N and water, and photosynthetic pigments available for vegetation health. Adam et al. (2010) asserted that features, namely N, chlorophyll pigments, and availability of water, govern the biochemical properties of crop growth, which ultimately relate to the plant productivity. As a result of the landfall of Hurricane Irma, the nutrient cycling and water cycling can be altered, causing the change in available water and N content for cultivated crops. Even though assessing the plant water content is challenging due to the difficulty of discriminating the leaf liquid water from atmospheric vapor, this is the most reasonable explanation for the variation of vegetation health based EVI with water content.
Further, EVI experienced a decline of range in the deciduous forested layer in comparison to the EVI in the evergreen forested layer, which may be due to the shedding of leaves. In response to the seasonal variations, especially in deciduous forested plants, leaf color turns to yellow and red from green (Archetti et al., 2013). Because of non-effective photosynthesis, yellow or red color leaves, and stress caused by the landfall of Hurricane Irma, the EVI post landfall of Hurricane Irma reduced significantly.

The behavior of the LAI with LST in grassland (Fig. 8a), evergreen forested (Fig. 8b), and deciduous forested (Fig. 8d) areas exhibits a logistic relationship. Significantly, mean LAI declines after the landfall of Hurricane Irma in all above-mentioned land uses. The deciduous tree leaves hold more surface area compared to the evergreen forest plants. Seasonally, deciduous forest plants shed their leaves in the Summer, starting from the end of July and August. In the Fall, the number of leaves available is significantly less in deciduous forested plants. However, the present study assessed the variation of biophysical and biochemical features in two adjacent seasons of the year. Thus, this might be a possible reason for having a low LAI, along with the impact caused by the climate change event.
Figure 7. The relationship of variation of EVI and GVMI before (October 07, 2017) landfall of Hurricane Irma in (a) grassland land uses, (b) evergreen forested land uses, (c) agricultural land uses, and (d) deciduous forested land uses in the Santa Fe River Watershed
Moreover, Hong and Lakshmi (2007) reported that the growth or maturity stage of plant species is also a key factor when reflecting the LAI in a vegetative land use. The study claimed that, in the vegetative stage, the LAI and chlorophyll-a content illustrates a linear relationship, whereas in the reproductive stage, the relationship of LAI and Chlorophyll-a content tends to be exponential. Therefore, the prevalence of different growth stages of specific plant species, especially with the grasses and evergreen forested plants, along with the climate change variations, can be influential factors in the change of LAI after the landfall of Hurricane Irma.

However, the agricultural and cultivated land use (Fig. 8c) of the study area denotes a decline of the change of LAI vs. LST, which might be due to the crop damage induced by Hurricane Irma. In terms of agricultural crops, vegetables such as broccoli, potatoes, and snap beans; fruits such as grapes, watermelons, citrus, and sugarcane; and other crops such as cotton and peanuts are grown in the study area (Institute of Food and Agricultural Sciences, 2020b). The nature of the leaf arrangements, physiology (C3 and C4 mechanisms of the photosynthesis pathways), and adaptations to effective photosynthesis are different. Moreover, sensitivity of the vegetation to natural climate change events also differs based on the vegetation species and type. The landfall of Hurricane Irma may have negatively impact some of comparatively sensitive broad leaves of cultivated crops in the locality. The resilience of the agricultural crops of the study area impacted by the landfall of Hurricane Irma is evidenced through the shift of the LAI and LST curve (Fig. 8c) to the left.
Figure 8. The relationship of variation of LAI (m²/m²) and LST (°C) before (October 07, 2017) the landfall of Hurricane Irma in (a) grassland land uses, (b) evergreen forested land uses, (c) agricultural land uses, and (d) deciduous forested land uses in the Santa Fe River Watershed.
The relationship of the EVI and LAI (Fig. 9) over four main vegetation land uses tended to be positive and yet showed a logistic relationship in cases with grassland (Fig. 9a), evergreen forested land uses (Fig. 9b), and agricultural land uses (Fig. 9c). Potithep et al. (2010) claimed that the EVI and LAI relationship displayed a linearity at all scales. Moreover, Alexandridis et al. (2020) reported that the relationship of the EVI and LAI is sensitive to the dry climatic conditions and tends to be a random and distributed relationship via the scatter plots behavior shown during the analysis. Further, linear and polynomial fit of the data were shown in broad leaf forests followed by needle-leaved forests land uses ($R^2 = 0.46-0.68$), especially, in shrublands, the linear regression was noted to be ($R^2 = 0.44-0.80$). Leaf area is the one of leaf traits vary in the leaf spectrum and relationships between leaf area and EVI is caused by the decline in NIR reflectance with pin presence of thick leaves. Additionally, leaf area is vital at the canopy level due to the light absorption by lignin and cellulose (Hinojo-Hinojo and Goulden, 2020). Thus, behaviors of the LAI and EVI scatter plots of the present study corroborates the idea of the logarithmic variation in the Leaf area and EVI. The findings of Myneni et al. (2002) corresponded with our study results, highlighting the fact that EVI and LAI relationships always do not follow linear relationships. However, the resultant logistic relationship of EVI and LAI in evergreen and grassland land uses might be due to the impact of EVI on leaf phenology LAI values. In addition, Kang et al. (2016) observed a logarithmic or power type trend of LAI (independent variable) and EVI (dependent variable) combination in agricultural plants such as wheat, maize, rice, and soya beans. Due to the less saturation effect of EVI and efficiency in photosystems in the beginning of plant development, it suggests that initial LAI growth has tremendously influenced the enhancement of EVI (Kang et al., 2016). This phenomenon is clearly justified by the evidence that most of land uses depicted a significant growth of LAI up to 2 ($m^2/m^2$) (Fig. 9). Further, Potithep et al. (2013) revealed that
EVI increases from leaf expansion to saturation period, causing higher LAI in the vegetation. When the leaf area is broader it can house more pigments to enhance the greenness and primary productivity of the vegetation. However, our results show a lower increment of EVI with LAI after the landfall of Hurricane Irma. This may be due to the influence of the landfall of Hurricane Irma on the growth and greenness of the vegetation through its alteration of the water, nutrient, and gases exchanges with the environment. The lack of available factors for successful photosynthetic cycles (C3 and C4) in plants abates the primary productivity of plants. As the growth of the leaves is impacted by the climate change event, primary productivity in grass, forested plants, and agricultural crops and lushness of the vegetation are also reduced. In addition, in response to the seasonal variations, especially in deciduous forested plants, leaf color turns to yellow and red from green. The non-effective photosynthesis of yellow or red color leaves is one of the potential causes for having a reduced EVI and LAI relationship after the landfall of Hurricane Irma.
Figure 9. The relationship of variation of EVI and LAI (m²/m²) before (October 07, 2017) the landfall of Hurricane Irma in (a) grassland land uses, (b) evergreen forested land uses, (c) agricultural land uses and (d) deciduous forested land uses in the Santa Fe River Watershed.
3.4.2. Functional Capacity Fluctuations

With regards to the derivation of $F$, Table 8, Table 9, and Table 10 summarizes the major outcomes of the variation of $F$ among grassland, evergreen forested land, and deciduous forested land in pre and post cases of landfall of hurricane Irma. The $F$ of EVI with GVMI, LAI with LST as well as EVI with LAI combinations were significantly reduced after the landfall of Hurricane Irma because of disturbance to the greenness and the productivity of the vegetation (Table 8, Table 9, Table 10). With regards to the negative consequences of hurricanes, hurricanes alter the wind-vegetation canopy interactions. The effects of past hurricane events, for instance, can cause fine root mortality, direct canopy damages (Lugo, 2008), significant nutrients flux transfer from canopy to soil due to canopy damages, and reduction of nutrient availability and annual net primary productivity due to impact on soil microbial interactions. Additionally, hurricanes and cyclones also cause defoliation, resulting in short term stem growth reduction, high mortality of forest plants, and affecting tree maturity (Lin et al., 2020). Gong et al. (2021) stated that LAI is lowered after the hurricane event compared to the pre-condition. On the other hand, EVI and the average canopy height of forests were drastically reduced after the hurricane. The phenological cycles of forested ecosystems can also be greatly impacted by the presence of landfall of hurricanes (Li et al., 2007). In other words, these plant functions driven rates on vegetative land uses are declined after the hurricanes. Thus, the scenarios were observed among selected functional capacities calculated using the biophysical combinations in the present study. The major potent reason might be that the photosynthesis was affected by the landfall of Hurricane Irma, all functions associated with the plants may be altered. Therefore, the functions such as expansions of leaf area, enhancement of vegetation health (greenness), and all other metabolism and physiology were greatly impacted by the hurricane. Thus, these findings show that the influence on the hurricane
forced the plants in these vegetative ecosystems to lower their ecosystem and metabolic functionality.

Table 8. Ecosystem Functional Capacity (F) Analysis of EVI and GVMI

<table>
<thead>
<tr>
<th>Biophysical features combination</th>
<th>Land use types</th>
<th>Before/After</th>
<th>( R^2 )</th>
<th>( F ) value</th>
<th>( r ) (gradient)</th>
<th>Equations</th>
</tr>
</thead>
</table>
| EVI (y axis) and GVMI (x axis)   | Grassland Before     | 0.8987       | 0.99     | 10.4180        |                   | \[
\ln \left( \frac{\text{EVI}_{\text{GVMI}}}{1 - \text{EVI}_{\text{GVMI}}} \right) = 10.418 (\text{GVMI} - \text{GVMI}_{\text{min}}) - 1.1266
\]
|                                 | After                | 0.7010       | 0.96     | 5.4460         |                   | \[
\ln \left( \frac{\text{EVI}_{\text{GVMI}}}{1 - \text{EVI}_{\text{GVMI}}} \right) = 5.446 (\text{GVMI} - \text{GVMI}_{\text{min}}) - 0.9747
\]
| Evergreen forested Before       | 0.9464               | 1.02         | 10.2661  | \[
\ln \left( \frac{\text{EVI}_{\text{GVMI}}}{1 - \text{EVI}_{\text{GVMI}}} \right) = 10.2661 (\text{GVMI} - \text{GVMI}_{\text{min}}) - 1.0742
\]
| After                           | 0.8975               | 1.01         | 5.1696   | \[
\ln \left( \frac{\text{EVI}_{\text{GVMI}}}{1 - \text{EVI}_{\text{GVMI}}} \right) = 5.1696 (\text{GVMI} - \text{GVMI}_{\text{min}}) - 0.9677
\]
| Deciduous forested Before       | 0.9545               | 1.04         | 13.7850  | \[
\ln \left( \frac{\text{EVI}_{\text{GVMI}}}{1 - \text{EVI}_{\text{GVMI}}} \right) = 13.785 (\text{GVMI} - \text{GVMI}_{\text{min}}) - 1.5409
\]
| After                           | 0.9019               | 1.02         | 5.6303   | \[
\ln \left( \frac{\text{EVI}_{\text{GVMI}}}{1 - \text{EVI}_{\text{GVMI}}} \right) = 5.6303 (\text{GVMI} - \text{GVMI}_{\text{min}}) - 0.8426
\]
| Agricultural lands Before       | 0.7211               | 0.97         | 12.0190  | \[
\ln \left( \frac{\text{EVI}_{\text{GVMI}}}{1 - \text{EVI}_{\text{GVMI}}} \right) = 12.019 (\text{GVMI} - \text{GVMI}_{\text{min}}) - 1.1982
\]
| After                           | 0.6707               | 0.95         | 8.5961   | \[
\ln \left( \frac{\text{EVI}_{\text{GVMI}}}{1 - \text{EVI}_{\text{GVMI}}} \right) = 8.5916 (\text{GVMI} - \text{GVMI}_{\text{min}}) - 1.5427
\]
### Table 9. Ecosystem Functional Capacity (F) Analysis of LAI and LST

<table>
<thead>
<tr>
<th>Biophysical features combination</th>
<th>Land use types</th>
<th>Before /After</th>
<th>R²</th>
<th>F value</th>
<th>r (gradient)</th>
<th>Equations</th>
</tr>
</thead>
</table>
| Grassland                        | Before               | 0.7768        | 1.02 | 1.2256  |              | \[
|                                  | After                | 0.7327        | 0.93 | 1.1940  | \[ \ln \left( \frac{\text{LAI}_{\text{LST}}}{1 - \text{LAI}_{\text{LST}}} \right) = 1.2256(\text{LST} - LST_{\min}) - 5.0916 \] |
|                                  |                      |               |      |         |              | \[ \ln \left( \frac{\text{LAI}_{\text{LST}}}{1 - \text{LAI}_{\text{LST}}} \right) = 1.1940(\text{LST} - LST_{\min}) - 3.7740 \] |
| Evergreen forested               | Before               | 0.7456        | 1.14 | 1.3978  |              | \[
|                                  | After                | 0.7208        | 1.07 | 0.9524  | \[ \ln \left( \frac{\text{LAI}_{\text{LST}}}{1 - \text{LAI}_{\text{LST}}} \right) = 0.9524(\text{LST} - LST_{\min}) - 3.2542 \] |
| Deciduous forested               | Before               | 0.7791        | 1.02 | 1.8759  |              | \[
|                                  | After                | 0.7878        | 0.89 | 1.3025  | \[ \ln \left( \frac{\text{LAI}_{\text{LST}}}{1 - \text{LAI}_{\text{LST}}} \right) = 1.3025(\text{LST} - LST_{\min}) - 3.0970 \] |
| Agricultural lands               | Before               | 0.6144        | 0.79 | 3.2312  |              | \[
|                                  | After                | 0.6078        | 0.75 | 0.7341  | \[ \ln \left( \frac{\text{LAI}_{\text{LST}}}{1 - \text{LAI}_{\text{LST}}} \right) = 0.7341(\text{LST} - LST_{\min}) - 0.7210 \] |
Table 10. Ecosystem Functional Capacity (F) Analysis of EVI and LAI

<table>
<thead>
<tr>
<th>Biophysical features combination</th>
<th>Land use types</th>
<th>Before /After</th>
<th>R²</th>
<th>F value</th>
<th>r (gradient)</th>
<th>Equations</th>
</tr>
</thead>
<tbody>
<tr>
<td>EVI (y axis) and LAI (x axis)</td>
<td>Grassland Before</td>
<td>0.8832</td>
<td>0.94</td>
<td>0.2252</td>
<td>0.94</td>
<td>( \ln \left( \frac{EVI_{LAi}}{1 - EVI_{LAi}} \right) = 0.2252(\text{LAI} - \text{LAI}_{\text{min}}) - 0.7311 )</td>
</tr>
<tr>
<td></td>
<td>After</td>
<td>0.7413</td>
<td>0.93</td>
<td>0.1473</td>
<td>0.93</td>
<td>( \ln \left( \frac{EVI_{LAi}}{1 - EVI_{LAi}} \right) = 0.1473(\text{LAI} - \text{LAI}_{\text{min}}) - 0.5970 )</td>
</tr>
<tr>
<td>Evergreen forested Before</td>
<td>0.8465</td>
<td>0.97</td>
<td>0.1959</td>
<td></td>
<td></td>
<td>( \ln \left( \frac{EVI_{LAi}}{1 - EVI_{LAi}} \right) = 0.1959(\text{LAI} - \text{LAI}_{\text{min}}) - 0.7560 )</td>
</tr>
<tr>
<td></td>
<td>After</td>
<td>0.7156</td>
<td>0.95</td>
<td>0.1167</td>
<td>0.95</td>
<td>( \ln \left( \frac{EVI_{LAi}}{1 - EVI_{LAi}} \right) = 0.1167(\text{LAI} - \text{LAI}_{\text{min}}) - 0.5153 )</td>
</tr>
<tr>
<td>Deciduous forested Before</td>
<td>0.7635</td>
<td>1.29</td>
<td>0.7228</td>
<td></td>
<td></td>
<td>( \ln \left( \frac{EVI_{LAi}}{1 - EVI_{LAi}} \right) = 0.1947(\text{LAI} - \text{LAI}_{\text{min}}) - 0.7228 )</td>
</tr>
<tr>
<td></td>
<td>After</td>
<td>0.6688</td>
<td>1.15</td>
<td>0.5916</td>
<td>1.15</td>
<td>( \ln \left( \frac{EVI_{LAi}}{1 - EVI_{LAi}} \right) = 0.109(\text{LAI} - \text{LAI}_{\text{min}}) - 0.5916 )</td>
</tr>
<tr>
<td>Agricultural lands Before</td>
<td>0.7786</td>
<td>0.89</td>
<td>0.3791</td>
<td></td>
<td></td>
<td>( \ln \left( \frac{EVI_{LAi}}{1 - EVI_{LAi}} \right) = 0.3791(\text{LAI} - \text{LAI}_{\text{min}}) - 0.5778 )</td>
</tr>
<tr>
<td></td>
<td>After</td>
<td>0.6119</td>
<td>0.82</td>
<td>0.2957</td>
<td>0.82</td>
<td>( \ln \left( \frac{EVI_{LAi}}{1 - EVI_{LAi}} \right) = 0.2957(\text{LAI} - \text{LAI}_{\text{min}}) - 0.8134 )</td>
</tr>
</tbody>
</table>
3.4.3. Ecosystem Resilience Assessment

Estimations and predictions of the resistance and resilience of plant species, especially in forested land uses, are vital, as the earth is more prone to high intensity hurricane events due to global climate change (Walsh et al., 2016). The use of F can aid in understanding and managing vegetation ecosystem responses to withstand climate change. The understanding of the phenomena of the ecosystem resilience process of declined biophysical and biochemical features of the vegetation due to the landfall of Hurricane Irma enables us to address our third research question. The decline of the range of the EVI and LST curve post landfall of Hurricane Irma (Fig. 6a) demonstrates the ecosystem resilience of the study area with respect to the vegetation greenness and temperature variation. When the health or the greenness of the vegetation declines, it affects EVI values. For example, the gradual reduction of the rate of change of EVI in front of LST when EVI reached 0.5 at 23 (°C), shifting the EVI and LST curve leftward in the range of 18 (°C) to 23 (°C) (Fig. 6a) post the hurricane event, illustrates the capacity of the vegetation to cope with the ecological stress driven by Hurricane Irma. Herbert et al. (1999) explained that both structural and functional resistance provide support to resist extreme weather events. Further, during their study, they identified that structurally damaged tree crowns, roots, and leaf areas, and functionally damaged primary productivity recover significantly slower from hurricane driven events. Anderegg et al. (2018) explained that plant vegetation shows morphological and physiological changes as a response to the water stress; hence, it may affect the water, energy, and heat fluxes. Also, these changes can impact the severity of climate change driven events, for example, hurricanes, floods, forest fires, and droughts.

In addition, the patterns of biophysical parameters variations of the agricultural and deciduous forested land uses were significantly altered, as shown by the post Hurricane Irma event
Agricultural crops have relatively soft and slender tree trunks compared to the evergreen forested wood plants. Moreover, maturing deciduous plants are also composed of growing slender tree trunks. Therefore, the wind driven effects cause damage to the crown and stem of those plants. Francis and Gillespie (1993) and Peterson (2000) claimed that slender and growing plants experienced more severe damage than other plants due to the higher tension exerted by the hurricane. These potential damages caused during the Hurricane Irma event are explained by the lower mean EVI recorded during the study, as it reduces the vegetation greenness. However, the recovery process of these damaged plants is well described by the regrowth of survived trees. Poorter et al. (2010) asserted that sprouting capacity and carbohydrate reserving tend to increase after an extreme weather event, although slowly. In addition, Paz et al. (2018) determined that the plant resilience capacity to withstand a climate change event depends on certain factors, namely specific leaf area, wood density, and slenderness of plant species. Tree slenderness and leaf area positively affect the resilience rate, while the wood density negatively affects the vegetation resilience of post hurricane incidents. Moreover, they explained that narrow trees with large crowns are more prone to severe physical damages by hurricanes. Thus, in the present study our study results correspond with the information that agricultural crops and growing deciduous forested plant that have slender dense crowns are more highly affected, which is reflected by the low rates of variations of EVI and LAI following the Hurricane Irma incident (Table 7). Further, the magnitude of the shifting of the curve elucidates the resistance of the vegetative surfaces ecosystem to withstand the landfall of Hurricane Irma. Less survivorship of diverse vegetation weakens the absorption of the green band of the electromagnetic spectrum.

The phenology in vegetation is driven by climate, with water, temperature, and radiation as constraints to vegetation activity. However, the range of EVI increments with LAI decreased
due to the landfall of hurricane Irma (Fig. 7e). The change of EVI with LAI showed similar changes when EVI was 0.49 and 0.63 both pre and post landfall of Hurricane Irma. However, the variation of EVI with LAI was significantly influenced for all other values. In other words, the mean values of EVI and LAI were lower in the post Hurricane Irma event. This phenomenon of the present study aligned with the results presented by Herbert et al. (1999), which show that LAI does not recover until 2 years’ following the hurricane event. Further, Harrington et al. (1997) and Potithep et al. (2013) revealed that higher leaf area values of the vegetation cause higher drag forces with respect to air dynamics, making those trees more vulnerable. For instance, many species of deciduous and agricultural crop plants contain broad leaf area, thus they are influenced by the effect of the landfall of Hurricane Irma. Hence, the variation of the EVI with LAI in agricultural and deciduous land uses follow an irregularity post landfall of Hurricane Irma. Along with the physical damages, the reduced leaf area provides an explanation for the lower primary productivity post Hurricane Irma when compared to pre-Hurricane Irma. This causes a lower EVI growth rate with lower LAI in the deciduous forested and agricultural land uses (Table 8).

In terms of combining biochemical features with other biophysical features of the vegetation analysis in this study, the reduced FPAR values post hurricane landfall of Irma (Table 7) illustrate how the primary productivity was affected due to this single climate change event. Xu et al. (2013) investigated the significant loss of gross primary production after a storm event occurred in China, which impacted FPAR, temperature, ET, and other biochemical features of leaf structure. Qin et al. (1992) outlined that, even if the photosynthesis rate of young plants less than 1-year in age are higher than older plants, the photosynthetic activity declination also depends on the time taken to expand leaves. However, as there existed a diversity of plant species in the study area, this also can be a potential effect of reduction of FPAR, along with the landfall of Hurricane
Irma. Frazier et al. (2013) clarified that, depending on the time scale, some vegetative land uses such as deciduous plants show a short-term resilience of gross primary productivity after a disaster event, while the evergreen-forested land use does not present a resilience until around 65 days have passed since the extreme event happened. Apart from that, even though some plant parts can absorb PAR for a short time duration while being subjected to partial uprooting and breakage of branches of plants, it is not as effective as PAR absorption by healthy plants. Moreover, present study results correspond with the findings of Frazier et al. (2013), namely that grassland land use shows a higher resilience because of its adaptability and tolerance. During this study, it was proven that grassland land uses followed a similar pattern of logistic variation following the Hurricane Irma event.

However, overall ecosystem resilience depends on the trade-off between the growth rates, resistance of plant species to external stresses, and capacity of plant species to recover. In addition, the adaptation to conserve water in water stress conditions depends on the usable amount of stored carbohydrates and other structural and functional aspects of plant species over different land uses. Further, recovery processes of root damages, stem damages, leaf area, canopy crown, and primary productivity are also time dependent. Thus, within the scope and the results of present study, the prediction of the shifting of the tipping point of the ecosystem vegetation balance cannot be well understood.
CHAPTER FOUR: NONLINEAR PHASE SHIFTS IMPACT MARGINAL ELASTICITY OF CANOPY VEGETATION IN INTERMITTENT EXTREME WEATHER EVENTS

4.1. Introduction

Episodes driven by extreme weather events have intermittent impacts on the structure of the canopy cover and phenology of vegetation activity because they alter the energy exchanges between land and the atmospheric system. The changing climate oftentimes results in increased vegetation mortality and disturbances, especially in woodland and forested ecosystems (Carnicer et al., 2011). Although most research focuses on exploring climate change effects on entire ecosystems (Yan et al., 2014), vegetation canopies alone can play a key role in maintaining land atmospheric interactions while assimilating consecutive extreme weather events. Coupling biochemical and biophysical features of vegetation via geophysical and geospatial analysis provides a platform for exploring the impact of extreme weather on the resistance and resilience of the vegetation canopy (Kumar et al., 2014). Climate change causes a variety of vegetation responses, such as a reduction in annual gross primary productivity (GPP) and net primary productivity, decline of biomass of vegetation, and significant changes in plant species abundance and composition (Duveneck et al., 2014). The canopy vegetation resistance, resilience, and thus elasticity, which is a function in terms of resistance and resilience, are critical indicators for quantifying the ability of vegetation to withstand climate change stressors such as hurricanes, floods, and droughts (Jian et al., 2017). Vegetation canopies exhibit a response trajectory of changes of structures and functions in pre and post disturbance scenarios (McDowell et al., 2015). Canopy vegetation resistance, resilience, and elasticity variations caused by intermittent extreme weather events have not been well studied, especially regarding patterns of nonlinear phase shifts. Understanding vegetation canopy resilience, resistance, and elasticity in response to cyclic extreme
weather regimes (floods and droughts) is vital for climate change impact assessment and successive carbon cycle responses.

Given the significance of the biosphere atmosphere interactions and the variations in global changes, more attention has been drawn to climate induced traits of vegetation (Keenan et al., 2014). In plant communities, there is a tradeoff between the resistance to climate change and the growth and functional capacities of plant species (Loehle, 1998). However, the effect of alternating dry and wet events on canopy vegetation resistance and resilience has yet to be thoroughly explored. The ecosystem resistance, or, its “ability or capacity to persist during a disturbance event, measured via simultaneous effect of the disturbance factors on the response indicator” is critical for balancing the ecosystem (Pimm, 1984; DeRose and Long, 2014). On the other hand, the ecosystem resilience, defined as the “ability of an ecosystem to continue and maintain the functions and status with regards to the disturbance,” is crucial for the recovery of the ecosystem (Pimm, 1984; DeRose and Long, 2014). From an ecosystem perspective, ecosystem resilience maintains the flow of ecosystem functions and services and shows immediate responses to climate changes (Anderegg et al., 2020). Extreme weather events tend to alter the ecosystem resilience of plants, especially in forested areas, and convert the respective land use pattern when events exceed the tipping point (Reyer et al., 2015; Seidl et al., 2017). Ecosystem elasticity enables the assessment of ecosystem health and indicates the potential for rebounding behavioral and structural traits to the initial stage following external disturbances (Jian et al., 2017). The combined effect of the resistance and resilience to external disturbances is accounted as the ecosystem elasticity attribute. Thus, maintaining or restoring the ecosystem resilience is important for sustainable climate change adaptation and mitigation. Based on this foundation, ecosystem indicators such as resilience,
resistance, and elasticity can elucidate the behavioral patterns that are helpful for climate change mitigation and adaptation of an ecosystem under stressful conditions.

To investigate the vegetation canopy health and status, numerous biophysical and biochemical indices can be used. For instance, leaf area index (LAI) is one of the controlling features of biophysical feedbacks, as it provides an indication of the solar radiation absorbance amount due to warming effects and evaporation and transpiration processes, along with the canopy resistance (Kala et al., 2014). LAI serves as a critical attribute in land surface models due to its association with the albedo of terrestrial surfaces, as it intercepts and portions precipitation for runoff, evaporation, and ground falls (Fang et al., 2019). The greenness of the vegetation canopy, reflected by the enhanced vegetation index (EVI), has been widely used for climate change assessment applications in deciduous and evergreen forests (Phompila et al., 2015), and agricultural and grassland uses (Kath et al., 2019). EVI can be employed to elucidate the influence of climate mediated changes on canopy resistance, as it represents the photosynthetic productivity and health of the plants. In addition to EVI, the fraction of absorbed photosynthetically active radiation (FPAR) is used to study vegetation productivity, as it employs the photosynthetic ability of plants. Moreover, FPAR features energy exchange between the atmosphere and vegetative surfaces (Dong et al., 2016). GPP is heavily dependent on these vegetation indices, and Sims et al. (2008) developed a model based on EVI and land surface (LST) to explore the GPP on ecosystems. Liu et al. (2015) has studied the GPP estimation over land cover types using remote sensing LAI and FPAR. Soil thermodynamics and land surface meteorology governed by LST drives vegetation health and productivity. However, the effect of extreme weather events may vary depending on the vegetation land use types, which exhibit diverse adaptations to external disturbances.
Hence, the science questions to be answered in this study are: (1) how does the relationship of featured indices associated with four main vegetative land uses (agricultural, deciduous forested, evergreen forested, and grassland) reflect responses to extremely dry and wet events in the Santa Fe river watershed?, and (2) how can the ecosystem resilience, resistance, and elasticity changes over the selected land use types be used to describe the cascade effects of extreme weather events in Santa Fe river watershed? Therefore, the objectives of the current study are to (1) demonstrate the impacts of extremely dry and wet events using geospatial technology for feature extraction from four main vegetative land use types, and (2) compare the vegetation canopy’s resilience, resistance, and elasticity capacity globally and marginally over a suite of intermittent extreme weather events. The hypotheses of the study are as follows: (1) there exists no significant difference of canopy resilience, resistance, and elasticity capacity in pre and post extreme climate change events, and (2) the surface energy driven by the LST influences the variation of ecosystem indicators of vegetation canopy due to climate change.

4.2. Methodology

4.2.1. Study Period Selection

The Santa Fe river watershed located in north-east Florida; United States of America was selected as the study area. Generally, the wet season goes from May to October while the dry season begins from November to April (Florida Climate Center, 2017). To pinpoint the extreme weather events, Standardized Precipitation Index (SPI) was calculated using the Ichetucknee flood monitoring station in the study area and it provided information to elucidate the nature of extreme dry and wet conditions (Table 11). Significantly, first alternating dry and wet events occurred in March to April 2017 to April to May 2017, the SPI value was recorded to be -1.73 indicating a
very dry condition and in April 2017, the SPI was recorded to be 1.59 symbolizing a very wet condition. Further, second alternating event was noted to be shown from August to September 2017 and September to October 2017 showing -1.55 SPI and 1.21 SPI.
Table 11. Calculated SPI Values Using Meteorological Drought Monitor Software (Belayneh and Adamowski, 2012) Using the Ichetucknee Flood Monitoring Precipitation Information Located in the Santa Fe River Watershed from 2016 to 2019. The Categorization of SPI Value Classes is Expressed as Follows; SPI >2 = extremely wet, 1.99 > SPI > 1.5 = very wet, 1.49 > SPI >1.0 = moderately wet, 0.99 > SPI > -0.99 = near normal, -1 > SPI > -1.49 = moderately dry, -1.5 > SPI > -1.99 = very dry, SPI < -2 = extremely dry

<table>
<thead>
<tr>
<th>Year</th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
<th>Jun</th>
<th>July</th>
<th>Aug</th>
<th>Sep</th>
<th>Oct</th>
<th>Nov</th>
<th>Dec</th>
</tr>
</thead>
<tbody>
<tr>
<td>2016</td>
<td>-1.15</td>
<td>1.71</td>
<td>0.62</td>
<td>-0.66</td>
<td>0.65</td>
<td>-0.79</td>
<td>-1.01</td>
<td>0.33</td>
<td>0.73</td>
<td>-1.05</td>
<td>-1.68</td>
<td>0.33</td>
</tr>
<tr>
<td>2017</td>
<td>-0.82</td>
<td>-0.46</td>
<td>-1.73</td>
<td>1.59</td>
<td>-1.02</td>
<td>1.28</td>
<td>-0.98</td>
<td>-1.55</td>
<td>1.21</td>
<td>0.66</td>
<td>0.19</td>
<td>-1.09</td>
</tr>
<tr>
<td>2018</td>
<td>1.17</td>
<td>-0.54</td>
<td>0.52</td>
<td>0.05</td>
<td>1.3</td>
<td>-1.15</td>
<td>0.8</td>
<td>0.01</td>
<td>-0.76</td>
<td>-0.9</td>
<td>0.63</td>
<td>1.47</td>
</tr>
<tr>
<td>2019</td>
<td>0.8</td>
<td>-0.74</td>
<td>0.61</td>
<td>-1.01</td>
<td>-0.92</td>
<td>0.65</td>
<td>1.18</td>
<td>1.22</td>
<td>-1.19</td>
<td>1.28</td>
<td>0.98</td>
<td>-0.72</td>
</tr>
</tbody>
</table>
4.2.2. Satellite Data Processing

The MODIS sensor that is composed of 36 spectral bands was employed for the present study. The MODIS images of biophysical features and biochemical features such as for EVI, LAI, GPP, LST, and FPAR were retrieved from the Land Processes Distributed Active Archive Center (LP DAAC, http://lpdaac.usgs.gov) covering the study period (EVI (MYD13A1, 500m, 16-day), LAI (MCD15A2H, 500m, 8-day), GPP (MYD17A2H, 500m, 8-day), FPAR (MCD15A2H, 500m, 8-day), and LST (MYD21A1N, 1000m, 1-day)). First, retrieved satellite images were projected from the MODIS Sinusoidal projection to WGS84 geographic coordination systems. The satellite images were downloaded in Geotiff format. LST images were subjected to processing and obtained the average of consecutive daily images to align with 8-day temporal resolution. LST images were resampled to unify the 500 m spatial resolution using nearest neighborhood method in resampling technique in ArcGIS 10.3 software. For each case, satellite images of biophysical and biochemical features 8 days before the event, on the event, and 8 days after the event were analyzed using ArcGIS 10.3.

4.2.3. Data Analysis

4.2.3.1. Resilience Assessment

Resilience can be expressed as the time for a particular ecosystem to recover to the initial state prior facing the disturbance or a stress (DeRose and Long, 2014; Chang and Wen, 2017). Hence, the resilience was calculated using the following equation 8.

\[
\text{Resilience} = \frac{P_n - P_p}{t}
\]  

(8)
Where, $P_n$ is the normal condition of the biophysical or biochemical feature in the ecosystem, $P_p$ is the condition of the biophysical or biochemical feature facing an impact in the ecosystem, and $t$ is the time taken.

### 4.2.3.2. Resistance Assessment

Resistance can be expressed as the capacity for an ecosystem to remain constant during a disturbance or a stress (equation 9 (DeRose and Long, 2014; Chang and Wen, 2017).

\[
\text{Resistance} = \frac{F_n - F_p}{F_p} \cdot \frac{P_n - P_p}{P_p} \tag{9}
\]

Where $F_n$ is the normal condition of a forcing factor, $F_p$ is the particular condition of a forcing factor during the disturbance or stress. During the analysis, SPI (normalized) was identified as the forcing factors. Based on that, addition of all three forcing factors were included for the data analysis (equation 10).

\[
\text{Resistance} = \left( \frac{\text{SPI}_n - \text{SPI}_p}{\text{SPI}_p} \right) \cdot \frac{P_n - P_p}{P_p} \tag{10}
\]

Where, $\text{SPI}_n$ is the normal condition of normalized SPI, $\text{SPI}_p$ is the particular condition of normalized SPI during the disturbance or stress

### 4.2.3.3. Ecosystem Elasticity Assessment

Ecosystem elasticity provides an indication of the healthiness of the ecosystem. It is termed as the ability of behavioral and structural pattern to echo to the prior stage during a disturbance or
stress. Elasticity can be depicted via the resistance and resilience to disturbance or stress (Jian et al., 2017). The weight factors given to the resilience and resistance were obtained from the judgmental approach based on the external disturbances in the areas. Majority of the land uses prevailed in the Santa Fe watershed area are natural ecosystems (Fig. 1). Based on this criterion, the weighting factor of the resistance should be emphasized more than the resilience. Hence, 0.3 and 0.7 coefficients were introduced into the ecosystem elasticity calculation as follows (equation 11).

\[ \text{Elasticity} = 0.3 \times \text{Resilience} + 0.7 \times \text{Resistance} \quad (11) \]

The variation of resilience in terms of LAI and GPP were calculated over the period to elucidate the ecosystem impacts. Similarly, change of resistance in terms of LAI and GPP were analyzed where SPI was considered as the forcing factors for ecosystem balance. To portray the ecosystem stability level, ecosystem elasticity was calculated based on the period.

4.2.3.4. Correlation Analysis

To assess the relationship of biophysical and biochemical features of vegetation, the Spearman’s correlation analysis was conducted (Zou and Mõttus, 2017). The coefficient derived from the Spearman’s correlation uses as an indication of the strength of the relationship among two features utilized in the present study. As this analysis does not carry any dependency on data distribution, it can be applied to identify the extreme event-based correlation of biophysical and biochemical features in the study.
4.2.3.5. Nonlinear Phase Shifts of Biophysical and Biochemical Features

The phase shifts of the biophysical and biochemical parameters were calculated via change percentage followed by each event period (Park et al., 2015). In the analysis, for each event, the difference gained from beginning of the event and beginning of the next event. Thereby, the change percentage of biophysical and biochemical parameters were presented to illustrate the variation of features over the period.

4.2.3.6. Sensitivity of Marginal Resilience, Marginal Resistance, and Marginal Elasticity

In addition, the marginal resilience, marginal resistance, and marginal elasticity were calculated using the gradient changes of the resilience, resistance, and elasticity curves. The variation of the marginal resilience, marginal resistance, and marginal elasticity over the period were represented to understand the sensitivity of the ecosystem in terms of these three features over the period.

4.3. Results

4.3.1. Variation of Resilience, Resistance, and Elasticity of LAI and GPP over the Period

Notably, two major peaks of high LAI and GPP resilience events were recorded beginning from March to April (the first alternating adjacent dry and wet scenario) and August to September (the second alternating adjacent dry and wet scenario) (Fig. 10a and Fig. 10b) in cases where alternating very dry and very or moderate wet conditions prevailed throughout the study period (Table 11). According to the LAI resilience (Fig. 10a), a substantial increase was observed in evergreen forested land uses during the period, with 0.75 of resilience in April and 0.94 of resilience in September. With regards to deciduous forested land uses, LAI resilience was 0.75 in
April and 0.94 in September. However, agricultural and grassland land uses displayed a reduced resilience level compared to forested land uses (Fig. 10a). This difference is caused by the higher adaptability of forest plants such as *Pinus* spp., *Tsuga* spp., *Quercus* spp., and *Acer* spp., to climate variations compared to other vegetative ecosystems (Duveneck and Scheller, 2016). For instance, *Pinus* spp. forest plants exhibit leaves adaptations to conserve available water (tiny leaves and waxy epicuticular, reduced leaf area and shiny leaf), seeding germination adaptations, transpiration, and stomatal conductance with changing water content, etc. (Parolin et al., 2010). Moreover, *Pinus* spp. germination adapts through wide genetic variations and stability. Meanwhile, deciduous plant species such as *Quercus* spp., can resprout and regenerate from shoots on the rhizome. Interestingly, the landfall of Hurricane Irma occurred in the study region during September 2017, which was a severe wet event (natural disturbance) that could potentially impact vegetation canopies. In comparison to the short-term agricultural crops and some grass species, forests plants’ adaptations heavily showcase a higher capacity of forest canopies to return to their initial stage after an ecological disturbance such as the landfall of Hurricane Irma or a drought.

The findings of the study revealed that agricultural land uses exhibit a lower level of LAI resilience in August to September (second alternating adjacent dry and wet scenario) as compared to March to April (first alternating adjacent dry and wet scenario). In opposition, the LAI resilience of forests and grassland land uses exhibited a higher value in the second alternating weather transition. In this case, recurring extreme dry and wet events were witnessed in the Santa Fe watershed (Table 11). Alternating external environmental stresses such as drought and flood events force short lived fragile agricultural crop species to curtail plant leaf area and photosynthesis activity. Thus, at a certain point, the symmetry of functional capacity and the tipping point of
agricultural ecosystems can be altered prior to cyclic extreme wet and dry events, indicating a potential cause for reduced resilience over intermittent extreme climate events.

Additionally, deciduous forested and evergreen forested land uses presented a higher GPP resilience in April (152.07 and 167.03, respectively) and in August (104.32 and 102.62) (Fig. 10b). On the contrary, a declined resilience regime was noted in agricultural and grassland land uses during April and June. In the context of terrestrial GPP, this observation gives credence to the basis of plant growth and its role in atmospheric CO₂ regulations. Forest ecosystems, including rainforests and temperate forests (deciduous and evergreen), account for the majority of the global terrestrial GPP. Factors such as increased seasonal water deficit, shifts in precipitation patterns, and increasing drought frequency and severity, diminish the terrestrial GPP, impacting the physiological, structural, and functional aspects of forest plants. For example, stomatal conductance, controlled by water availability and atmospheric CO₂, is influenced by drought conditions. Hence, as the sensitivity of these forests are influenced by these extreme environmental conditions, forests become vulnerable to decreasing resilience.

The breakthrough points of our findings primarily indicated a remarkable fall of LAI resilience (0.18) in July (Fig. 10a), where it was challenged by two adjacent, recurring very dry and very wet events (Table 11). Similarly, GPP resilience values decreased sharply for all four land uses in July. 15.07 and 15.49 lower canopy level GPP resilience of deciduous forested and evergreen forested were observed in July (Fig. 10b). The prolonged droughts and rainfall events created massive variations in the soil moisture and temperature. Deficiency of water leads to a reduction in water potential and water stress conditions. In contrast, excessive quantities of water in soil pores results in oxygen deficits and affects nutrient absorption and availability. These external forces create a physiologically stressful environment for plant growth and metabolism.
Consequently, cascade effects of the external intermittent disturbances collapse forests plants canopies morphology and physiology. Thereby, plant species tends to be more vulnerable due to declined resilience. These observations indicate the rapid reduction of resilience of LAI and GPP in July.

The dryness level, obtained by the SPI with the aid of the precipitation of the Ichetucknee rain gauge station, was considered as a stress factor. Based on that, the resultant resistance of LAI and GPP were inversely related to the resilience of LAI and GPP biophysical features (Fig. 10c and Fig. 10d). The two resistance curves in Figures 10c and 10d denote a 3-4 times significantly higher magnitude of resistance in July compared to the other months. On the other hand, the resistance was dramatically lower in March, April, August, and September (Fig. 10c and 10d). July was detected as a normal condition in terms of the dryness levels calculated from the SPI, while March, April, August, and September were marked by recurring very dry and moderate wet events. Plant species go through a lot of physiological stress due to extreme weather events. The plant canopies hold many vulnerable plant parts such as tendering flowers, leaves, branches, and fruits. When the stress factor transcends the tolerance capacity of plants, the plants’ resistance to withstand stress or disturbance diminish rapidly. The decline of resistance in March, April, August, and September highlights the fact that intermittent extreme weather events force plant-based ecosystems to alter plant physiology. Despite the critical alternation due to weather changes in previous months, significantly higher resistance was noted in July.

Deciduous forested and evergreen forested land uses indicated a moderately higher resistance of LAI compared to the agricultural and grassland land uses (Fig. 10c). In severe drought, the forest plants attempt to reduce the leaf size, especially at the canopy level, to conserve water. Furthermore, plants show a resistance to stomatal conductance, leading to low evaporative
demand by plants. Consequently, plant leaf phenology and morphology are negatively affected, seizing their leaf growth to withstand extreme climatic events and rapidly reducing canopy level LAI in externally stressed conditions. In addition, ecosystem equilibrium is dependent on the threshold level or the tipping point of the ecosystem. Intermittent extreme weather events break and destabilize the equilibrium of forest ecosystems, causing unbridled resistance capacity. Contrastingly, agricultural lands are subjected to frequent harvestings of yield based on the percentage of short crops in the field. Some agricultural crops such as carrots and potatoes are fully uprooted during the harvesting process, triggering huge canopy leaf area reduction in the field. On the other hand, many agricultural crops have shorter lifespans and higher vulnerability compared to forest plants. Likewise, the grassland species are composed of higher growth rates and shorter life spans. Collectively, these factors serve as strong evidence of the variation of resistance of LAI.

Correspondingly, resistance performed by the GPP exhibited a trend similar to the LAI resistance change during the period (Fig. 10c and 10d). Evergreen forested and grassland GPP resistance recorded a higher value in July (0.13), during which time normal environmental conditions were observed. During April and May, the evergreen forested and grassland GPP resistance were noted as 0.01, the lower values of the period. Even though some grassland species can respond to extreme weather conditions, weather events increase the rapidity of short-term tissue dying in grassland communities. Apart from that, abrupt changes of climatic factors may affect the photosynthetic pigments and surface layers of plant tissues at the canopy, resulting in retardation of the CO\textsubscript{2} synthesis in plants.

To explore the flexibility of ecosystems to resist natural and anthropogenic disturbances, elasticity provides a quantitative measurement on how vegetative ecosystems cope with stressful conditions. The current study revealed that evergreen forested and deciduous forested land uses
illustrated comparatively higher LAI elasticity (8.52 and 7.14 in July, correspondingly) (Fig. 10e). On the contrary, the grassland ecosystem exhibited a declined LAI elasticity (5.72) in July. Further, the range of the LAI elasticity in all four land uses in other adverse climatic events was observed as 0.37 to 4.00. July represented a near normal condition in the dryness assessment attribute based on the SPI calculations (Table 11). However, March, May, and August experienced events associated with very or moderate dryness in the SPI spectrum. In the forest ecology, drought and heat induced mortalities of forest plants was experienced due to the disturbances. However, the dying off or malfunctioning of forest plant canopies is a discriminating force that differentially distresses tree species. It alters the size, age, and spatial structure of forest plant leaves in different ways. As the canopy is impacted in extreme events, the plant LAI tends to show a decreased elasticity in comparison to the normal environmental conditions. Thus, LAI elasticity in July is favored by the normal environmental conditions, whereas the extreme conditions lower the elasticity of LAI. Furthermore, variation of LAI elasticity demonstrates a trend similar to the LAI resistance in all four land uses. Out of the two determining factors of the elasticity of LAI, the LAI resistance dominates the LAI resilience. Therefore, the ability of LAI resistance reflection outshines the LAI resilience outcomes in the LAI elasticity analysis in the present study.

In terms of the GPP elasticity of the land uses, we noticed 45.63 and 50.12 in deciduous forested and evergreen forested in April under a moderate wet condition, whereas a very low range of GPP elasticity in July (Fig. 10f). The higher GPP elasticity of forested ecosystems is due to the dominance of the GPP resilience over the GPP resistance. For the GPP elasticity, the GPP resilience contributes more substantially in comparison to the GPP resistance. GPP of evergreen forests and deciduous forests exhibits a high capacity to recover immediately after disturbances. Hence, the higher GPP resilience elucidates the fact that ecosystems show an increased GPP
elasticity as sensitivity enhances. Moreover, agricultural and grassland land uses exhibited a substantial reduction of GPP elasticity in comparison to forested ecosystems. In agricultural lands, growing, fruiting, harvesting, and land preparation seasons of some common species, namely watermelon, carrots, guava, blue berry, snap beans, peanuts, orange, lettuce, and cucumber are varied over the year. During harvesting seasons, agricultural fields become more exposed to disturbances. In addition, some crop plants species must be uprooted for the harvesting. This results in the GPP declining after harvesting cultivated lands.
Figure 10. Resilience, Resistance, and Ecosystem elasticity values of main four selected vegetative land use patterns (agricultural, deciduous forested, evergreen forested, and grassland) in the Santa Fe watershed over the study period (March 2017 – October 2017). a, Resilience in terms of LAI (m²/m²). b, Resilience in terms of GPP (kg C/m²). c, Resistance in terms of LAI.
4.3.2. Relationship of Biophysical and Biochemical Features over Four Selected Vegetative Land Use Patterns in Extreme Events

Given the relationship of biophysical and biochemical features in plant canopies, the four land uses appeared to outline different levels of significance of dry event and wet events (Fig. 11). As the temperature is fundamentally altered by the dynamics of climates, LST triggers the variation and correlation of other biophysical and biochemical features in dry and wet episodes in a watershed. Across deciduous forested and evergreen forested land uses, the EVI and LAI changes were correlated at 0.81 – 1.00 (p < 0.01) LST in both extreme wet and dry events (Fig. 11c – Fig. 11f). Additionally, grassland EVI and LAI were heavily linked with LST variation in both wet and dry events at 0.81 – 1.00 (p < 0.01) (Fig. 11g and Fig. 11h). By contrast, a unique finding in the current study demonstrated that agricultural LAI and EVI is related to LST at a lower level than other land uses at 0.61 – 0.81 (p < 0.01). Unlike the forested land uses (except economically managed timber forests), the agricultural areas are subjected to continuous field preparation and harvesting seasons. In north eastern Florida, where Santa Fe river watershed is located, lettuce, carrots, cucumber, snap beans, orange, tomatoes, etc. are grown as agricultural crops. Depending on the life span and varied growth rates of species, the agricultural fields are harvested frequently in massive scale to achieve economic goals. Additionally, some crops are planted using a crop rotational system to overcome external disturbances such as pests and to obtain all the nutrients at different depths of the soil. In this scenario, some agricultural crop fields are kept uncultivated for some periods. Ground level support given from the root systems and the soil medium act as a key stimulus to nourish the canopy of plants. The soil moisture, fueled by the LST and the porosity to
retain soil water, appeared to change rapidly. Thus, agricultural practices that weaken the ground supporting system can cause inconsistencies in EVI and LAI. These observations may clarify why, compared to forested land uses, the LAI and EVI values associated with agricultural land display a declined interdependency on the LST.

Terrestrial primary productivity determined by multiple factors works rigorously in biosphere – atmosphere integration in response to climate changes. Among the four vegetative land uses analyzed, all four land uses exhibited the integrity of GPP and LST at a similar level of correlation (0.61 – 8.00, at p < 0.01) in both wet and dry events. LST is considered one of the GPP determinants on land, among other biophysical and biochemical features. This conveys the idea that contribution to the GPP fluctuations over the four land uses is mirrored by similar LST changes in four land uses. Nevertheless, reduced FPAR and LST linkage was identified in the agricultural land use in the wet event-based scenario (Fig. 11b). Because of the fragility of some crops used in agriculture compared to the forest plants, crop canopies can be easily damaged in an event like a heavy hurricane. Furthermore, elevated temperatures and rainfalls can directly alter the ecophysiology of the C4 (for instance, corn and sugarcane) and C3 (for example, beans) mechanisms in crop plants. When the chlorophyll pigments that facilitate the CO\textsubscript{2} synthesis process are affected, gas exchange fails due to closure of stomatal openings. This causes malfunctions of chlorophyll pigments, resulting in less photosynthetically viable pigments on leaves. In addition, rapid alterations in soil temperature result in cell ruptures in leaves and crops. This correlates with the low FPAR and LST recorded in agricultural fields.

Interestingly, in the wet season, represented by the landfall of Hurricane Irma in September 2017, connectivity variation of the LAI and EVI with FPAR and GPP explains the lower level (0.41 – 0.60, p < 0.01) in agricultural land uses (Fig. 11b). In a similar fashion, there was a very
low relation of LAI and GPP (0.21 – 0.40 correlation, at p < 0.01) observed in the grassland land uses, while the correlation of EVI and LAI with FPAR and GPP tended to be higher (0.81 – 1.00, at p < 0.01) in forested land uses (Fig. 11d and Fig. 11f). This declined relationship of the GPP and LAI in grassland and agricultural land uses is critically proven by the variation of resilience of the LAI and GPP of these two lands uses in September 2017 (Fig. 10a and Fig. 10b). In the LAI resilience plot, the agricultural and grassland land uses expressed a lower resilience in September compared to the forest land uses (Fig. 10a), along with a significantly higher value of resilience of GPP in agricultural and grassland in September (Fig. 10b). Conjointly, the fluctuations of LAI resistance and GPP resistance of agricultural and grassland in September 2017 caused reduced feedback in the correlation analysis.
Figure 11. Correlation of biophysical and biochemical features. a), Dry event in agricultural land use. b, Wet event in agricultural land use. c, Dry event in deciduous forested land use. d, Wet event in deciduous forested land use. e, Dry event in evergreen land use. f, Wet event in evergreen land use. g, Dry event in a grassland land use. h, Wet event in grassland land use. The correlation of the features was significant at 0.01 (2-tailed, Spearman’s correlation analysis).
4.4. Discussion

4.4.1. The Non-linear Phase Shifts of Biophysical and Biochemical Features

Significant fluctuations of climatic and meteorological factors affect the biophysical and biochemical dynamics of vegetation canopies in terrestrial environments. Hence, the interaction and interdependence of distinct biophysical and biochemical features of canopy vegetation development in the four selected land uses motivate advanced exploration of research question 1 with reference to the changing intermittent weather events. The current study outcomes assert that the energy provided by the LST by changing the dryness and wetness of the nature strengthens and sustains the biosphere-atmosphere interactions of the four selected vegetative land uses. For instance, the fluxes of canopy level EVI and LAI in deciduous forested and evergreen forested land uses over the phase changes of climate are well explained by the changes of LST (Fig. 12f, Fig. 12g, Fig. 12j, Fig. 12k, Fig. 12l, and Fig. 12o). Galvão et al. 2011 demonstrated that the increasing trend of EVI of evergreen forested habitats correlates with the higher temperature induced by the dry season period. To gain the higher LAI and EVI reflected via the enhanced canopy growth in forested ecosystems, the LST dynamics caused by the transition wet to dry season is critical (Liu et al., 2018). The strong positive correlation found in the analysis indicates that an increase in temperature drives the canopy development in temperate deciduous forests (Park et al., 2015). Significantly, this phenomenal theory of biophysical feedback observed during the nonlinearity of weather shifts is clarified by the reduced change percentage of LAI and EVI in deciduous forested and evergreen forested in April (wet event), followed by the growth of EVI and LAI in deciduous forested and evergreen forested in May (Fig. 12). In other words, the dramatic ups and downs of the nonlinear weather changes emphasize the higher interdependency of EVI and LAI of forested ecosystems on the LST in the correlation analysis of this study.
When the high temperature of soil favors forest plant growth in between the tolerance capacity plants, it enables metabolic activities such as evaporation, transpiration, and carbon synthesis for plant development at the optimum level. According to the first law of thermodynamics, since the energy is not destroyed, the proportion of heat energy received from LST and air temperature is invested in favor of sustainable functioning of metabolism activities in plants such as transpiration, leaf and canopy expansion, photosynthesis, etc. Thus, thermodynamically, LST increment within the tolerance limit favors the enrichment of higher leaf area and greenness of the forest vegetation. However, in cases where the energy fluxes patterned by LST are limited in wet conditions, biophysical and biochemical feature development of forest plants are hindered due to the lack of energy for metabolic stimulations. Hence, the relationship of EVI and LAI with changing thermodynamics guided by LST in deciduous forested and evergreen forested land uses corresponds with the impact of alternating weather patterns.

The correlation analysis conducted in the study illustrated that deciduous forested and evergreen forested GPP exhibited a positive assembly of LAI, EVI, FPAR, and LST in both the dry event and the wet event that happened in March and September, respectively (Fig. 12). As an example, in a dry event in March, deciduous forests experienced a 8.9% GPP increase, with 17.3% of LST, 6.5% of EVI, and 12.4% of LAI growth, whereas 7.6% of GPP reduction was experienced when 10.55% of LST, 6.5% of EVI, and 11.7% of LAI were reduced in a wet event in September in the same land use category (Fig. 12f to Fig. 12j). There is thus a tradeoff between biophysical features and carbon synthesis capacity in forested land uses in varying climates. The EVI relationship (Shi et al., 2017), and the EVI, LAI, and FPAR interaction (Liu et al., 2015) aid in the determination of the terrestrial GPP of forests over different climatic periods. The carbon fluxes
are more vulnerable and sensitive in the non-forested ecosystem as compared to the forest ecosystem, as the tolerance is restricted by its functional capacity alterations (Wu and Chen, 2013).

Further, findings in the current study also highlight the importance of the water availability of the soil, controlled by the LST, as a key proxy for the healthiness of a grassland ecology. In reference to the grassland land use dynamics, the influence of the LST on the variability of EVI and LAI is conveyed via the event-based analysis of feature changes (Fig. 12p, Fig. 12q, and Fig. 12t). Even if the canopy density, architecture, complexity, and soil litters are not abundant and diverse in grasslands, LST, along with the soil moisture, contributes to the improvement of some biophysical features in response to the episodic biosphere-atmosphere carbon and water exchanges in a changing climate (Potts et al., 2006). Some grass species exhibit increased resilience over other species in extreme drought events. Grasslands with a higher diversity of heat tolerant plants continue their ecosystem functions in a changing climate because those grass species can potentially store comparatively less water and carbon during a dry period. When grass species exhibit a lower critical leaf water potential, the physiological tolerance of species to in soil water content changes (Craine et al., 2013). Therefore, some of these adaptations support grass communities to maintain their biophysical features for a viable population.

GPP and LST linkage over the grassland land use showed a reduction of GPP with declined LST in a wet event scenario (Fig. 12r and Fig. 12t). However, the correlation analysis did correlate at a medium level, relating the changes of GPP with LST in grasslands (Fig. 11h). The carbon uptake mechanism of grass species connects with the land-atmospheric interactions, as the primary production depends upon some abiotic factors such as solar radiation, moisture, and CO₂. Heavily wet conditions generated by extensive precipitation, floods, and hurricanes, can impact erosion, altering the nutrient content of fertile soil and uprooting some sensitive grass species. Nutrient
turnovers and the mortality of some grassland species due to water logging and uprooting accelerate the rapid fall of GPP during extreme wet events. This suggests a diminishing influence of LST on the decline GPP of the grassland land uses in the present study.

In agricultural fields, the capabilities of crop species to withstand alternating weather patterns imply that the vulnerability of this land use has led to a low to moderate link of biophysical and biochemical features. In fact, especially in the dry event in March, the 5% of GPP change was defined by the 25% of LAI and 15.8% of LST (Fig. 12b, Fig. 12c, and Fig. 12e). Among the carbon assimilation methods in plants, the C4 photosynthetic mechanism is the most productive for maximizing the yield due to the low photorespiration and increased efficiencies of water and nitrogen use (Yadav and Mishra, 2019). Apart from that, photosynthesis in higher plants is a temperature dependent physiological process as it involves enzymatic reactions (Monroe et al., 2014). The thermal and water deficit-based stresses impacted by the frequent dry and wet events result in growth retardations and protein denatures in some sensitive crop plants through the period. In C3 plants, the photosynthetic rate in high temperatures is directed by the sensitivity of the enzyme Rubisco activase to thermal denaturation and electron transport (Makino and Sage, 2007). Thus, photosynthetic biomass production using the C3 mechanism is dependent on external disturbance conditions like droughts, hurricanes, and floods. Therefore, C4 crop plants such as corn, maize, and sugarcane can synthesize more carbon over C3 plants, namely beans, potatoes, etc. Consequently, the total GPP of crop fields is governed by the combination of carbon assimilation via C3 and C4, while the high ratio of C4 plants/total plants favors more agricultural productivity (Júnior et al., 2019). In addition, varied harvesting periods of crop plants species also influence the fluctuations of GPP. These arguments offer critical justifications for varying GPP over the analysis.
Figure 12. The non-linear phase shifts of biophysical and biochemical parameters in terms of change percentage of the four main vegetative land uses over the period (March 2017 – October 2017). a, agricultural (ΔEVI %). b, agricultural (ΔLAI %). c, agricultural (ΔGPP %). d, agricultural (ΔFPAR %). e, agricultural (ΔLST %). f, deciduous forested (ΔEVI %). g, deciduous forested (ΔLAI %). h, deciduous forested (ΔGPP %). i, deciduous forested (ΔFPAR %). j, deciduous forested (ΔLST %). k, evergreen forested (ΔEVI %). l, evergreen forested (ΔLAI %). m, evergreen forested (ΔGPP %). n, evergreen forested (ΔFPAR %). o, evergreen forested (ΔLST %). p, grassland (ΔEVI %). q, grassland (ΔLAI %). r, grassland (ΔGPP %). s, grassland (ΔFPAR %). t, grassland (ΔLST %).
4.4.2. Sensitivity Analysis of Marginal Resilience, Marginal Resistance, and Marginal Elasticity Based on the LAI and GPP

The occurrence of interchanging severe wet and dry incidents in a watershed may interfere with the biophysical and biochemical attributes of the vegetations (Thompson et al., 2009). Extreme climatic episodes driven by LST and precipitation changes (in terms of SPI) offer an opportunity to understand the sensitivity of vegetative ecosystems via alterations with reference to the external changes in the environment. The observed variations of marginal resilience, marginal resistance, and marginal elasticity of this study based on LAI and GPP in land uses corroborate the cascade effects of intermittent climate for ecosystem sustainability, laying the foundation to explore research question 2.

Given the importance of deciduous forested ecosystems, LAI based marginal resilience showed a low sensitivity in June to July, which was a transition from a wet event to a normal environmental condition preceding a 0.060°C LST increment. Further, it displays high sensitivity in extreme event-based transitions (Table 12). The transition from June to July event was the second lowest sensitivity recognized in the LAI based marginal resilience in evergreen forest ecosystems (Table 12) in a 0.065°C LST increment. In addition, LAI and GPP resilience analysis conducted through the period claimed the lowest recorded resilience in July (Fig. 10a and Fig. 10b) in both deciduous and evergreen forested land uses. Forest resilience in stressful conditions evolves from ecosystem states in past. It is transmitted via plant species adaptations and resources that encourage recovery to the initial state (Johnstone et al., 2016). In addition, key components (severity and duration) of stresses reshape the forest ecosystem equilibrium. As per the SPI, the Santa Fe river watershed experienced a few adjacent dry and wet event occurrences from March to June, and these reoccurrences of climatic events induced physiological and behavioral stress on the forest plant species to adapt and absorb the varying environmental conditions in a short time.
period. With regards to the forest plants’ biology, the leaf phenology and leaf development are strongly responsive to the temperature (Dai et al., 2014). Initially, leaves need low temperatures to induce break bud dormancy, and then higher temperatures to encourage cell growth (Chuine, 2000). Combined, the temperature fluctuations spur leaf development through the year. This principle can be applied to describe the observed low sensitivity of LAI marginal resilience in June to July (wet event to a normal event) and the higher sensitivity LAI marginal resilience in the July to August transition (normal event to dry event). As bud dormancy and cell growth are facilitated in adjacent events, this serves as strong evidence of the variation of sensitivity of marginal resilience of LAI in forests from June to August.

The recorded marginal resilience of LAI is reflected in the marginal elasticity of the LAI in the two types of forested ecosystems. The sensitivity of the marginal elasticity of LAI illustrated an increased value (0.2257) in the June to July transition, while it expressed a lower sensitivity (0.1565) in the July to August transition in deciduous forested land use (Table 12). The evergreen forested land use exhibited a similar trend in the marginal elasticity of LAI. This also linked with the recorded higher LAI elasticity in deciduous forested land use in July (Fig. 10e). During a disturbance, forests are prone to lose their ecological balance when the disturbance level exceeds the threshold value (Johnstone et al., 2016). As the metabolism and physiology are impacted at the individual plant level, and ecological functions and services are disturbed at ecosystem levels, the forest plants are unable to extend the flexibility of the leaf development process in a stressed situation fueled by climate change. In contrast, this theory is employed in the reverse order in a normal environmental condition with least or no disturbance. By adhering to the second law of thermodynamics, based on the assumption of closed ecosystem concept, in a no disturbance situation the entropy decreases, while a disturbed situation influences the increased entropy.
Thereby, in a low entropic case (least disturbed or no disturbed event), growth and expansion of leaves of forest plants is supported by enhanced LAI. Thus, findings in the current study correspond with the information that the variation of energy driven by LST changes the sensational levels of resilience.

From the perspectives of the terrestrial carbon budget, the forest ecosystems are considered photosynthetic engines that convert sunlight into biochemical energy through carbon capturing. However, the carbon synthesis efficiencies of forest plants are constrained by the rate of climate change (Wei et al., 2017). Therefore, the inconsistencies in carbon capturing processes in the middle of an adverse weather event imbalance the resilience, resistance, and elasticity of GPP. The highest GPP resilience peak witnessed among deciduous forested and evergreen forested land uses in March to April (Fig. 10b) highlighted the intense sensitivity of marginal GPP resilience from March to April (Table 12). The reduction of LST projects this marginal resilience peak in forest ecosystems. The dynamics of LST determine the decaying rates of litter to enhance soil fertility, ion exchange capacities, and essential minerals absorption for plant growth. Thereby, this shift of climatic factors from a very dry event to a moderate wet event in forest ecosystems located the effect on a carbon sequestration process in its incapability to restate the initial conditions before perturbation (Sims et al., 2008). A similar shift in the April to May case yielded a much higher marginal resilience in both deciduous forested and evergreen forested land uses (Table 12), thus fostering the idea that intermittent weather changes negatively influence the canopy level GPP resilience. The energy inputs in these adverse climate change events aligned with the LST in forest land uses, highlighting the extensive sensitivity in the canopy level marginal resilience of GPP.

The GPP marginal elasticity suggested the negative impact of sudden climate changes on the primary productivity of forest canopies. The present study identified the March to April
transition of events as the climax of the sensitivity of elasticity of GPP in forest habitats (Table 12). The fall of temperature boosted this sensitivity of GPP resilience in land surfaces with low entropy. Conversion from a dry to a wet environment reduces the margin of kinetic energy. Therefore, the energy gap for this activity is smaller. On the other hand, the disturbance – response traits in forest communities provide details on the evolutionary, physiological, and morphological adaptations gained from past times. Subsequently, forest plant species have developed survival and regeneration strategies due to the pressure from recurring stresses (Keeley et al., 2011). For a fundamental process like photosynthesis, forest plants have adapted the material and resources needed to recover in an intense disturbance or stress. However, these adaptations in forest canopies can only overcome the disturbances if they remain within its tolerance capacity (Simard et al., 2011). Exceeding the tolerance capacities of forest canopies due to adverse weather conditions distresses the flexibility of forest canopies and plant bodies to perform their metabolic functions and ecosystem services. This suggests that the nonlinear transition of climatic events that happened in the Santa Fe river watershed increased the vulnerability of the marginal elasticity of the primary productivity of forest land uses.
Table 12. Sensitivity Analysis of Marginal Resilience, Marginal Resistance, and Marginal Elasticity Based on the LAI and GPP as the Main Two Biophysical and Biochemical Features Triggered by the LST (°C) of Deciduous Forested and Evergreen Forested Land Uses in the Santa Fe River Watershed in March 2017 to Oct, 2017 (DF stands for the deciduous forested land uses and EF stands for the evergreen forested land uses).

<table>
<thead>
<tr>
<th>Period</th>
<th>Marginal resilience</th>
<th>Marginal resistance</th>
<th>Marginal elasticity</th>
<th>LST</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DF</td>
<td>EF</td>
<td>DF</td>
<td>EF</td>
</tr>
<tr>
<td>LAI</td>
<td>GPP</td>
<td>LAI</td>
<td>GPP</td>
<td>LAI</td>
</tr>
<tr>
<td>Mar</td>
<td>0.00</td>
<td>0.01</td>
<td>2.99</td>
<td>3.69</td>
</tr>
<tr>
<td>– Apr</td>
<td>62</td>
<td>26</td>
<td>37</td>
<td>12</td>
</tr>
<tr>
<td>Apr</td>
<td>0.01</td>
<td>0.01</td>
<td>2.85</td>
<td>2.77</td>
</tr>
<tr>
<td>– May</td>
<td>26</td>
<td>26</td>
<td>22</td>
<td>04</td>
</tr>
<tr>
<td>May</td>
<td>0.00</td>
<td>0.00</td>
<td>0.68</td>
<td>0.80</td>
</tr>
<tr>
<td>– Jun</td>
<td>28</td>
<td>32</td>
<td>68</td>
<td>66</td>
</tr>
<tr>
<td>Jun</td>
<td>0.00</td>
<td>0.00</td>
<td>2.40</td>
<td>2.88</td>
</tr>
<tr>
<td>– Jul</td>
<td>04</td>
<td>62</td>
<td>13</td>
<td>67</td>
</tr>
<tr>
<td>Jul</td>
<td>0.01</td>
<td>0.02</td>
<td>2.67</td>
<td>2.90</td>
</tr>
<tr>
<td>– Aug</td>
<td>88</td>
<td>52</td>
<td>48</td>
<td>44</td>
</tr>
<tr>
<td>Aug</td>
<td>0.00</td>
<td>0.01</td>
<td>1.80</td>
<td>1.03</td>
</tr>
<tr>
<td>– Sep</td>
<td>62</td>
<td>26</td>
<td>88</td>
<td>33</td>
</tr>
<tr>
<td>Sep</td>
<td>0.01</td>
<td>0.01</td>
<td>0.47</td>
<td>1.80</td>
</tr>
<tr>
<td>– Oct</td>
<td>88</td>
<td>26</td>
<td>30</td>
<td>50</td>
</tr>
</tbody>
</table>

89
CHAPTER FIVE: CONCLUSION

The present study demonstrates the impact of the landfall of Hurricane Irma in the Santa Fe River Watershed, Florida, based on the feature extraction of remote sensing images and spatial analysis techniques to compare the biophysical and biochemical features pre and post landfall of Hurricane Irma. We found that vegetation-based biophysical and biochemical features, namely EVI, LAI, and FPAR, were reduced post landfall of Hurricane Irma in the study area. The coevolution of biophysical and biochemical features over space highlighting the ecosystem adaptability and resilience mechanisms contributed to understanding the impacts on vegetation canopy, cover, and health, caused by the cascade effect of the landfall of Hurricane Irma. In addition, biophysical features that govern the land-atmosphere interactions, such as LST, ET, and GVMI were significantly reduced as a result of the hurricane’s landfall impact. Moreover, the human modified urban land uses, and open surface water showed a low level of EVI, LAI, FPAR, GVMI, compared to the forested and agricultural land uses, whereas LST and ET were significantly higher. In terms of coevolution of features over space, firstly, P3 (LAI and LST) revealed the comprehensive representation of the impact caused by the landfall of Hurricane Irma as the best combination of biophysical and biochemical features, and P1 (EVI and LST) served as the second for demonstrating the influence of the cascade effect on vegetation over the pre and post landfall periods.

Our findings confirm the hypotheses of the present study that there exists a significant difference of spatial and temporal variation of biophysical features pre and post landfall of Hurricane Irma, and integration of pairwise comparison of biophysical and biochemical features portray the continued impacts driven by the landfall of Hurricane Irma better than a single biophysical feature can reveal. The F of the ecosystem has declined in terms of EVI, LAI and LST
analysis over grassland, evergreen forested, deciduous forested, and agricultural land uses, as examined in the study area. However, future implications of vegetation indices using geophysical technology can be extended by focusing on multiple cyclic climate change events in sequence to critically comprehend the trend and effect on vegetation in different land uses.

In summary, the strong correlations of LAI, EVI, GPP, and LST biophysical and biochemical features catalyzed during the period of interest eco the more adaptive and strategic behaviors of deciduous forested and evergreen forested land uses in both extreme dry and wet events. In addition, grassland land uses followed by the agricultural land uses endorsed a comparative lower correlation of LAI, EVI, and GPP with LST dynamics in the study area. Remote sensing technology-based findings of the current study manifests the descriptive dominance in metabolism and acclimatization of forest ecosystems over non-forested ecosystems to stand by cyclic effects of adverse climate change. To understand the ecosystem status in terms of recovery, two peaks observed in LAI and GPP resilience curves in March to April and August and September uphold the judgment that extreme alternating weather events make vegetative canopies more resilient. Even though the wet season extends from May to October and dry season starts from November to April, the SPI displays how the climate has been dramatically changed over the year. Thus, in counter to resilience, the visualized declined LAI and GPP resistance in very dry and wet incidents reinforce the susceptibility of vegetative canopies of forests and non-forested land uses to tolerate fluctuating weather beyond the tolerance limits. Synergies between LAI resilience and elasticity, and GPP resistance and elasticity highlights the interdependency of these attributes to demonstrate the striking stress forced by nonlinear weather shifts. The employability of LST as the solar engine to promote these other biophysical and biochemical feature variations was significantly remarkable because metabolic, biological, and physiological activities of vegetation
canopies are synchronized with LST thermodynamically. To regulate sustainable functions and services of forests and other vegetative ecosystems, it is vital to acknowledge the behavior of biophysical and biochemical feedbacks to cope with recurring climate change. The present study elucidates the importance of remote sensing-based technicality to adapt and mitigate climate change to ensure ecosystem sustainability.
REFERENCES


Institute of Food and Agricultural Sciences, (2020b). https://sfyl.ifas.ufl.edu/agriculture/crops/ accessed on 09/08/2020


[https://doi.org/10.1080/01431169008955102](https://doi.org/10.1080/01431169008955102)


disturbance across complex mountainous terrain: The pattern and severity of impacts of tropical cyclone Yasi on Australian rainforests. Remote Sensing, 6(6), 5633-5649.


NOAA GOES-16 satellite image.

https://www.ospo.noaa.gov/Organization/History/imagery/Irma/index.html. (accessed on 03/20/2021)

NOAA GOES-16 satellite image.

https://www.ospo.noaa.gov/Organization/History/imagery/Irma/index.html. (accessed on 03/20/2021)


MODIS EVI to estimate terrestrial ecosystem gross primary production of multiple land cover types. *Ecological Indicators*, 72, 153-164.


113
