Leiden University

ICT in Business and the Public Sector

Leveraging Machine Learning and Synthetic Controls to Study Resilience Using Satellite Images in the Context of the Wine Industry

Name:	Anran Liu
Student number:	s2754541
Date:	August 14th, 2023
1st supervisor:	Dr. A.H. Zohrehvand
2nd supervisor:	Dr. M. Baratchi

MASTER THESIS

Leiden Institute of Advanced Computer Science (LIACS)

Leiden University

Niels Bohrweg 1 — 2333 CA Leiden — The Netherlands

ABSTRACT

The study of organizational resilience is crucial for organizations to adapt and thrive in the face of challenges. However, the prevailing method for quantitatively measuring resilience is through the construction of a tool known as a "resilience scale." Due to the unique attributes inherent to different organizations, limitations exist regarding applicability and accuracy. In this study, we propose a novel organizational resilience measurement approach by leveraging NDVI data from satellite imagery and employing synthetic control methods to simulate future counterfactual paths. We compare the historical averaging method with the synthetic control method to assess strengths, weaknesses, effectiveness and use scenarios in both methods. Our findings demonstrate that the synthetic control method outperforms the historical averaging method, providing more accurate and robust measurements. Furthermore, we will demonstrate the applicability of synthetic control methods to temporal data with periodic patterns. This research contributes to advancing the measure of organizational resilience and highlights the potential of satellite imagery and synthetic control methods in enhancing resilience assessments.

ACKNOWLEDGEMENTS

I am deeply grateful to my supervisors, Dr. Miros Zohrehvand and Dr. Mitra Baratchi, for their invaluable guidance and unwavering support throughout this project. Their consistent involvement, insightful feedback, and constructive suggestions have been instrumental in shaping the trajectory of my research. Their dedication to my academic growth has truly been a cornerstone of my progress.

A special note of appreciation goes to Miros for his continuous encouragement and mentorship. His guidance during our regular meetings has given me valuable insights and perspectives that have significantly enriched my work. Equally, I extend my heartfelt gratitude to Mitra for her technical expertise and generous assistance, which have been indispensable in navigating the intricacies of my research.

I would also like to extend my thanks to Laurens for his valuable contributions to my research project. His willingness to share his knowledge and insights has been immensely beneficial.

Finally, I wish to acknowledge the unwavering support of my family and friends. Their encouragement and belief in my capabilities have been a constant source of inspiration.

Contents

INTRODUCTION

In recent decades, the world has witnessed many unpredictable events that have posed significant threats, including natural disasters, public health crises, and financial downturns. These events have resulted in substantial property damage, diminished productivity, and loss of life and well-being, exposing the inherent vulnerability and fragility of our societal systems. As a result, individuals and institutions have recognized the need to develop effective strategies to address and mitigate the adverse effects of such shocks and events.

Organizational resilience, derived initially from ecological principles, has garnered significant attention especially in social science, management, and economics fields in recent years. It refers to the capacity and functionality of a system to respond to external changes using prevention, coping, recovery, and adaptation at various levels (Bhamra et al., 2011). Extensive research has demonstrated the finding that resilient organizations are better equipped to withstand adverse environmental conditions, enabling them to persevere and thrive amid crisis compared to other organizations with the same situation. (Annarelli & Nonino, 2016; Ge et al., 2016; Clarke, 2008).

This study's focus is the wine industry, which, like other manufacturing sectors, faces challenges within its supply chain and confronts risks tied to environmental changes. Climate shifts and extreme weather events resulting from global warming have adversely affected crop yields and production. Resilience emerges as a critical factor in enabling the wine industry to respond adeptly to external changes and sustain growth momentum despite adversity.

While prior research on organizational resilience has primarily concentrated on conceptualization and empirical studies within specific domains, there is ongoing refinement of its conceptual boundaries. Efforts have been made to provide clearer definitions and enhance understanding (Burnard & Bhamra, 2011; McCarthy et al., 2017). Criticisms have arisen due to the vagueness and inconsistency surrounding the concept (Linnenluecke, 2017), necessitating empirical evidence to consolidate its research value. Studies have explored the relationship between organizational resilience and outcomes such as improved financial performance (De Carvalho et al., 2016), enhanced competitiveness (Webb & Schlemmer, 2006), and service quality (Annarelli, Battistella, & Nonino, 2020). Supply chain research has also focused on risk management to ensure stability amidst disruptions (Colicchia et al., 2010; Spieske & Birkel, 2021; Wieland & Durach, 2021).

Yet, despite the increasing emphasis on empirical studies since 2015, there remains a dearth of relevant quantitative research, creating gaps to be addressed (Hillmann & Guenther, 2021). Thus, there is a need to conduct more in-depth quantitative studies that examine the measurement of resilience, enabling a better understanding and utilization of organizational resilience.

The most common approach to measuring organizational resilience involves scales designed to align with the study's focus, followed by data analysis for validation (Richtnér & Löfsten, 2014; Hillmann & Guenther, 2021). However, this approach has limited applicability and requires the involvement of experts and more importantly fails to adapt to dynamic system changes Alternatively, using performance outcomes as resilience measures has gained traction. This approach provides a more realistic assessment of a system's state and recovery post-shock (Dutta, 2017; Desjardins et al., 2019). Despite its advantages, it requires identifiable metrics strongly correlated with resilience, appropriate timeframes, and inclusion of comparative reference groups for accurate assessment (Ilseven & Puranam, 2021).

Taking these factors into consideration, our research is aimed at addressing the constraints inherent in existing methods and pursuing avenues to advance the measurement of organizational resilience. The primary objective of this project is to explore new methods for quantifying organizational resilience, with a specific focus on the wine industry as a case study.

By harnessing the potential of cutting-edge techniques, including machine learning and satellite image correlation, we endeavor to introduce a novel and versatile method for quantifying resilience – synthetic control method. This approach capitalizes on the insight that when observed units constitute a small fraction of the overall entities, combining unaffected units offers a more appropriate comparison than relying on any single unaffected unit (Abadie et al., 2010). As a result, the synthetic control method estimates treatment effects by creating a synthetic control group in the absence of an actual control group. The treatment effect quantifies the difference between an area or organization after the implementation of a specific policy, intervention, or event, and a control group that did not undergo the same intervention (Abadie et al., 2015).

In addition to the synthetic control method, we propose an alternative reference method known as the "historical data averaging method." The historical data averaging method involves establishing historical data as a baseline control group. To better understand the efficacy of these two approaches, we conduct a comprehensive comparison and analysis of their outcomes, considering factors such as effect performance and applicable scenarios. Overall, this research endeavors to contribute to the academic and practical understanding of organizational resilience by introducing an innovative and adaptable approach that combines machine learning and satellite imagery. By leveraging these advancements, this study aims to enhance the measurement and evaluation of resilience in the wine industry, opening new possibilities for resilience assessment in various industries and contexts.

this article is structured as follows: Section 2 presents the theoretical background, including a literature review of the various theories and concepts related to the approach. Section 3 explains the dataset and the design of the methods. Section 4 covers the results analysis of the two methods. In Sect. 5, we discuss the results and provide directions for future work.

THEORETICAL BACKGROUND

In this section, we provide a comprehensive review of the theoretical background that underpins the topic of organizational resilience. Drawing upon existing literature, we explore the fundamental concepts, theories, and frameworks that have shaped our understanding of resilience in organizational settings. Additionally, we review the contributions made by previous researchers in this field, highlighting their valuable insights and findings. We conclude by redefining the concept of organizational resilience and describing the research framework.

2.1 Definition of organizational resilience

The concept of organizational resilience originated from the ecological system theory, where it is defined as the capacity of a system to absorb disturbance, undergo change, and retain its essential function, structure, identity, and feedback (Holling, 1973). Researchers have observed that certain organizations perform better than others when responding to unexpected events and sudden changes (Fiksel et al., 2015; Gittell et al., 2006). The increased frequency of unexpected major events, such as terrorism, along with the growing complexity and interdependence of social, economic, and technological domains, has exposed organizations to a greater risk of failure (e.g., Allen and Powell 2013; Kambhu et al. 2007). Consequently, this has driven the surge in research on organizational resilience in the business and management field since the early 2000s (Linnenluecke, 2017).

Initially, scholars primarily focused on conceptualising organizational resilience and engaged in thorough discussions and analyses to provide more transparent and more precise definitions. For instance, Horne and Orr (1998) defined organizational resilience as the ability of an organization to adapt to changing circumstances and continue functioning effectively. Sutcliffe and Vogus (2003) described it as maintaining positive adjustment under challenging conditions. Another study by Gittell et al. (2006) explored airline resilience performance after 9/11 and defined organizational resilience as an organization's dynamic ability to grow and evolve adaptively over time, ultimately influencing its strategy implementation and performance. Boin and van Eeten (2013) provided a more detailed delineation and framing of organizational resilience, viewing it as an ability to anticipate, prepare for, respond to, and adapt to incremental changes and sudden disruptions to survive and prosper over time.

Organizational resilience has undergone significant expansion and extensive study. However, the literature reveals a need for more consensus and uniformity in its definition, reflecting the diversity of research directions and goals. Different perspectives have emerged, including adaptive strategies, reactive approaches, resource utilization, early response, and various other perspectives (Hillmann, 2021). These varied research directions contribute to the multifaceted understanding of organizational resilience. Moreover, a statistical analysis of previous studies highlighted that most definitions of organizational resilience encompass two or more attributes, emphasizing its multidimensional nature (Hillmann & Guenther, 2020). Predictability, stability, adaptability, inverse growth, and inclusiveness are all attributes that have emerged in past studies—however, the frequency with which different attributes were mentioned varied. For example, adaptive capacity was frequently mentioned, along with coping capacity, reinvention capacity, and predictive capacity. The analysis also revealed the diversity of attributes associated with the definition of organizational resilience. Different research perspectives view organizational resilience as a competency in different contexts. For example, some scholars view it as an organization's ability to remain stable in the face of shocks. In contrast, others emphasize the ability to actively absorb external changes and turn them to their advantage.

Aligned with the focus and purpose of this research project, we define organizational resilience as the capability of an organization to rebound to its original state following an external shock. These shocks encompass various adverse events that disrupt the initial state. Given the context of this article, which centers on a wine estate, relevant events primarily include natural disasters such as wildfires, frosts, and droughts. Our analysis will explore the strength of this capacity across different dimensions.

2.2 How do we measure organizational Resilience?

The measurement of organizational resilience is a burgeoning field encompassing various research and practice directions across disciplines such as risk management, disaster management, operations management, leadership, and change management. Recognised as a crucial capability for organizations to navigate the increasingly dynamic and uncertain world, understanding and effectively measuring organizational resilience have become imperative (Seville et al., 2015). However, despite the growing number of empirical studies, measuring organizational resilience poses significant challenges for researchers.

2.2.1 Management-Based Measurement Approaches

To address these challenges, researchers have explored different measurement methods and approaches to enhance our understanding of organizational resilience. In the realm of management, Lee, Vargo, and Seville (2013) undertook a comprehensive study to develop a tool for measuring and comparing organizational resilience. Their work involved conducting a systematic literature review and a long-term survey of 68 organizations in New Zealand. By dividing organizational resilience into four distinct segments, namely leadership and strategy, culture and values, people and community, and resources and systems, the authors identified specific resilience indicators using survey questions. This approach resulted in a total of 13 indicators, enabling organizations to identify their strengths and weaknesses before crises occur.

Other researchers, such as Chowdhury and Quaddus (2017), have used a similar measurement tool with minor refinements to assess the organizational resilience of critical infrastructure providers. They adjusted the Likert scale, indicator names, and descriptions and subsequently validated the reliability of the resulting tool using Cronbach's alpha. Their study further analyzed the results based on industry types, employing t-tests and classification analysis to gain deeper insights.

Moreover, scholars have adopted variations of the organizational resilience scale by incorporating and refining existing scales through insights derived from expert interviews and financial data (e.g., Chen et al., 2021; Gentile et al., 2019; Sweya et al., 2020). These efforts aim to contextualize resilience within specific domains. For example, Chen's study incorporated dimensions like strategic resilience, cultural resilience, relationship resilience, capital resilience, and learning resilience, drawing from previous studies. The measurement of cultural resilience was based on studies by Costanza et al. (2016) and Ramón and Koller (2016), while relational resilience measurement drew from Shore et al. (1990) and Vogus and Sutcliffe (2007).

2.2.2 Alternative Measurement Approaches

Beyond management-based approaches, researchers have explored alternative methods for measuring organizational resilience. For instance, Aleksić et al. (2013) suggested assessing the organization resilience potential of SMEs using fuzzy cognitive maps to evaluate the contributing factors for each business process. Fuzzy set theory is a research approach that can deal with problems relating to ambiguous, subjective and imprecise judgments, and it can quantify the linguistic facet of available data and preferences for individual or group decision-making (Shan et al., 2015a). Organizational resilience may be analyzed as a fuzzy issue

(Pendall, Foster, and Cowell, 2010) since it is the combined effect of receiving many factors that are not clearly defined (Carvalho et al., 2008). Therefore, using fuzzy models allows for the most accurate assessment of resilience factors possible. In the assessment process, the researcher designed criteria including leadership, information and communication, human resources, risk management, and supply chain management, among others, and tested them on a case study of an SME in the process industry. The results showed that the SME had moderate to high resilience potential (citation).

2.2.3 Recovery-Oriented Measurements and Financial Indicators

In addition, from the perspective of recovery, scholars have used recovery time, level of recovery, initial vulnerability and potential loss averted to measure organizational resilience (Erol, Henry, Sauser, et al.,2010). Scholars also measure resilience in terms of outcomes, like financial performance. Ortiz-de-Mandojana and Bansal (2016) proposed that organizational resilience is an underlying, path-dependent construct with outcomes that can be measured. They conducted hypothesis testing using data from 121 U.S. firms through matching pair over a 15-year period. Their study demonstrated that specific indicators of financial performance, such as financial volatility, sales growth, and survival rates, reflect organizational resilience to a certain degree.

2.3 Synthetic control

The Synthetic Control Method (SCM) has gained widespread usage in recent years for evaluating the impact of interventions and outcomes (Abadie & Gardeazabal, 2003; Abadie et al., 2010, 2015; Ben-Michael et al., 2021; Zohrehvand et al., 2023). This approach constructs artificial control groups by selecting units resembling the intervention units from those that haven't experienced the intervention. In doing so, researchers simulate counterfactual outcomes that represent performance in the absence of the intervention. SCM finds application in various policy evaluations, such as assessing the effects of tobacco control programs (Abadie et al., 2012), measuring the economic impact of tax reforms (Adhikari & Alm, 2016), and investigating the relationship between governance changes and spending reduction (Roesel, 2017). SCM's versatility allows its application across political, economic, and social contexts.

Based on a collection and analysis of previous literature, the SCM approach has been discussed in great depth in applications and shows the multitude of possibilities. This method is only some-powerful and certainly, there are some limitations to this method. Abadie, Diamond and Hainmueller (2015) suggest that the SCM method is not recommended when a suitable control group cannot be constructed, i.e., when the correlation between the observed unit and the original data set is not up to the standard. In contrast, the experimental results would have been more prominent if the fitted ensemble of the original dataset had better simulated the experimental group, addressing the problem of bias correction for inexact matches (Abadie and Imbens, 2011). Because in the original method, the authors aimed to use the weighted values of each type of ensemble as a control group. However, due to factors such as modeling errors, environmental changes or external disturbances, it is difficult to end up with very precise results.

Scholars are investigating a variety of methods to achieve bias minimization and improve the precision of control groups. For example, scholars have proposed the augmented integrated control method (ASCM) to address the high degree of fit that cannot be achieved with the SCM alone. The Ridge ASCM is best described as an augmented SCM based on a ridge regression model that recognizes negative weights and uses extrapolation to improve the preprocessing fit. The Ridge ASCM avoids overfitting noise, improves the accuracy of the results, and was validated against the 2012 Kansas tax cut in the case of its impact on economic growth (Ben-Michael & Rothstein, 2021) . Another branch is the generalized synthetic control (GSC) method, which combines the synthetic control method with linear fixed effect models.

It employs a latent factor approach to address causal inference problems and provides valid uncertainty estimates. As a result, GSC can handle multiple treated units and variable treatment periods, improving efficiency and reducing the need for individual matching (Xu, 2017). For example, Zohrehvand et al. (2023) use Doudchenko and Imbens' (2017) synthetic control (DISC) method in Mergers and acquisitions (M&A) research. He analyzed the performance of Family Dollar and Dollar Tree, two large discount retailers in the general merchandise industry, before and after the completion of the M&A in 2015 through the dimension of shareholder returns. The results demonstrate the adaptability of the methodology in this area and open up possibilities for broader research.

RESEARCH DESIGN AND METHODS

3.1 STUDY AREA

The study focused on American Viticultural Areas (AVAs), a collection of 271 winegrowing regions in the United States. For this research, a carefully selected subset of 14 AVAs was chosen based on specific criteria, with a primary emphasis on including areas both impacted and unimpacted by the Glass Fire in Northern California during the 2020 wildfire season.

The criteria for selecting these AVAs were defined by key components. Firstly, the chosen areas were limited to a size of less than 300 acres, as larger areas might introduce additional complexities. Secondly, preference was given to regions established before 2010. This selection was based on the growth cycle and size of grapevines, as well as the timing of image collection, ensuring relatively stable conditions for areas established prior to 2010. Lastly, the chosen AVAs exhibited minimal changes in Normalized Difference Vegetation Index (NDVI) data between 2017 and 2023.

Name	**Interpretation**
OBJECTID	Id
Name	Name of AVA
Id	Not use
Area	AVA's cultivation area
States	Continent to which AVA belongs
Phase	Climate Type
Level_	Elevation
Contains	The selected AVA contains the listed AVAs
Within	The selected AVA is within the listed AVAs
Establish	Established time
Status	Established Status
CFR_Sectio	Location in CFR
Partially_	The selected AVA is partially overlap with the listed AVAs
Note	Note
Counties	Counties to which AVA belongs
Shape_Area	Shape area
Shape_Leng	Shape length
selected	Selected or not
geometry	GPS coordinates(Circles)

Table 1. Dataset field meaning

Name	Area	States	Geometry
Monticello	235.551252	Virginia	-121.541963098142 36.666800211857
Potter Valley	75.610935	California	-123.006862416652 38.8498486078256
Ramona Valley	199.288575	California	-123.045032989206 47.5332165344136
Shenandoah Valley	118.07	Virginia	-88.5117345119528 37.0585957806172
Sierra Pelona Valley	118.07	California	-120.867515068736 38.953896344212
St. Helena	20.292511	California	-119.037317560212 36.6577420797992
Sta. Rita Hills	23.398320	California	-122.443563143963 38.4818455409617
Temecula Valley	201.811840	California	-118.658790546661 35.1420882969951
Atlas Peak	82.627783	California	-121.338791859765 36.3397617711635
Bell Mountain	13.295671	Texas	-120.122839545975 34.6679738120383
Calistoga	32.415558	California	-120.761410049607 38.5249452457511
Chalone	20.846268	California	-122.76099411987 38.5093532399772
Diamond Mountain District	12.627637	California	-121.233129303134 37.2902960636805
Escondido Valley	67.635895	Texas	-123.184715470587 45.034129256

Table 2. Dataset

The Glass Fire, a devastating wildfire that occurred between September 27 and October 20, 2020, originated near Glass Mountain Road in Deer Park, Napa County, and also affected Sonoma County. Rapidly escalating from a single 20-acre brush fire, it merged with two smaller fires, eventually covering approximately 11,000 acres by the night of September 27 (California Department of Forestry and Fire Protection [CAL FIRE], 2020).

Conversely, the study also encompassed AVAs that remained unaffected by recent wildfires, enabling a comparative analysis between regions with and without wildfire-related impacts. This approach facilitates the identification of potential differences in vineyard zones' characteristics and assesses the resilience of viticultural regions to wildfire events.

To gather the necessary data, the researcher accessed the AVA Map Explorer tool, a valuable resource offered by the U.S. federal government, providing comprehensive information on these viticultural regions. The subsequent meticulous processing and merging of shape files from this tool resulted in a dataset encompassing vital information about each AVA, such as geographical boundaries, climate conditions, soil composition, and other pertinent factors crucial for grape cultivation and wine production.

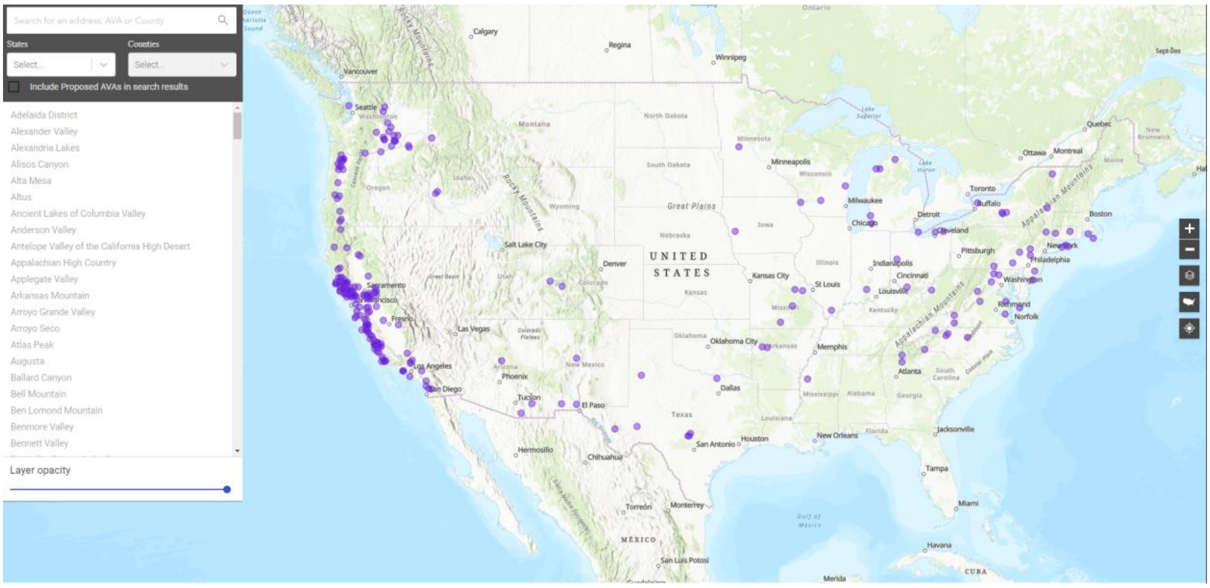

Fig 1. AVA map

The satellite images used for this study were sourced from the Sentinel-2 satellite mission, which is a part of the Copernicus program and is known for providing high-resolution, multispectral images over land and coastal waters ("Copernicus Sentinel-2 Mission," n.d.). These images constitute a valuable resource for researchers and industry participants, as they offer crucial insights into land cover, vegetation health, and various environmental variables, enabling systematic monitoring of terrestrial surface changes over time.

In this study, the researchers proactively accessed and processed the Sentinel-2 satellite images, extracting relevant data based on precise geolocation. Specifically, satellite images with cloud cover thickness of less than 50% in the target area were acquired from April 2017 to April 2023. For analysis, the researchers obtained the Level-2A product, which had undergone atmospheric correction, providing higher data quality. To ensure data stability and accuracy in monitoring changes and trends over the specified period, the researchers initiated two key preprocessing steps: cloud and outlier removal. This proactive approach entailed the systematic elimination of clouds and outliers from the image data, thereby reducing potential interference and enhancing the overall reliability of the dataset. This preparatory step was crucial for subsequent calculations, particularly in the computation of the Normalized Difference Vegetation Index (NDVI).

3.2 GENERAL APPROACH AND WORKFLOW

In this study, we collected a dataset that includes GPS coordinates for each region, enabling precise location within satellite images. To obtain these images, we utilized Sentinel Hub and downloaded data from the Sentinel-2 mission. By selecting specific spectral bands, we focused on capturing important characteristics of the target areas in the satellite image. These bands include blue (band 2), green (band 3), red (band 4) and near-infrared (band 8) spectral bands and cloud masks. The use of cloud masks allowed us to identify and exclude areas covered by clouds, which could otherwise introduce noise and inaccuracies in our analysis.

Among the selected spectral bands, bands 4 and 8 were used to calculate the Normalized Difference Vegetation Index (NDVI), which is the most widely used index in vegetation health analysis (Rouse et al., 1974). It is extensively employed to identify the health status of vegetation and provide information on the spatial and temporal distribution of vegetation communities and biomass. Therefore, variations in NDVI values and other general vegetation indices the ongoing changes and trends in vegetation dynamics (Lasaponara. 2022). Bands 2, 3, and 4 were utilized to generate a true color image, facilitating easy observation and analysis of image content.

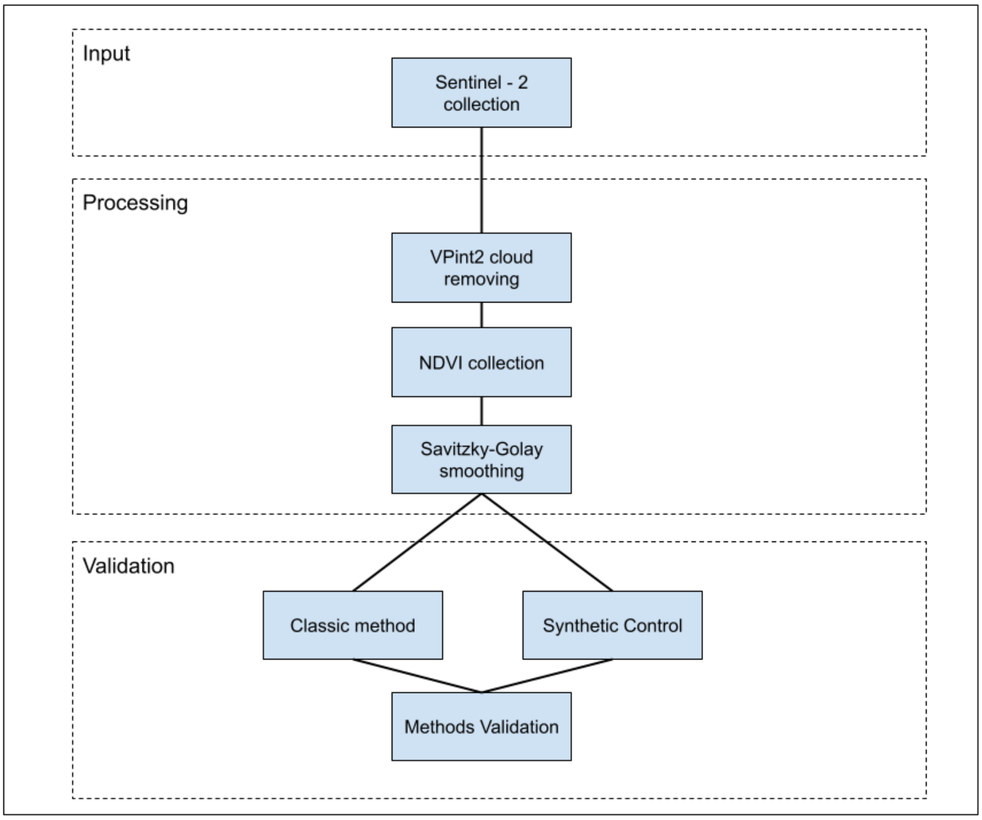

Fig 2. Experiment method overview

3.2.1 Cloud removing

Despite the significant advancements facilitated by the Sentinel satellite mission, it is crucial to acknowledge the inherent susceptibility of satellite image quality to atmospheric phenomena such as water vapor, airborne impurities, and refraction. These limitations introduce instability and pose various challenges during subsequent data analysis stages. Therefore, prior to extracting the Normalized Difference Vegetation Index (NDVI) and conducting experimental procedures, meticulous data cleansing and noise removal are essential to ensure data integrity and enhance analytical robustness.

The persistent presence of clouds in satellite images hinders the acquisition of high-quality images. We employ the Vpint2 method to address this concern, widely recognized for its effectiveness in cloud removal (Arp, Baratchi, & Hoos, 2022). This technique involves identifying and removing pixels classified as cloud-covered within the image. Subsequently, corresponding pixels from a contemporaneous cloud-free reference image, closest in temporal proximity, are extracted and inserted into their original positions within the primary image (citation). This meticulous procedure safeguards against the detrimental impact of cloud presence, thereby enhancing the reliability and fidelity of subsequent analyses.

Following the completion of the interpolation and cloud removal procedures, a noticeable reduction in the presence of outliers within the dataset is achieved. However, certain residual noise artifacts still persist, affecting the accuracy of the data. A thorough examination is conducted to identify reflection anomalies associated with extreme outliers to mitigate this effect. Consequently, specific data points that exhibit a pronounced influence on the dataset are selectively removed, and their positions are subsequently filled with the mean value of the respective variable.

By implementing these rigorous data cleaning and noise removal steps, we ensure that the dataset is more reliable and accurate for further analysis.

3.2.2 NDVI calculation

After completing the preparatory measures, the subsequent step involves utilizing satellite bands B04 (infrared spectrum) and B08 (near-infrared spectrum) to compute the Normalized Difference Vegetation Index (NDVI) and integrate it into the dataset. This index is derived from multispectral imagery by combining the near-infrared (NIR) and red (RED) bands, and its calculation is defined by the following mathematical formula:

$$NDVI = (NIR - RED)/(NIR + RED) \tag{1}$$

The computation of NDVI enables the quantification of vegetation vitality, facilitating the characterization and analysis of vegetation dynamics and health within the study area.

To ensure high-quality normalized vegetation index (NDVI) time series, which is critical for numerous applications, various noise reduction methods have been proposed in the literature to minimize residual noise and reconstruct more reliable NDVI time series. Some of these methods include the harmonic analysis of time series (HANTS) (Roerink et al., 2000), Temporal Window Operation (TWO) (Park et al., 1999), logistic function-fitting (Beck et al., 2006; Elmore et al., 2012; Cao et al., 2015), and the Savitzky-Golay smoothing technique (Chen et al., 2004; Verger et al., 2011).

In this study, the researchers chose to employ the Savitzky-Golay smoothing technique due to its effectiveness in reducing noise and preserving the overall trend of the data. The method utilizes a sliding window to fit a polynomial function, and the least squares method is used to determine the optimal coefficients for the fit (Schafer, 2011). This approach ensures that the Savitzky-Golay filter removes high-frequency noise and rapid fluctuations while retaining the essential patterns and trends within the dataset (Chen et al., 2021).

Moreover, The Savitzky-Golay filter is a simple extension of the moving average, which is one of the most widely used algorithms in the NDVI smoothing literature (Hird and McDermid, 2009; Pettorelli et al., 2005). For example, Chen et al. (2004) applied this filter to enhance the quality of satellite derived NDVI data for vegetation monitoring in a tropical rainforest region. Verger et al. (2011) utilized the Savitzky-Golay smoother to improve the long-term NDVI time series analysis in arid regions. These examples demonstrate the effectiveness and versatility of the Savitzky-Golay method in various environmental studies, further justifying its application in this research.

3.3 Measurement

To compare the resilience levels of different regions affected by hill fires, two distinct methods were employed to create control groups representing counterfactual results. The focus was on examining the length and speed of recovery as relevant indicators of regional resilience. The detailed description of both methods, as well as the design of validation and comparison experiments, is provided below.

3.3.1 Commonly practiced approach

Option A, commonly referred to as the conventional practice approach, involves utilizing historical NDVI data as a control group to measure regional resilience. Historical NDVI data have found extensive application in ecological and environmental studies, encompassing the evaluation of changes (Spruce et al., 2014), predictions of future trends (Firozjaei et al., 2021), and assessment of activities' impact (Wang et al., 2022). The dynamics of NDVI data are characterized by distinctive patterns, intra-annual seasonal cycles, and stable trends across years (De Jong et al., 2013). In instances of trend deviations, analysis based on historical trends allows for identifying the inception of these shifts and delving into the underlying causes of vegetation change as well as measure recovery.

In this approach, we make the underlying assumption that historical monthly NDVI data, constituting the baseline dataset, exhibit relative stability in the absence of external interventions. By juxtaposing the post-disruption NDVI values against the expected baseline values, we can promptly identify substantial deviations attributable to the influence of hill fires. These deviations serve as reliable indicators of disturbances and the subsequent recovery, consequently quantifying the level of resilience exhibited.

Specifically, we first evaluated NDVI trends for each region through October 2020, with the goal of initially assessing the suitability of measuring historical NDVI data as a baseline control group. If the NDVI trend was significantly different from year to year starting in 2017, and more specifically if data such as annual NDVI maxima and minima fluctuated significantly, this area would be removed from the data set. Subsequently, we selected historical monthly NDVI median values specific to each region as the control group. Using the median is less affected by outliers or extreme values than the mean and better represents typical values (Jamali et al., 2012). In instances where data gaps occur due to inclement weather or technical constraints, we took a pragmatic approach by replacing these gaps with median NDVI values for the same period in other years. This method ensures the coherence and continuity of the baseline dataset, effectively addressing potential interruptions in the data.

It is pertinent to acknowledge that although the stability assumption is well-founded, long-term shifts like those influenced by global warming could potentially impact it. Long-term data beyond 10 years will allow the opportunity to observe gradual trends in surface vegetation (Gutman & Ignatov, 1995). Despite considering the study period from 2017 to 2023 relatively short and the impact minimal, we adopted rigorous analysis, closely examining annual changes during the dataset selection process to maximize the reliability and robustness of the dataset employed.

As of October 2020, we are aware of the trend-breaking point attributed to the Glass Fire, a mountain fire that occurred in Northern California. This significant disruption event serves as a pivotal moment for our analysis. The metrics for measuring resilience levels will be based on the intensity of the disruption event within each region and the subsequent rate of recovery. This approach enables us to quantitatively evaluate how different regions respond to disturbances like hill fires and the subsequent pace of recuperation. By utilizing this framework, we aim to gain insights into the comparative resilience levels of various regions, shedding light on their abilities to withstand and rebound from such disruptive incidents.

To measure recovry duration of the post-disruption, the R_{time} is formulated as:

$$R_{time} = \sum I(\frac{NDVI_{AC}}{NDVI_{BASE}}) < T)$$

- R_{time} represents the "resilience over time" metric for a specific region.
- $I(x)$ is the indicator function, which returns 1 if the condition x is true, and 0 if it's false.
- $NDVI_{AC}$ is the actual post-disruption NDVI value for a given time period.
- $NDVI_{BASE}$ represents the baseline NDVI value for the same time period.
- T is a predefined threshold value, and in our research $T = 0.92$.

The purpose of this formula is to quantify the time required for an area to fully recover from a disruption event and return to its original state. The value of $\frac{NDVI_{AC}}{NDVI_{BASE}}$ represents the deviates from the baseline NDVI. A value of less than 0.92 indicates that the area has not yet fully recovered from the disruption and current month add to the recovery time. Conversely, a value equal to or greater than 0.92 suggests that the vegetation index has rebounded to at least 92% of the baseline level, implying that the area has nearly or completely recovered from the disruption.

In determining the threshold of 0.92, we initially considered a range interval of [0.9, 1] for potential thresholds. Subsequently, we conducted experiments by assessing the discrepancy between the total number of recovery months and the actual recovery time across different threshold values. We concluded that a threshold of 0.92 is a relatively accurate. Opting for a higher threshold (e.g., 0.99) may necessitate a more extended recovery period, while selecting a lower threshold (e.g., 0.90) might result in a more lenient assessment. Thus, the choice of 0.92 as the threshold value strikes a balance between precision and practicality, aligning well with the recovery process's dynamics and characteristics.

Another indicator, event intensity $Intensity(x)$ will be defined by the following equation:

$$Intensity(x) = \int_{t1}^{t2} (NDVI_{AC}(t) - NDVI_{BASE}(t))dt$$

- $Intensity(x)$ represents the "event intensity" metric for a specific region, reflecting the integrated difference between actual NDVI values and baseline NDVI values over a defined time interval subsequent to experiencing a disruption.
- $t1 \; and \; t2$ is the starting and ending point of the recovery period.
- $NDVI_{AC}(t)$ is the actual NDVI value at time t.
- $NDVI_{BASE}(t)$ is the corresponding baseline NDVI value at the same time t.

The approach aim to quantify the intensity of a disruption event by calculating the integral of the difference between actual NDVI values and baseline NDVI values over a specified time interval. This method captures the cumulative magnitude of changes between the two datasets throughout the recovery period. The calculated intensity value provides insights into the cumulative impact of the disruption event on the region's vegetation. A higher intensity value indicates a more substantial disruption that resulted in significant discrepancies between the actual and baseline conditions, both in terms of magnitude and duration. On the other hand, a lower intensity value suggests a less severe disruption with relatively minor deviations and quicker recovery.

3.3.2 Alternative approach: synthetic control

The core idea of synthetic control method is to combine information from mutiple observations to create an integrated control group rather than seeking a single control or average in a neighbourhood of controls to assess the impact of a particular intervention or event (Abadie & Gardeazabal, 2003; Abadie, Diamond, & Hainmueller, 2010). In the context of this method, the term "unit" pertains to individual entities or observational objects encompassed in the study. Specifically, the unit that has undergone the intervention is designated as the "treated" unit, while the unit that has not been subjected to the intervention serves as the "untreated" unit. This nomenclature helps to differentiate between the entities that have experienced the intervention's effects and those that have not, thereby facilitating clear and concise communication of the research framework.

First we divided all the units into two categories, one that has received the effects of the intervention and one that has not been affected by the intervention. So, we suppose the dataset includes J units: $j = 1,2,3,\ldots,J$. Unit $J(j = 1)$ is the treated unit, while the remaining units represent the untreated group. $t = T_0$ is the point that intervention happened. Let Y_{jt} as observed at the time t. So, let Y_{jt}^0 denotes non-observe NDVI value would be in the region J that are not affected by the intervention. Y_{jt}^1 denotes NDVI value at point t if it is affected by intervention. When $t < T_0$:

$$Y_{jt} = Y_{jt}^0 \quad (t < T_0 , j = 1)$$

When $t > T_0$:

$$Y_{jt} = Y_{jt}^1 \quad (t > T_0 , j = 1)$$

For the unit $j = 2,3,\ldots,J$:

$$Y_{jt} = Y_{jt}^{0} \quad (t < T_0, j = 2,3,4,\ldots,J)$$

So, the causal effect of intervention at the time t is:

$$\tau_j(t) = Y_{jt}^{1} - Y_{jt}^{0}$$

Assume that there exists a series of weights for the unit $j = 2,3,\ldots,J$ such that Y_{jt}^{0} can be represented by the following equation:

$$\tau_1(t) = Y_{jt}^{1} - \sum_{j=2}^{j} w_j Y_{jt}$$

The optimization objective is to find the optimal weights combination, which makes the estimated synthetic control path closest to the actual observed control path in the time period between t and T:

$$arg_{w2,\ldots wj} min \sum_{t:t<T} |\tau_1 \ (t) - \tau_1{}^{est} \ (t)|$$

$\tau_1(t)$ is the actual observed treatment effect after time t, indicating the actual impact of the intervention. $\tau_1{}^{est} \ (t)$ is the estimated treatment effect after time t, denoting the effect estimated in the model. By minimizing these differences, the optimization algorithm can find the best weight configuration $(w_2, \ldots w_j)$ that makes the synthetic control path as similar as possible to the actual control path.

In our case, the dataset exhibits temporal regularity and undergoes dynamic changes, introducing a higher level of complexity compared to traditional scenarios involving single-policy interventions. To address this complexity and surmount the limitations of existing methodologies, we have opted for the advanced synthetic control (Neural Continuous Synthetic Control) approach proposed by Bellot and Schaar (2021) to estimate counterfactual outcomes.

By introducing the vector field f, we employ matrix-vector multiplication involving$f(Y_{1,s}^{0})\ dY_S{}^{0}$ spanning from time t_0 to the time t as the application of the influence of f on the latent path in a matrix, thereby constructing a more intricate model for the control path. And the $d{Y_S}^0$ signifies the variation of the latent path of the untreated unit over the time interval $[t_0, t]$. This innovation can be understood as a novel nonlinear extension of the conventional linear discrete-time synthetic control method (Bellot & Schaar, 2021).

The counterfuactual path Y_{1t}^0 can be represented using the following equation:

$$Y_{1,T}^0 + \int_T^t f(Y_{1,s}^0) d{Y_S}^0, t \in (T, t_m]$$

So, the causal effect of intervention at the time t is:

$$\tau_{1,t} = Y_{1,t}^0 - Y_{1,T}^0 - \int_T^t f(Y_{1,s}^0) d{Y_S}^0, t \in (T, t_m]$$

To uphold interpretability, a central tenet of the synthetic control method, the present approach introduces a weighted diagonal matrix to govern the influence of control paths. This extension defines potential counterfactual states as follows:

$$Y_{1,T}^0 + \int_T^t f(Y_{1,s}^0) W d{Y_S}^0, t \in (T, t_m]$$

We use loss function $L(y_1(t), {y_1}^{est}(t))$ to evaluate the difference of countfactual estimation and observed value. To optimize the parameter estimation, a gradient descent algorithm is employed. This algorithm backpropagates through both the ODE solver and the continuous state dynamics, facilitating the parameter updates as demonstrated in previous studies [13, 24]. It seeks to minimize the composite objective function R, which includes various loss terms and a regularization term linked to the weighted diagonal matrix W. The formula for solving the optimization problem is as follows:

$$arg_{\theta,n,v,w} min \sum_{t:t<T} L(y_1(t), {y_1}^{est}(t)) + \lambda \sum_{j=1}^{j-1} |[W]_{jj}|$$

θ, η, v, w: : These are the parameters to be optimized, corresponding to the parameters of the neural networks θ, η, v, and the weight matrix W.

$t: t < T$: This is a set of time points, representing all time points within the time range before the intervention occurs. This set is used to limit the computation of the loss function to the pre-intervention period.

λ: This is the regularization parameter that balances the trade-off between prediction error and sparsity. It controls the number of non-zero elements in the weight matrix W.

$\sum_{j=1}^{j-1} \quad |[W]_{jj}|$: This is the second part of the loss function, summing up the diagonal elements W_{jj} of the weight matrix W, representing the contributions of each control path. This component of the loss encourages sparsity in the weight matrix W by using the absolute value operation.

This approach leverages controlled differential equations to model the latent counterfactual path and allows optimization within each function space. By adopting this approach, we have achieved improvements in the following aspects:

1. The continuous evaluation: Compared to the previous discrete value observations, this new method can be evaluated using paths connected between observation points. It is more flexible in time and better suited to dynamic systems.
2. Latent states: In real scenarios, observations are usually a function of latent states, and the dynamics of latent states follow differential equations. Therefore, the synthetic control method allows projecting this latent state into the observation space.
3. Transparency: Although the nonlinearity reduces the transparency to some extent, we ensure the sparsity of the control path Y0 by introducing regularization in the solution space. Therefore, the final result still possesses a very good interpretability.

3.3.3 Evaluation

By using synthetic control methods, we are able to obtain counterfactual estimates. This replaces the baseline as a control in the previous traditional method. In order to compare the accuracy of these two methods, we will evaluate them in the following aspects.

1. Treatment Effect Estimates: Compare the estimated treatment effects obtained from each method. Computes the resulting difference between treatment units and the counterfactual estimates provided by each method.
2. Prediction Accuracy: Evaluate the predictive performance of both methods by comparing their ability to forecast future outcomes after fully recovered.
3. Robustness Analysis: Conduct conducted a placebo analysis to simulate counterfactual result in the unaffected area with the actual trend, and thus to conclude the the degree of stability of the synthetic control method.

By evaluating these aspects, we can compare the accuracy, reliability, and efficiency of the traditional baseline method and the synthetic control method. This evaluation will help to determine which method is more suitable for obtaining counterfactual estimates in a specific case.

RESULT

4.1 Temporal and spatial trends of NDVI data

By calculating and visualizing the NDVI data from the dataset we can see that the data have a certain temporal pattern, with a significant increase in spring, a peak in summer, a significant decrease in autumn, and a stable annual minimum in late autumn and early winter. In addition, the characteristics of NDVI data are summarized in terms of mean, maximum, minimum, standard deviation, and annual rate of change.

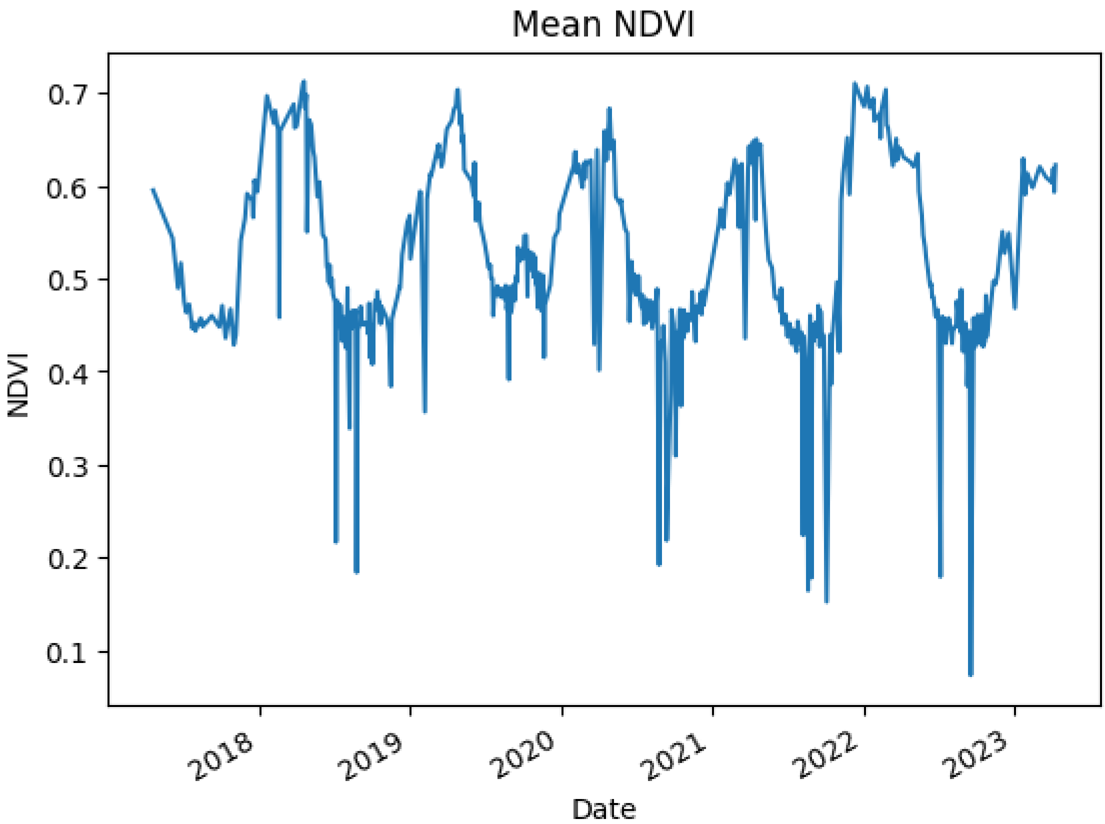

Fig 2. NDVI trend before the preprocessing

The researchers identified the impacted areas by looking for localization in the 2020 U.S. wildfire record and identified several areas that will be affected by wildfires in October 2020. These are the Diamond Mountain area, the St. Helena area, the Atlas Peak area, and the Monticello area. At the same time NDVI serves as supporting evidence, in the visualization of the NDVI change curve, the data undergoes a sudden drop. In particular, the minimum value of NDVI was significantly lower compared to previous years. This means that due to wildfires, some of the soil that once covered vegetation has been exposed and the vegetation area reduced. In particular, the minimum value of NDVI was significantly lower compared to previous years. This means that due to wildfires, some of the soil that once covered vegetation has been exposed and the vegetation area reduced.

4.2 Main results

In this section, we analyzed the results of measuring resilience by classical methods and by synthetic control methods for several regions, respectively.

First, we interpolate the cloud mask pixel points using the Vpint2 algorithm, for some outliers we selectively remove them. Despite efforts to enhance the image clarity, some degree of data fluctuation is still observable. This variability may be attributed to atmospheric disturbances, sensor errors, and other contributing factors. To mitigate this noise and improve the reliability and consistency of the data, a smoothing filter based on the Savitzky-Golay algorithm is applied. By employing this algorithm, the data undergoes a processing procedure that results in a more stable representation (See Fig 3,4,5). A comparative analysis between the original and processed data reveals a notable improvement in stability post-processing. This step is crucial as it ensures a more accurate and dependable dataset, thus enhancing the overall reliability of the findings.

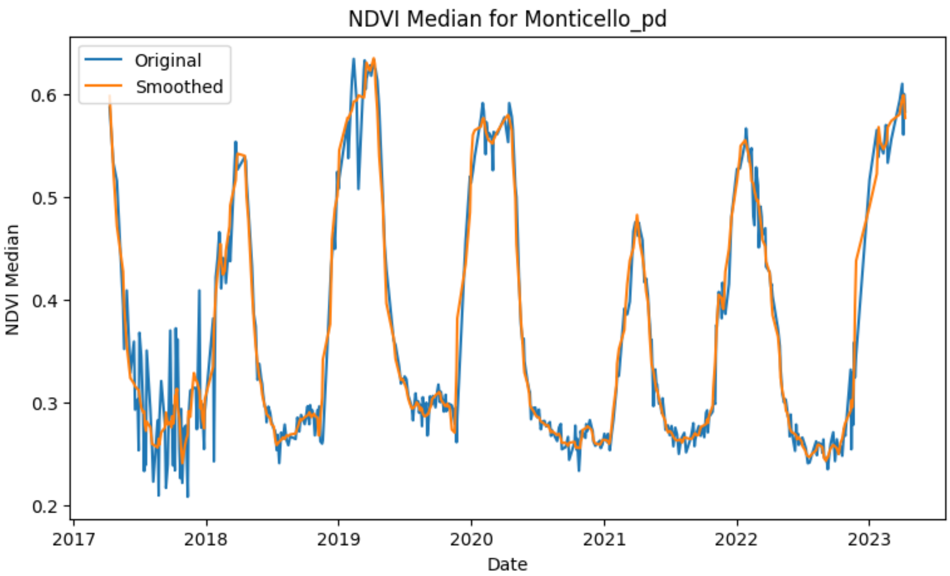

Fig 3. Region Monticello

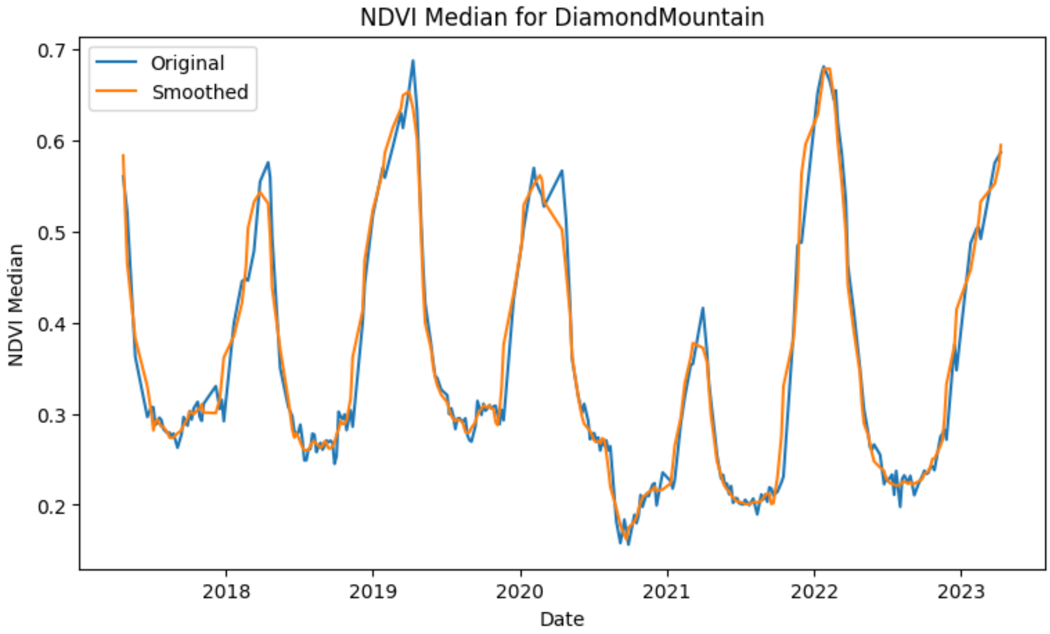

Fig 4. Diamond Mountain

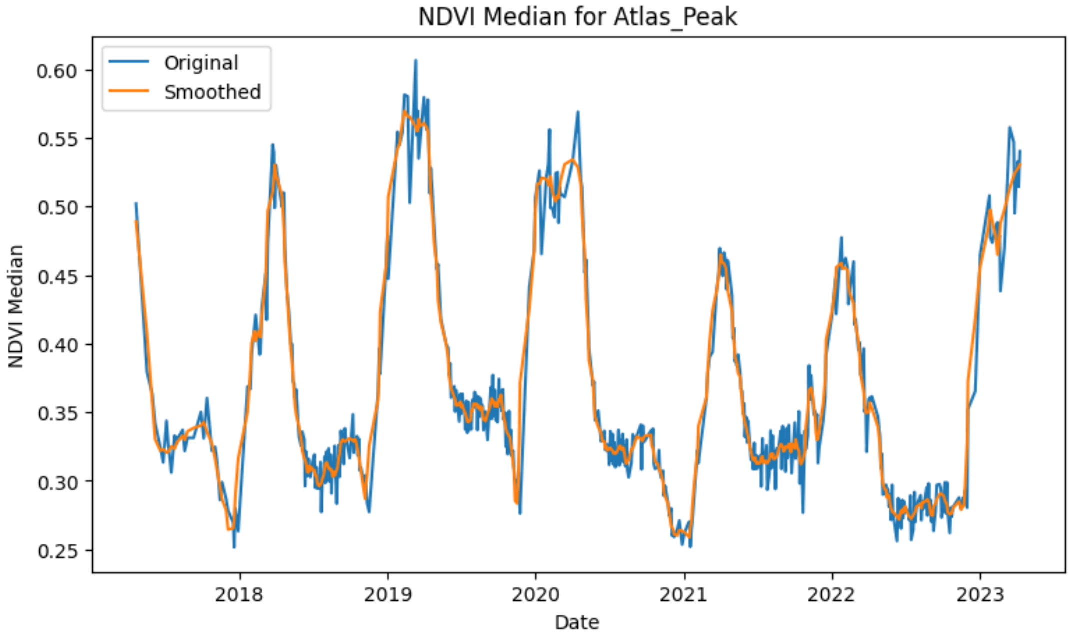

Fig 5. Atlas Peak

In the traditional approach to measuring resilience, the Baseline is determined by taking the historical average NDVI data before the onset of a natural disaster. The figure 6 illustrates the Baseline curve and the actual NDVI change curve.

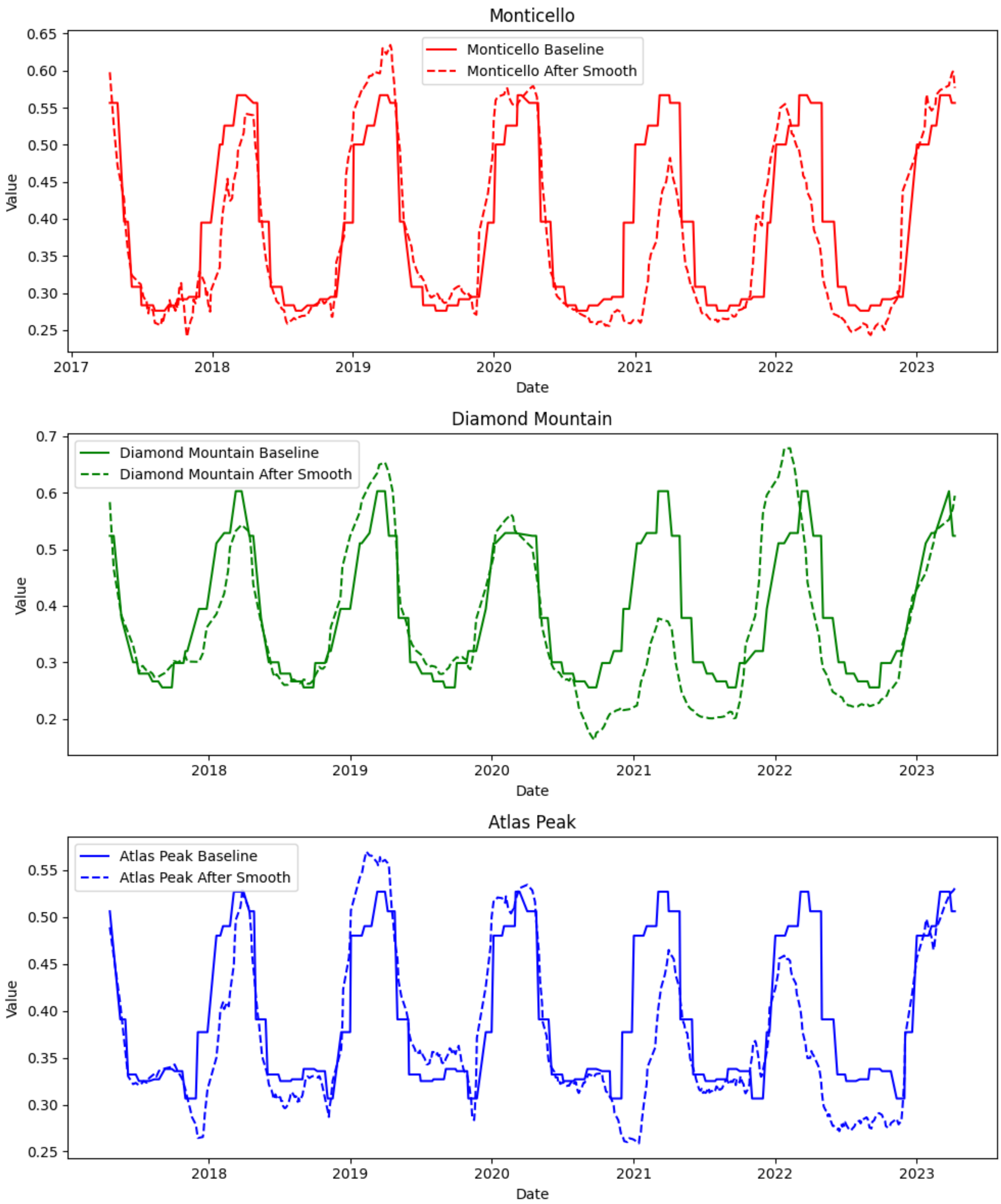

Fig 6. Comparison between two dataset

Prior to the event, the baseline data exhibited a considerable level of consistency compared to the observed data. It is essential to acknowledge that slight deviations between these datasets are expected due to the inherent variability of environmental conditions from year to year, resulting in minor fluctuations in the normalized difference vegetation index

(NDVI). These nuanced changes, which are not captured by the baseline dataset, can be observed as relatively stable within the overall trend .

The event took place between October and November 2020. During this period, a notable short-term decline in NDVI can be observed (see Fig 3), particularly in the Diamond Hill and Atlas Peak areas. Subsequently, a significant divergence in the persistence of the baseline data is evident across these three regions. Specifically, the Diamond Mountain area and Atlas Peak experienced a rapid and sustained decline in NDVI, remaining below historical averages for an extended period. It took several years for these regions to recover and regain normal NDVI levels. Although the Monticello area did not experience a sudden drop compared to the other regions, there was a noticeable decrease, and the subsequent trend in NDVI remained considerably lower compared to historical levels. The following table presents the outcomes obtained using traditional methods to measure resilience in the aforementioned regions.

Region	Event start	Event end	Period	Event intensity
Monticello	10/2020	08/2021	10	0.56
Diamond Mountain	10/2020	11/2021	13	1.24
Atlas Peak	10/2020	01/2023	26	1.37

Table 3. The measurement result use traditional method

By analyzing the information related to the event start date, event end date, duration, event intensity for each region, the following conclusions were drawn. The recovery period signifies the duration required for complete recuperation, and the event intensity indicates the integration of the actual NDVI and the historical contemporaneous data, which represents the severity and duration of the event. The Monticello area recovered within 8 months of the event, whereas the Diamond Mountain area necessitated 11 months for recovery, and the Atlas Peak area took a significant 26 months to fully recover. These findings indicate that the Atlas Peak area requires a lengthier period to return to pre-disaster conditions. The event intensity of the Monticello region is 0.56, which indicates a moderate level of activity in the Monticello region during that time period. In comparison, the disruption in the Diamond Mountain region was more severe with an event intensity of 1.24. This suggests a relatively intense event occurred in the Diamond Mountain region during that time period. During this timeframe, the Atlas Peak region experienced the longest and most severe wildfire, with an event intensity of 1.37.

Although the event intensities in Diamond Mountain and Atlas Peak are similar, the recovery time in Diamond Mountain is much shorter. This can be considered to be more resilient and better able to recover from negative situations after suffering a blow of the same scale. Correspondingly, the recovery time of the Monticello area and the Diamond Mountain area is similar. It can be considered that within the same time frame, the Diamond Mountain region can quickly recover to its original state, while the Monticello region recovers more slowly. From the comparison of the above two groups in Table 3, we can see that the recovery speed of the Diamond Mountain group is greater than that of the other two regions. Therefore, it can be seen that the Diamond Mountain Region has higher resilience.

These findings highlight the impact of the natural disaster on vegetation resilience. The sharp decrease in NDVI and its prolonged deviation from historical averages in the Diamond Mountain area and Atlas Peak demonstrate the severe and lasting effects of the event. Similarly, the significant decline in NDVI observed in the Monticello area indicates a substantial alteration in vegetation dynamics.

In the SCM, the performance comparison in the Fig 7 the left chart illustrates the effectiveness of the synthetic control method. The yellow curve represents the estimated counterfactual paths obtained through synthetic control, while the blue curve represents the actual NDVI change values.

The middle figure presents the corresponding treatment effect, which quantifies the difference between the counterfactual estimates and the observed trajectories. Positive treatment effect values indicate a beneficial impact on the organization, while negative values suggest a detrimental effect. Prior to the event, we observe treatment effects hovering around 0. This signifies the synthetic control group's ability to simulate the state of the experimental group before the event, ensuring a comparable baseline.

Following the event, the treatment effect experienced a sharp decline, indicating a significant immediate impact. Subsequently, it gradually rebounded and converged towards 0, reflecting the recovery process of the system after being subjected to an external shock. In the Monticello region, a slight decrease in the treatment effect is observed, consistent with the results obtained from the traditional method. This suggests that the area experienced a minor impact and quickly returned to its original state. In contrast, the Diamond Mountain area exhibits a faster recovery, reaching or even surpassing its pre-event condition within a year. On the other hand, the Atlas Peak area requires a more extended recovery period.

Overall, both the synthetic control and traditional methods effectively measure organizational resilience. However, the synthetic control method proves to be more accurate as it can capture the interplay of covariates and provide better counterfactual modeling. Its ability to estimate counterfactual paths and quantify treatment effects provides valuable insights into the impact of the natural disaster on vegetation dynamics and their subsequent recovery.

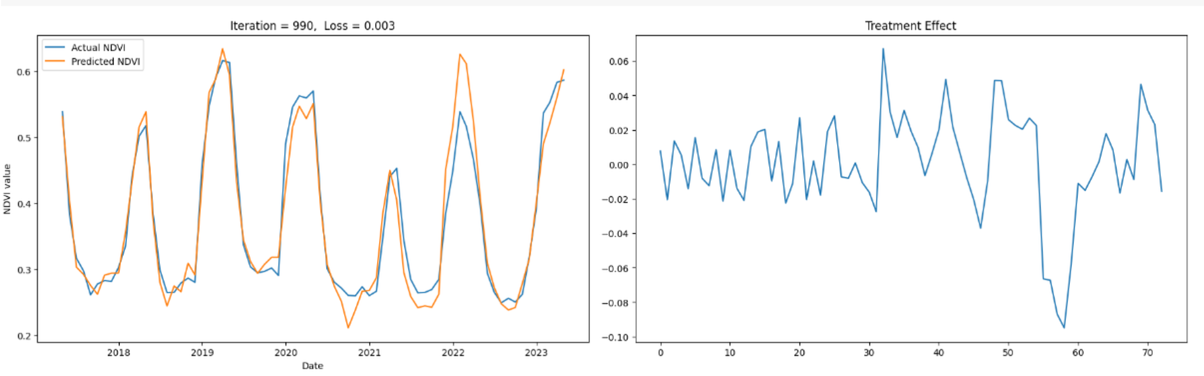

Fig 7(a). Syntactic control method on Monticello

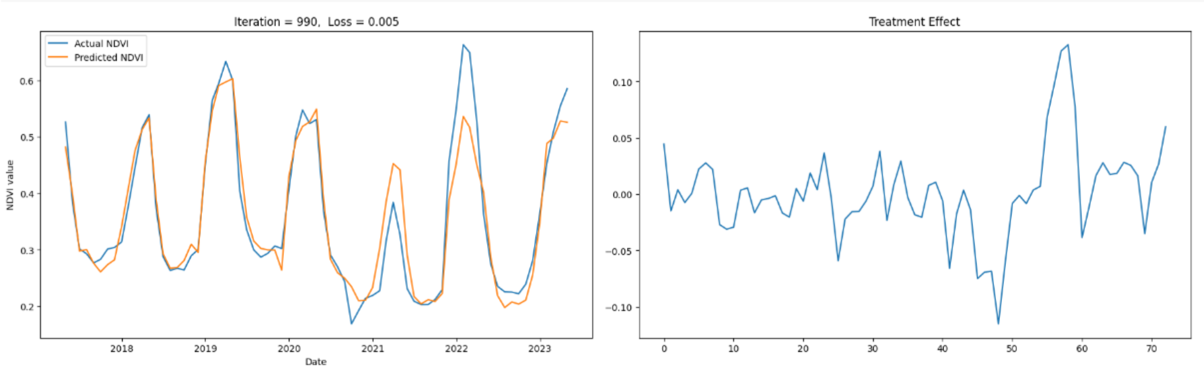

Fig 7(b). Syntactic control method on Diamond Mountain

4.3 Evaluation

4.3.1Placebo analysis

The placebo analysis serves as a pivotal step in evaluating the robustness of our findings and affirming the credibility of the treatment effect estimates. In order to execute this analysis, we leveraged the synthetic control method on regions that remained unaffected by the intervention. The fundamental objective of the placebo analysis revolved around investigating whether the applied methods would generate treatment effect estimates closely approximating 0 when no actual intervention was present. This validation process substantiates the efficacy of the synthetic control method in faithfully portraying the scenario.

For this analysis, we deliberately chose regions that had not experienced any disruptive event. Employing the same methodology as in our primary analysis, we proceeded to estimate the treatment effects in these regions. A noteworthy observation emerged on the left side of our analysis, where the actual trend and the estimated trend exhibited striking similarity, effectively overlapping. Moreover, from a statistical standpoint, the treatment effects exhibited a consistent fluctuation between 0 and 0.075. This pattern reinforced the conformity of our results to the anticipated outcomes. These findings indicate that the methods performed in alignment with expectations.

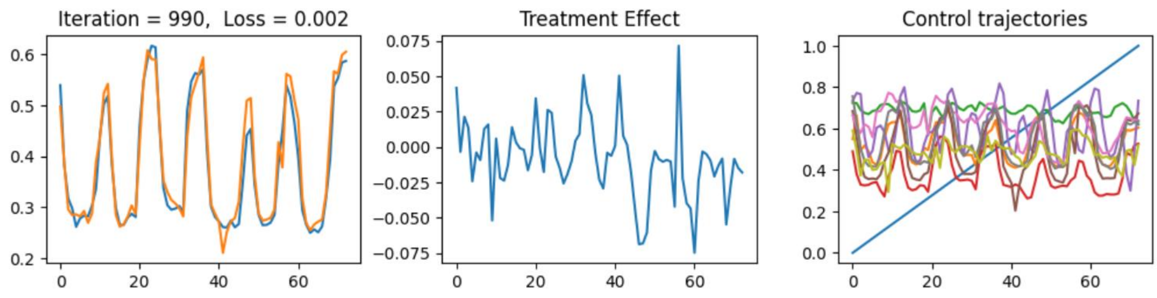

Fig 8. Placebo analysis

By rigorously validating our method through the placebo analysis, we reinforce the foundation of our study and enhance its credibility. This empirical process fortifies the position of the synthetic control method as a valuable tool in discerning treatment effects within a context characterized by the absence of actual interventions.

4.3.2 Comparison with two methods

In the comparative analysis of the two methods, we delved into the examination of the resemblance between the factual and estimated trends prior to the disruption, subsequently quantifying their respective goodness-of-fit through the determination of their R-squared (R_2) values. In the case of the historical data averaging method in the Altas area, the calculated R_2 value stood at 0.52. Conversely, the synthetic control method yielded a markedly higher R_2 value of 0.89.

The R_2 value of 0.52 for the historical data averaging method suggests a moderate level of correspondence between the method's estimates and the actual observations in the Altas area. On the other hand, the synthetic control method achieved an R_2 value of 0.89, signifying a significantly higher level of concordance between its estimated trend and the factual trend. This pronounced discrepancy in R_2 values indicates that the synthetic control method possesses a superior ability to closely replicate the actual trends, enhancing its potential for generating more accurate and reliable predictions.

Another perspective to evaluate the performance of the two methods involves assessing their impact on the simulation of the overall trend, particularly by examining the extent of deviation in peak values. In the context of the historical mean method, the peaks' highest and lowest values in 2021 generally align with the corresponding highest and lowest values of the actual curve. However, a one-month deviation in peak values is observed for the year 2022. Conversely, within the framework of the synthetic control method, the maximum and minimum values of peak points in both 2021 and 2022 consistently mirror those of the actual curve.

This comparative analysis underscores the synthetic control method's superiority in determining the overall trend's trajectory, yielding forecasts that are more precise and aligned with the actual trend. The coherence between the synthetic control method's predicted peak values and the actual curve demonstrates its capacity to effectively capture the underlying dynamics and nuances, enhancing its efficacy in forecasting future trends.

DISCUSSION

5.1 Finding of NDVI trend change

The heterogeneity of NDVI recovery levels are contingent upon the distinctive characteristics of different areas, including weather conditions, vegetation attributes, management approaches, restoration strategies, and policies (Kapucu, 2014; Miller & Ager, 2012; Arab et al., 2021). Notably, the exceptional recovery and subsequent enhancement observed in the Diamond Mountain area can be attributed to a confluence of factors. Firstly, the activation of robust coping mechanisms in response to adversity likely played a pivotal role in facilitating the region's recovery process. These mechanisms encompass adaptive strategies, resource allocation, and resilience-building activities that empower the system to rebound and reestablish its ecological equilibrium.

Furthermore, improvements in environmental conditions and enhanced management practices may have contributed significantly to the area's post-event growth and development. For instance, after a wildfire, changes in vegetation distribution disrupt the original balance, creating more favorable conditions for certain dominant crops (Saulino et al., 2023).

Additionally, the recovery process benefited from inorganic material derived from the burnt debris of mountain fires and favorable climatic conditions in the subsequent year, alongside other related positive factors (Martín-Alcón and Coll, 2016). The complexity of recovery processes is emblematic of the intricate relationships between environmental, ecological, and human factors, underscoring the need for comprehensive and context-sensitive approaches to resilience assessment and management.

In the context of the three examined cases, the findings emerging from the Diamond Mountain area hold a captivating allure. Notably, this region not only swiftly recuperated following the event but also exhibited an augmented state of vegetation activity that surpassed even the projections formulated through both conventional and synthetic control methods. This intriguing observation resonates harmoniously with the concept of the "recovery paradox," positing that certain entities, subjected to profound disruptions, have the potential to rebound to a state surpassing their initial conditions (Binswanger, 2001).

This concept is evidenced across a number of fields including ecology, economics, social sciences and organizational management. For example, Hora, Srinivasan and Basu (2019) unearthed a phenomenon in South India where underground water levels rebounded remarkably beyond anticipated levels—a parallel to the paradoxical resurgence we observe here. Similarly, within the realm of social sciences, investigations into recovery processes unveil intriguing paradoxes. Sabine (2018) described the phenomenon of job stressors, which is supposed to act as a positive stimulus in the recovery process, having a counterproductive effect. These studies collectively underscore the salience and significance of this concept, reaffirming its applicability as a pervasive phenomenon.

The related discussion also shows that a system as a complex whole is affected by a combination of factors, and final manifestation is multifaceted and context-dependent (Hora et.al, 2019). The Diamond Mountain case, alongside these diverse examples, beckons further investigation into the intricate web of factors that enable such remarkable resurgences. This exploration can substantially enhance our comprehension of resilience dynamics and potentially foster novel strategies for bolstering positive outcomes in the aftermath of upheavals.

5.2 Historical data approach and synthetic control approach

Another crucial point to discuss is the strengths and limitations of the employed methods and their applicability to different scenarios. Ayyub (2014) emphasizes that measuring absolute resilience requires evaluating organizational performance without disturbances, rendering the chosen measurement method pivotal. Sensier et al. (2016) exemplify this by contrasting projected macroeconomic outcomes with actual results to gauge resilience. Among our methods, modeling future trends using historical attributes aims to measure absolute resilience. However, this approach faces challenges in accurately fitting actual change curves due to system complexity. In our study, limited three-year historical data introduces instability and potential gaps, compromising baseline reliability. Longer datasets might stabilize data, yet assuming accurate future representation remains challenging considering event interferences and system dynamics.

The synthetic method is a relatively new approach in the field of resilience measurement. This approach quantifies relative resilience of an organization, where relative resilience refers to how well an entity performs relative to other similar entities, i.e., under the same conditions (Ilseven & Puranam, 2021). Notably, when contrasted with the assessment of absolute resilience, the measurement of relative resilience is relatively more straightforward due to the ease of identifying comparable entities and the simplicity of its implementation (Abadie, 2021).

Prior research has seen a substantial number of scholars discussing the efficacy and superiority of synthetic control methods in constructing counterfactual groups (Abadie, Diamond & Hainmueller, 2015; Mourtgos, Adams & Nix, 2022). Within the realm of resilience research, particularly in the context of recovery capacity, the synthetic control method is a very suitable research method. Moreover, synthetic control methods have been used by scholars for post-disaster recovery from major disasters (Fraser et a., 2022; Chen, 2022).

It is worth highlighting that using industries as instances and measuring industrial organizational resilience is the innovation of this article compared to previous ones. By utilizing the industry context, this study establishes a crucial linkage between measurements of organizational resilience and the application of synthetic control methods. This approach unveils how organizations operating within a specific industry tackle disruptions. This unique angle significantly contributes to the arena of resilience measurement methodologies. Furthermore, the analytical findings presented in this research offer a highly insightful lens to dissect the origins of resilience disparities among different regions. This investigation extends to the identification of pivotal factors that can, in turn, shape future strategies and policy implementations, thereby augmenting the overall enhancement of industry resilience.

5.3 Limitation and future direction

The synthetic control method undoubtedly introduces a more versatile and adaptable approach to estimating counterfactual trajectories. By considering temporal patterns and system dynamics, this method notably enhances accuracy when compared to the traditional approach. However, it is imperative to acknowledge certain limitations inherent to this method, which warrant attention for future research endeavors.

Central to the accuracy of the synthetic control method is the judicious selection of the donor pool, consisting of unaffected regions (Abadie, 2021). A robustly representative donor pool enhances the credibility of counterfactual estimations, ensuring a more accurate portrayal of the system's trajectory. Conversely, the inclusion of a biased donor pool or data from events that have experienced impact can significantly compromise the precision of synthetic control estimates. Bouttell et al. (2018) actively addressed this limitation in their study on evaluating population-level health interventions.

In our study, a notable example emerged when inconsistencies surfaced between initial treatment effect estimates for the Monticello area and actual observations. Subsequent investigation revealed that certain data points within the donor pool had also undergone changes in their external environment. Despite these changes, they remained part of the donor pool, leading to considerable errors in the final treatment effect estimation.

Another limitation we want to discuss is about data quality. The data sourced from satellite images introduces a certain degree of noise, demanding extensive preprocessing during the initial stages. Furthermore, the volatile nature of weather conditions occasionally results in the presence of invalid or missing data. These variables require careful consideration and subsequent resolution to ensure accurate measurements of resilience.

After we complete our study of vineyard settings with good results and feedback, we will be able to measure organizational resilience on a broader scale. To expand its application, researchers must refine the metrics employed to gauge resilience across different sectors. This could entail the development of industry-specific indicators and the incorporation of additional variables that capture the intricate dynamics of resilience (Fraser, Aldrich, and Small, 2021). By embracing more comprehensive metrics, the accuracy and relevance of resilience assessments stand to be significantly heightened. This advancement holds the promise of offering more robust insights into the adaptive capacity of organizations across various industries, thereby informing informed decision-making in the face of disruptions.

CONCLUSION

In conclusion, this study contributes to the field of organizational resilience measurement by examining the case of wine industry using satellite images and comparing historical data averaging method with the synthetic control method.

The findings demonstrate the advantage of the synthetic control method in accurately assessing the treatment effect and capturing the dynamics of organizational resilience. By constructing counterfactual outcomes and considering potential confounding factors, the synthetic control method provides a more robust and reliable measurement approach.

However, it is important to acknowledge the limitations of the synthetic control method, such as the potential impact of rebound effects and the dependence on data quality and availability. Future research is needed to address these limitations and further refine the methodology. Additionally, exploring advanced machine learning techniques and integrating diverse data sources could enhance the accuracy and applicability of resilience measurement in various industries.

Overall, leveraging satellite images and machine learning algorithms offers a promising avenue for studying and enhancing organizational resilience. By adopting a data-driven approach, organizations can proactively identify vulnerabilities, make informed decisions, and implement effective strategies to navigate challenges and ensure long-term sustainability.

REFERENCE

1. Bhamra, R., Dani, S., & Burnard, K. (2011). Resilience: the concept, a literature review and future directions. *International journal of production research*, *49*(18), 5375-5393.
2. Annarelli, A., & Nonino, F. (2016). Strategic and operational management of organizational resilience: Current state of research and future directions. *Omega*, *62*, 1-18.
3. Ge, L., Anten, N. P., van Dixhoorn, I. D., Feindt, P. H., Kramer, K., Leemans, R., ... & Sukkel, W. (2016). Why we need resilience thinking to meet societal challenges in bio-based production systems. *Current Opinion in Environmental Sustainability*, *23*, 17-27.
4. Clarke, M. (2008). Understanding and managing employability in changing career contexts. *Journal of European Industrial Training*, *32*(4), 258-284.
5. Pineda-Martos, R., & Calheiros, C. S. (2021). Nature-Based Solutions in Cities—Contribution of the Portuguese National Association of Green Roofs to Urban Circularity. *Circular Economy and Sustainability*, *1*(3), 1019-1035.
6. Burnard, K., & Bhamra, R. (2011). Organisational resilience: development of a conceptual framework for organisational responses. *International Journal of Production Research*, *49*(18), 5581-5599.
7. Lipper, L., McCarthy, N., Zilberman, D., Asfaw, S., & Branca, G. (2017). *Climate smart agriculture: building resilience to climate change* (p. 630). Springer Nature.
8. Colicchia, C., Dallari, F., & Melacini, M. (2010). Increasing supply chain resilience in a global sourcing context. *Production planning & control*, *21*(7), 680-694.
9. Lv, W. D., Tian, D., Wei, Y., & Xi, R. X. (2018). Innovation resilience: A new approach for managing uncertainties concerned with sustainable innovation. *Sustainability*, *10*(10), 3641.
10. Lim, S. S., Vos, T., Flaxman, A. D., Danaei, G., Shibuya, K., Adair-Rohani, H., ... & Pelizzari, P. M. (2012). A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990–2010: a systematic analysis for the Global Burden of Disease Study 2010. *The lancet*, *380*(9859), 2224-2260.
11. Spieske, A., & Birkel, H. (2021). Improving supply chain resilience through industry 4.0: A systematic literature review under the impressions of the COVID-19 pandemic. *Computers & Industrial Engineering*, *158*, 107452.

12. Wieland, A., & Durach, C. F. (2021). Two perspectives on supply chain resilience. *Journal of Business Logistics*, *42*(3), 315-322.
13. Tang, J. (2019). *Quantitative Assessment of Resilience in Complex Systems* (Doctoral dissertation, ETH Zurich).
14. Das, S., Das, B., Nath, K., Dutta, A., Bora, P., & Hazarika, M. (2017). Impact of stress, coping, social support, and resilience of families having children with autism: A North East India-based study. *Asian journal of psychiatry*, *28*, 133-139.
15. Ilseven, E., & Puranam, P. (2021). Measuring organizational resilience as a performance outcome. *Journal of Organization Design*, *10*(3-4), 127-137.
16. Abadie, A., Diamond, A., & Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. *Journal of the American statistical Association*, *105*(490), 493-505.
17. Abadie, A., Diamond, A., & Hainmueller, J. (2015). Comparative politics and the synthetic control method. *American Journal of Political Science*, *59*(2), 495-510.
18. Holling, C. S. (1973). Resilience and stability of ecological systems. *Annual review of ecology and systematics*, *4*(1), 1-23.
19. Linnenluecke, M. K. (2017). Resilience in business and management research: A review of influential publications and a research agenda. *International Journal of Management Reviews*, *19*(1), 4-30.
20. Allen, D. E., Singh, A. K., & Powell, R. J. (2013). EVT and tail-risk modelling: Evidence from market indices and volatility series. The North American Journal of Economics and Finance, 26, 355-369.
21. Kambhu, J., Schuermann, T., & Stiroh, K. J. (2007). Hedge funds, financial intermediation, and systemic risk. *Economic Policy Review*, *13*(3).
22. Seville, E., Van Opstal, D., & Vargo, J. (2015). A primer in resiliency: seven principles for managing the unexpected. *Global Business and Organizational Excellence*, *34*(3), 6-18.
23. Lee, A. V., Vargo, J., & Seville, E. (2013). Developing a tool to measure and compare organizations' resilience. *Natural hazards review*, *14*(1), 29-41.

24. Brown, C., Seville, E., & Vargo, J. (2017). Measuring the organizational resilience of critical infrastructure providers: A New Zealand case study. *International journal of critical infrastructure protection*, *18*, 37-49.

25. Chowdhury, M. M. H., & Quaddus, M. (2017). Supply chain resilience: Conceptualization and scale development using dynamic capability theory. *International Journal of Production Economics*, *188*, 185-204.

26. Chen, R., Xie, Y., & Liu, Y. (2021). Defining, conceptualizing, and measuring organizational resilience: A multiple case study. *Sustainability*, *13*(5), 2517.

27. Gentile, R., Galasso, C., Idris, Y., Rusydy, I., & Meilianda, E. (2019). From rapid visual survey to multi-hazard risk prioritisation and numerical fragility of school buildings. *Natural Hazards and Earth System Sciences*, *19*(7), 1365-1386.

28. Sweya, L. N., Wilkinson, S., Kassenga, G., & Mayunga, J. (2020). Developing a tool to measure the organizational resilience of Tanzania's water supply systems. *Global Business and Organizational Excellence*, *39*(2), 6-19.

29. Chen, Y., Cao, R., Chen, J., Liu, L., & Matsushita, B. (2021). A practical approach to reconstruct high-quality Landsat NDVI time-series data by gap filling and the Savitzky–Golay filter. *ISPRS Journal of Photogrammetry and Remote Sensing*, *180*, 174-190.

30. Saulino, L., Rita, A., Stinca, A., Liuzzi, G., Silvestro, R., Rossi, S., & Saracino, A. (2023). Wildfire promotes the invasion of Robinia pseudoacacia in the unmanaged Mediterranean Castanea sativa coppice forests. *Frontiers in Forests and Global Change*, *6*, 1177551.

31. Martín-Alcón, S., & Coll, L. (2016). Unraveling the relative importance of factors driving post-fire regeneration trajectories in non-serotinous Pinus nigra forests. *Forest Ecology and Management*, *361*, 13-22.

32. Shen, H., Li, X., Cheng, Q., Zeng, C., Yang, G., Li, H., & Zhang, L. (2015). Missing information reconstruction of remote sensing data: A technical review. *IEEE Geoscience and Remote Sensing Magazine*, *3*(3), 61-85.

33. Arp, L., Baratchi, M., & Hoos, H. (2022). VPint: value propagation-based spatial interpolation. *Data Mining and Knowledge Discovery*, *36*(5), 1647-1678.

34. Wang, J., Ding, Y., Wang, S., Watson, A. E., He, H., Ye, H., ... & Li, Y. (2022). Pixel-scale historical-baseline-based ecological quality: Measuring impacts from climate change and

human activities from 2000 to 2018 in China. *Journal of Environmental Management*, *313*, 114944.

35. Firozjaei, M. K., Sedighi, A., Firozjaei, H. K., Kiavarz, M., Homaee, M., Arsanjani, J. J., ... & Alavipanah, S. K. (2021). A historical and future impact assessment of mining activities on surface biophysical characteristics change: A remote sensing-based approach. *Ecological Indicators*, *122*, 107264.
36. Spruce, J., Hargrove, W. W., Gasser, J., Smoot, J., & Kuper, P. (2014, December). MODIS NDVI Change Detection Techniques and Products Used in the Near Real Time Forwarn System for Detecting, Monitoring, and Analyzing Regional Forest Disturbances. In *AGU Fall Meeting Abstracts* (Vol. 2014, pp. GC31A-0439).
37. De Jong, R., Verbesselt, J., Zeileis, A., & Schaepman, M. E. (2013). Shifts in global vegetation activity trends. *Remote Sensing*, *5*(3), 1117-1133.
38. Jamali, S., Seaquist, J., Eklundh, L., & Ardö, J. (2012, May). Comparing parametric and non-parametric approaches for estimating trends in multi-year NDVI. In *1st EARSeL Workshop on Temporal Analysis of Satellite Images; Department of Physical Geography and Ecosystem Science: Mykonos, Greece* (p. 6).
39. Gutman, G., & Ignatov, A. (1995). Global land monitoring from AVHRR: Potential and limitations. *International Journal of Remote Sensing*, *16*(13), 2301-2309.
40. Abadie, A., & Gardeazabal, J. (2003). The economic costs of conflict: A case study of the Basque Country. *American economic review*, *93*(1), 113-132.
41. Hird, J. N., & McDermid, G. J. (2009). Noise reduction of NDVI time series: An empirical comparison of selected techniques. *Remote Sensing of Environment*, *113*(1), 248-258.
42. Pettorelli, N., Vik, J. O., Mysterud, A., Gaillard, J. M., Tucker, C. J., & Stenseth, N. C. (2005). Using the satellite-derived NDVI to assess ecological responses to environmental change. *Trends in ecology & evolution*, *20*(9), 503-510.
43. Kapucu, N. (2014). Collaborative governance and disaster recovery: the National Disaster Recovery Framework (NDRF) in the US. *Disaster recovery: Used or misused development opportunity*, 41-59.
44. Miller, C., & Ager, A. A. (2012). A review of recent advances in risk analysis for wildfire management. *International journal of wildland fire*, *22*(1), 1-14.

45. Arab, A., Khodaei, A., Eskandarpour, R., Thompson, M. P., & Wei, Y. (2021). Three lines of defense for wildfire risk management in electric power grids: A review. *IEEE Access*, *9*, 61577-61593.
46. Hora, T., Srinivasan, V., & Basu, N. B. (2019). The groundwater recovery paradox in South India. *Geophysical Research Letters*, *46*(16), 9602-9611.
47. Sonnentag, S. (2018). The recovery paradox: Portraying the complex interplay between job stressors, lack of recovery, and poor well-being. *Research in Organizational Behavior*, *38*, 169-185.
48. Ayyub, B. M. (2014). Systems resilience for multihazard environments: Definition, metrics, and valuation for decision making. *Risk analysis*, *34*(2), 340-355.
49. Sensier, M., Bristow, G., & Healy, A. (2016). Measuring regional economic resilience across Europe: Operationalizing a complex concept. *Spatial Economic Analysis*, *11*(2), 128-151.
50. Mourtgos, S. M., Adams, I. T., & Nix, J. (2022). Elevated police turnover following the summer of George Floyd protests: A synthetic control study. *Criminology & Public Policy*, *21*(1), 9-33.
51. Fraser, T., Poniatowski, A., Hersey, N., Zheng, H., & Aldrich, D. P. (2022). Uneven Paths: Recovery in Louisiana Parishes after Hurricanes Katrina and Rita. *Available at SSRN 4004216*.
52. Chen, P. (2022). Analysis of the post-earthquake economic recovery of the most severely affected areas in the 2008 Wenchuan earthquake. *Natural Hazards*, *114*(3), 2633-2655.
53. Fraser, T., Aldrich, D. P., & Small, A. (2021). Seawalls or social recovery? The role of policy networks and design in disaster recovery. Global Environmental Change, 70, 102342.
54. Bouttell, J., Craig, P., Lewsey, J., Robinson, M., & Popham, F. (2018). Synthetic control methodology as a tool for evaluating population-level health interventions. *J Epidemiol Community Health*, *72*(8), 673-678.
55. Kong, J., Simonovic, S. P., & Zhang, C. (2019). Resilience assessment of interdependent infrastructure systems: a case study based on different response strategies. *Sustainability*, *11*(23), 6552.