

Summary of Commonly Used ENSO Indices

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Abstract. This paper introduces 12 commonly used El Niño-Southern Oscillation (ENSO) indices and compares their creation based on different datasets, regions, representing anomalies, functions, advantages, and limits. It summarizes two application cases for each of the three different ENSO indices: Niño 3.4, Ocean Niño Index (ONI), and the Multivariate ENSO index (MEI). The application examples for Niño 3.4 are ENSO prediction and drought pattern analysis; for ONI, they are responses of ice shelves and rainfalls to ENSO; and for MEI, they are building two modeling approaches for ENSO monitoring and hydrological events prediction. The summary of these ENSO indices demonstrates their importance in climate studies in providing simplified anomalies for building models and making scientists communicate with each other about their findings in ENSO-related climate variabilities in agriculture, fisheries, water resource management, disaster preparedness, etc.

Keywords: ENSO; ENSO index; Niño 3.4; ONI; MEI.

1. Introduction

A natural pattern of temperature fluctuations between the ocean and atmosphere caused by circulation in the central and eastern tropical Pacific Ocean is known as the El Nio-Southern Oscillation (ENSO). Extreme ENSO phases include El Nio (warming) and La Nia (cooling). The third phase, often known as ENSO-neutral, lies in between them. Each ENSO phase lasts between three and seven years, oscillating between warming and cooling phases that affect worldwide precipitation and temperature.

ENSO disturbs the ocean and atmosphere and exhibits different weather intensities. It is a crucial process that could significantly impact local weather, fisheries, agricultural productivity, droughts, flooding, public health issues (e.g., malaria spreading), and more. For example, one El Niño phase during 1997–98 resulted in a 10% drop in coffee production in Colombia, and coffee is the country's most important agricultural production [1]. Another example is the dengue fever outbreak related to an ENSO event during 2015-2016 in Southeast Asia and Brazil. The entire year was dominated by severe and lasting drought due to this ENSO event. It made individuals store water close to their homes, which increased the number of dengue-carrying *Aedes aegypti* and *Aedes albopictus* mosquitoes [2].

ENSO is a dominant global driver of climate variability. It relates to extraordinarily complicated interactions among climate, oceanic, and atmospheric parameters (e.g., zonal/ meridional winds), sea surface temperature, atmospheric convection, etc. None of the past ENSO events are identical, and the two extreme phases of ENSO are not mirror images [3]. However, it is hard to study complicated climate systems, for the needed direct measurement data are usually limited and unavailable. Scientists thus created indirect measurements, such as proxies, to estimate historical climate parameters (e.g., precipitation, temperature) to reconstruct past climate patterns and understand their long-term changes.

Several commonly used proxies, including sea surface temperature (SST), atmospheric pressures, wind patterns, and more, become essential to create indices in stating the behavior of the ENSO system. So that scientists can track, quantify, compare, research, analyze, forecast, and predict ENSO with reliable indices. Therefore, we must understand how the frequently used ENSO indices are created and worked in studying this climate system. The following sections of this paper will introduce 12 frequently used ENSO indices and analyze the use of three picked indices with several modeling cases. This paper will present the advantages and limits of different indices in their creation

and region representation and offer a more straightforward summary to assist researchers in picking suitable ENSO indices for future studies by giving several academic using cases with at least 70 cited times in the last five years.

2. Current Niño Indices

The dynamics of ENSO (El Niño-Southern Oscillation) are intricately linked to variations in sea surface temperature (SST) and atmospheric pressure. Various indices like the Southern Oscillation Index (SOI) and SST anomalies help in categorizing ENSO events based on factors like location, intensity, and timing. ENSO manifests in nine distinct patterns, including El Niño, La Niña, and subtypes like East Pacific (EP) and Central Pacific (CP) events [4,5]. These patterns are identified by examining SST variations in the tropical Pacific and their subsequent impact on global climatic conditions.

The driving forces behind ENSO circulation are not fully understood, but several large-scale atmospheric circulations have been associated with ENSO phenomena. One such driver could be the Walker Circulation, which moves warm, moist air from the western to the eastern Pacific. This circulation influences SST intensities and ocean currents, becoming stronger during La Niña and weaker during El Niño events. Other atmospheric circulations like the Pacific South American (PSA) and Pacific North American (PNA) patterns also interact with ENSO, although their relationships are not fully understood [6].

To track ENSO effectively, NOAA employs multiple proxy indices that represent periodic fluctuations in SST and atmospheric pressure across the equatorial Pacific. These indices include Niño 1.2, Niño 3, Niño 3.4, Niño 4, ONI, SOI, and MEI. Each index focuses on different geographical regions and offers unique insights into ENSO's various aspects. Among these, the Niño 3.4/ONI index is most commonly used to monitor ENSO's evolution and its global impacts.

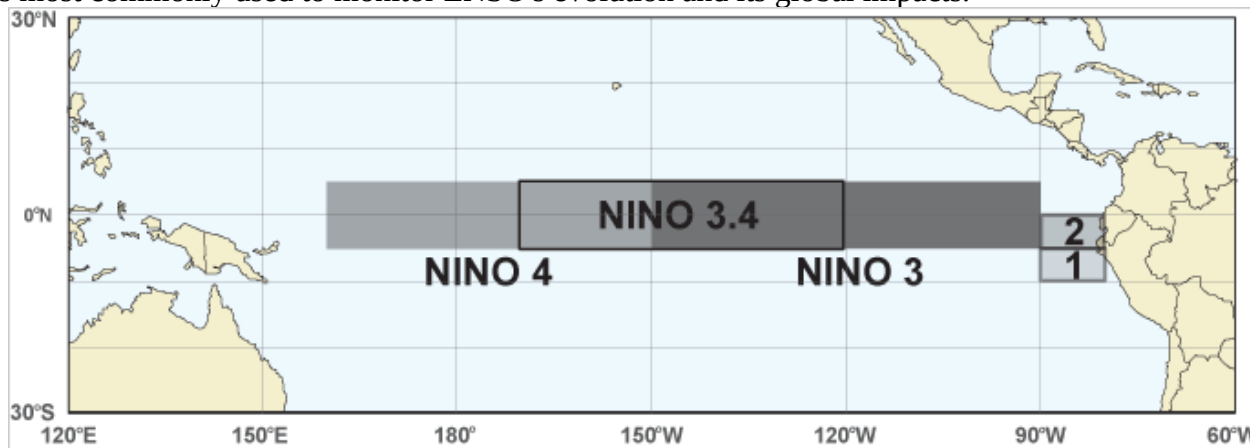


Fig. 1 Region of Interest of Different ENSO Proxy Indexes

In summary, understanding ENSO involves a multifaceted approach that employs various indices to monitor changes in SST and atmospheric pressure. These indices help in categorizing and understanding the complex patterns and impacts of ENSO on global climate.

2.1. Niño 4, Niño 1.2, Trans-Niño Index (TNI), and Modoki Index

The Niño 4 index, situated in the central equatorial Pacific, is derived from the Monthly NOAA ERSST V5 dataset. This index is characterized by lower variability in Sea Surface Temperature (SST) anomalies, possibly due to its distance from coastlines and the influence of ocean currents and atmospheric conditions. However, its focus solely on SST anomalies may limit its ability to capture the full range of ENSO variability. On the other hand, the Niño 1.2 index covers a smaller but more volatile region near the coast of South America. It is sensitive to upwelling cold water and is significantly affected by both El Niño and La Niña events [7-9].

The Trans-Niño Index (TNI) was introduced to quantify SST anomaly gradients, often used in conjunction with Niño 3.4. Researchers have found correlations between TNI and various phenomena, such as tornado outbreaks in the U.S. and vegetation changes in Saudi Arabia [10-12].

The Modoki index, developed by the Japan Agency for Marine-Earth Science and Technology (JAMSTEC), focuses on SST anomalies in specific regions of the equatorial Pacific. It aims to identify the unique tripolar pattern of ENSO Modoki, which differs from the classical ENSO. However, it has limitations in detecting the full impact of ENSO on SST changes [14-16].

Several improved versions of the Modoki index have been developed, such as El Niño Modoki II (MII) and the Improved El Niño Modoki Index (IEMI), to better capture the nuances of ENSO Modoki events.

2.2. Niño 3 and Japanese Meteorological Agency ENSO Index (JMA)

Originally designed to monitor El Niño events, the Niño 3 index was later found to be less effective in capturing the broader ocean-atmosphere interactions associated with ENSO. As a result, Niño 3.4 and the Oceanic Niño Index (ONI) were developed to offer a more comprehensive view. The Sea Surface Temperature (SST) anomalies for Niño 3 are calculated over a specific region in the equatorial Pacific, using data from various sources like satellites, buoys, and ships [7].

On the other hand, the Japanese Meteorological Agency ENSO Index (JMA) is derived from COBE-SST datasets and focuses on a region similar to that of Niño 3. Unlike other indices, JMA also monitors the Indian Ocean Dipole (IOD) phenomenon. It defines an El Niño or La Niña event based on a deviation of $\pm 0.5^{\circ}\text{C}$ in SST anomalies for six consecutive 5-month periods or more. JMA stands out for its ability to identify more enduring and pronounced El Niño events, being less susceptible to noise compared to the traditional Southern Oscillation Index (SOI) and more robust than ONI [17].

2.3. Niño 3.4, Oceanic Niño Index (ONI), and a Relative Niño 3.4 Index

Table. 1 Similarity and Differences between Niño 3.4 and ONI

	Similarity	Differences		
	Geographical Coverage & Proxy Anomalies	Calculation Method (calculate the anomalies of SSTs relative to a reference period)	Temporal Resolution (monthly mean values of SST anomalies)	Threshold Duration Criteria (employ a threshold to determine the presence of El Niño/ La Niña conditions)
Niño 3.4	5°N-5°S, 170°W-120°W; SST anomalies	5-month running mean	More detailed monthly information	exceed $\pm 0.4^{\circ}\text{C}$; lasts at least six consecutive months
ONI		3-month running mean	Longer-term average data over 3-months	exceed $\pm 0.5^{\circ}\text{C}$; lasts at least five consecutive months

The most popular indices for identifying El Niño and La Niña occurrences are the Niño 3.4 and ONI. Still, ONI has a different calculation method, threshold duration criteria for ENSO events, and temporal resolution, as shown in Table 1.

Niño 3.4 and the Oceanic Niño Index (ONI) are among the most widely used metrics for tracking El Niño and La Niña events. However, they differ in their calculation methods, event duration criteria,

and temporal resolution. Niño 3.4 measures Sea Surface Temperature (SST) anomalies by comparing current temperatures to a 30-year average. This index is particularly useful for understanding ENSO-related interactions in the central equatorial Pacific, a region that has a strong teleconnection with North America [7,9,18-20].

ONI, on the other hand, employs a three-month rolling average of SST anomalies in the Niño 3.4 region. It serves as a standardized metric that can be used for early climate warnings. The ONI region is significantly influenced by the Equatorial Undercurrent, a major ocean current that flows against the surface currents from west to east near the equator. This undercurrent's strength is often reflected in ONI values, particularly during El Niño events [21].

Recent studies by Li et al. have shown that the relative Niño 3.4 index and the Niño 3.4 index are the most effective in capturing the global impact of ENSO on precipitation and surface temperatures. These indices outperform others like the Modoki index, which is less effective in capturing ENSO's influence on temperature variations. The Southern Oscillation Index (SOI) in Australia, for example, has a strong correlation with precipitation but a weaker relationship with surface temperature [21,22].

In summary, while Niño 3.4 and ONI are valuable tools for understanding ENSO, they are not sufficient on their own. To get a comprehensive understanding of ENSO and its global impacts, it's crucial to use a combination of these indices along with other metrics like the relative Niño 3.4 index.

2.4. Southern Oscillation Index (SOI) and Bivariate El Niño-Southern Oscillation Index (BEST)

The SOI is a metric that quantifies the monthly average sea level pressure difference between the Tahiti and Darwin stations, using on-site data. This index serves as an atmospheric gauge for ENSO, specifically capturing the vigor of the Walker circulation. Unlike broader Southern Oscillation measures, the [T+D] focuses on short-term or localized events. Similar to how ONI and Niño indices operate but in a noisier data environment, a positive SOI signals La Niña conditions, while a negative SOI indicates El Niño. It's worth noting that data from the Tahiti station prior to 1935 should be used cautiously due to its limited and inconsistent nature [7,22,23].

BEST, on the other hand, is a composite index that merges normalized Niño 3.4 SST and SOI data. It provides a statistical assessment of the intensity and spatial distribution of El Niño and La Niña events. Positive BEST values are indicative of El Niño, negative values suggest La Niña, and values close to zero imply neutral conditions. When BEST values are correlated with ERA-Interim precipitation anomalies, they can offer insights into precipitation patterns during El Niño and La Niña events. For instance, a positive correlation with BEST values suggests increased precipitation during El Niño, while a negative correlation suggests the opposite during La Niña events [24].

2.5. Bi-monthly Multivariate ENSO index (MEI.v2)

The MEI.v2 is a comprehensive index that incorporates five key variables related to ENSO: sea level pressure (SLP), sea surface temperature (SST), meridional and zonal wind components at the surface, surface air temperature, and outgoing longwave radiation (OLR). These variables are used to construct the leading empirical orthogonal function (EOF) over the tropical Pacific region. The data for these variables are sourced from a variety of platforms, including satellites, in-situ measurements, the JRA55 reanalysis dataset, and NOAA's Physical Sciences Laboratory (PSL). For example, SLP and wind data are gathered from the NCEP/NCAR Reanalysis project, while SST data is obtained through NOAA's Optimum Interpolation Sea Surface Temperature (OISST) methodology.

Researchers utilize EOF analysis or principal component analysis to dissect the MEI.v2 dataset into orthogonal basis functions. These functions capture the primary patterns of variability in the ENSO system. Each EOF comprises a spatial configuration and an associated time series, aiming to distill the dataset into a minimal set of independent variables without losing essential information. Unlike Niño indices, which focus solely on SST anomalies to indicate El Niño or La Niña events, the MEI offers a more nuanced, multivariate view of the ENSO system. It accounts for the seasonal nature of ENSO and minimizes the impact of higher-frequency intraseasonal fluctuations. As a result,

MEI.v2 is often used in conjunction with other indices like SOI, Niño 3.4, the Coupled ENSO Index (CEI), and the Proxy-based ENSO Index to provide a comprehensive understanding of ENSO's long-term trends. Although MEI can be extended back to 1871 using historical SLP and SST data, this is a more complex task compared to using SST-only indices [25].

3. Case Study

3.1. Examples of Niño 3.4

Niño 3.4 is a widely utilized index for studying ENSO, forecasting climatic conditions, and understanding their impact on diverse climatic zones. For example, Yan and colleagues applied an advanced deep learning model called the "EEMD-TCN hybrid approach" to long-term ENSO predictions using historical Niño 3.4 and SOI data from 1871 to 2019 [26]. This model surpassed conventional ENSO forecasting methods by capturing intricate patterns and dependencies in the data. The study revealed that Niño 3.4 provided more accurate predictions than SOI, especially when using 1-month lead data. The EEMD-TCN approach was particularly effective, outperforming other models like LSTM in various lead-time predictions. However, it struggled with the spring predictability barrier, showing increased errors for extended forecasts during intense El Niño or La Niña periods. In another study focused on drought patterns in Northeast Brazil, Cunha and team used Niño 3.4 to explore the link between severe droughts and El Niño events [27]. Their findings indicated that major droughts in the years 1982–1983, 1992–1993, and 1997–1998 were closely tied to El Niño occurrences. They also found that El Niño could exacerbate and extend severe droughts, as seen in the 2015–2016 event.

Niño 3.4 has proven to be invaluable in a range of research areas, from ENSO modeling to understanding El Niño-induced disease outbreaks and droughts. Its inclusion in scientific studies offers critical insights into the complexities of climate variations related to ENSO.

3.2. Examples of ONI

In the realm of climate research, the Oceanic Niño Index (ONI) has been instrumental in various studies. Paolo and his research group, for instance, used ONI to investigate how ENSO events affect the Antarctic ice shelf in the Pacific sector [28]. They employed locally weighted regression (LOWESS) to remove long-term trends in ice-shelf height records. Their analysis revealed a strong correlation between ONI and changes in ice-shelf height, denoted as $\delta h(t)$, especially in the Amundsen Sea region. The study found that fluctuations in ONI often lead to rapid changes in $\delta h(t)$, sometimes even triggering shifts in the Amundsen Sea Low (ASL) indices. During intense El Niño events, the study noted an increase in ice-shelf height due to snow accumulation, although the overall mass of the ice shelf decreased due to basal melting.

In another study, Supari and his team used ONI to examine the impact of ENSO on rainfall patterns in East Asia [29]. They correlated ONI with two specific indices: consecutive wet days (CWD) and consecutive dry days (CDD), which represent periods of extreme wetness and dryness in Indonesia. Their findings showed that El Niño events typically result in reduced rainfall in southern China and Indochina, while La Niña events lead to increased rainfall in northern China and Japan. The study also highlighted the varying effects of La Niña and El Niño on cyclonic and anti-cyclonic circulations, respectively.

These examples underscore the versatility and utility of ONI in climate research, from ENSO monitoring and modeling to weather forecasting and long-term trend analysis.

3.3. Examples of MEI

The Multivariate ENSO Index (MEI) has been a cornerstone in various research endeavors, particularly in understanding the complexities of the El Niño-Southern Oscillation (ENSO). One such study by Zhang and his team employed MEI to assess the uncertainties in ENSO monitoring. They used a comprehensive atmospheric model simulation approach that considered the signal-to-noise

ratio related to ENSO's ocean-atmosphere dynamics [30]. Their analysis revealed that a fixed metric often fails to accurately capture ENSO patterns, especially during mild to moderate events. However, by employing a probabilistic approach based on MEI data for November and December, they were able to provide a more reliable assessment of ENSO's strength, particularly for events occurring after 1980. This methodology has the potential to improve decision-making in various sectors, including water management and public safety.

In another innovative study, Bracken and colleagues used MEI in a Bayesian hierarchical model to perform non-stationary frequency analysis of different hydrological variables [31]. They aimed to estimate the likelihood of rare hydrological events, such as floods. The study utilized MEI data from ESRL/NOAA to capture the temporal variations and the influence of ENSO on the hydrological variables. When applied to Taylor Park Reservoir in Colorado, USA, this Bayesian approach offered several advantages over traditional methods, including reduced uncertainty and the ability to capture linear and nonlinear dependencies between variables.

MEI and its various versions, like MEI.v2 and MEI.ext, serve as versatile tools not just for ENSO monitoring but also for studying its long-term trends, predicting seasonal changes, and understanding the intricate interactions between the ocean and atmosphere.

4. Conclusion

By going through the creation, dataset, region, advantages, limits, and identification of El Niño, neutral phases, and La Niña of 12 commonly used ENSO indices, the commonly used Niño 3.4, ONI, and MEI are picked to become the case study examples in Section 3. All the picked example articles have at least 70+ cited times in the last five years and thus are considerable to study before exploiting ENSO-related studies with similar topics in these introduced studies. The examples using cases of Niño 3.4 are ENSO prediction and discovery of ENSO-related drought patterns in NEB. For ONI, the cases are the finding of East Asian rainfall patterns and the reaction of the Pacific-sector Antarctic ice shelf to ENSO. MEI and its different versions are used in two different modeling approaches: a probabilistic approach for ENSO monitoring and a Bayesian hierarchical approach for predicting the occurrence potentials of ENSO-related hydrological events.

Besides the overview of frequently used ENSO indices mentioned above, other studies on climate variability indices have been published within the last five years. These could offer guidelines for picking appropriate datasets and indices in researching climate systems with large-scale coupled air-sea interactions. For instance, Norel et al. examined four main types of climate variability associated with coupled ocean-atmosphere interactions using exploratory analysis, autocorrelation, and wavelet analysis. They studied four indices for each climate phenomenon, including the Niño 3.4 index and principal PDO index for ENSO and Pacific Decadal Oscillation (PDO) in the Pacific Ocean and the NAO index and AMO index for North Atlantic Oscillation (NAO) and Atlantic Multi-decadal Oscillation (AMO) in the Atlantic Ocean, to determine the temporal representation of the four modes.

Overall, ENSO indices are frequently used in monitoring and predicting ENSO and climate variabilities. They are essential tools for climate modeling, simulation, and weather forecasts. ENSO indices can simplify the big data related to ENSO into manageable metrics, which makes it easier to interpret the behavior and influences of ENSO and its related climate events from mass data, allowing scientists to communicate and share their results more effectively. Choosing appropriate ENSO indices in climate modeling can provide reliable and considerable information to policymakers, thus helping reduce negative social impacts caused by extreme climate events, including droughts, heat waves, tropical cyclones, floods, marine heat waves, extreme temperatures, potential infectious disease outbreaks, etc. With the global warming trend, ENSO study will become more crucial in agriculture, fisheries, water resource management, and disaster preparedness for ENSO-related natural disasters will become more frequent with greater destructions in the future.

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