big data and cognitive computing

Article

Social Trend Mining: Lead or Lag

Hossein Hassani *, **Nadejda Komendantova** , **Elena Rovenskaya** and **Mohammad Reza Yeganegi**

International Institute for Applied Systems Analysis (IIASA), Schloßpl. 1, 2361 Laxenburg, Austria; komendan@iiasa.ac.at (N.K.); rovenska@iiasa.ac.at (E.R.); yeganegi@iiasa.ac.at (M.R.Y.)
* Correspondence: hassani@iiasa.ac.at

Abstract: This research underscores the profound implications of Social Intelligence Mining, notably employing open access data and Google Search engine data for trend discernment. Utilizing advanced analytical methodologies, including wavelet coherence analysis and phase difference, hidden relationships and patterns within social data were revealed. These techniques furnish an enriched comprehension of social phenomena dynamics, bolstering decision-making processes. The study's versatility extends across myriad domains, offering insights into public sentiment and the foresight for strategic approaches. The findings suggest immense potential in Social Intelligence Mining to influence strategies, foster innovation, and add value across diverse sectors.

Keywords: social intelligence; data mining; open data; search engines; review; lead and lag

check for updates

Citation: Hassani, H.; Komendantova, N.; Rovenskaya, E.; Yeganegi, M.R. Social Trend Mining: Lead or Lag. *Big Data Cogn. Comput.* **2023**, *7*, 171. https://doi.org/10.3390/bdcc7040171

Academic Editors: Min Chen, Maria Chiara Caschera, Patrizia Grifoni and Fernando Ferri

Received: 21 July 2023
Revised: 24 October 2023
Accepted: 2 November 2023
Published: 7 November 2023

1. Introduction

The importance of social trend mining lies in its ability to provide stakeholders with a deep understanding of user behavior, preferences, and sentiments. By leveraging the vast amount of data available from the internet including search engines, businesses gain real-time insights into market dynamics, consumer trends, and competitive intelligence. These data also have a high potential to inform research in the public interest.

Big Data Analytics using available information provided by various search engines (for instance, Google) has opened a new golden opportunity [1,2]. In addition, such an approach can also be used to measure people's engagement, priority, and sentiment over time. For example, Google Trends [3] allows users to analyze the popularity of keywords and phrases on Google over time. It can be used for a variety of purposes, including analyzing public opinion, tracking the spread of information and news, and identifying trends in consumer behavior. Here are a few examples of studies that have used Google Trends data. For instance, Google Trends data has been used to predict the GDP growth in the United States [4]; Google Trends data was utilized to analyze tourism demand in various countries [5]; ref. [6] used Google Trends data to predict stock market returns in China; and [7] used Google Trends data to predict the spread of infectious diseases. These are just a few examples; there are many more studies and articles that have used Google Trends data in various ways (see, for example, [8–17]).

The landscape of online networks and interaction mediums has been significantly transformed by the advent of social media platforms. Unlike their predecessors, social media platforms exhibit distinctive characteristics such as openness, participatory dynamics, flexibility, robustness, and creativity. These platforms, akin to real-life social networks, establish virtual connections between individuals, giving rise to the small-world phenomena that characterize them (see, for instance, [18–25]. Recent statistics reveal that the average social media user maintains 8.4 active accounts and dedicates around 145 min daily to engaging across various social media platforms. Amidst this vibrant virtual environment, numerous challenges have emerged concerning the extraction and analysis of content generation, modification, and dissemination across diverse topics on social media. This paper draws on a recent review [26] and various other sources [27–33] to delve into the multifaceted challenges inherent in social media mining and analysis, shedding light on the complexities of understanding and navigating this dynamic landscape.

The novelty of this paper lies in its innovative approach to social trend mining, which leverages open access data and Google Search engine data to provide comprehensive insights into user behavior, and trend identification. By integrating time series analysis and advanced analytical methods, this paper offers a fresh perspective on understanding and harnessing social data for decision making. Furthermore, this paper introduces the novel application of wavelet coherence analysis and phase difference to uncover hidden relationships and patterns within social data, enhancing our ability to identify leading and lagging trends. This unique combination of methodologies and its adaptability to various domains make the paper a pioneering contribution to the field of social trend mining.

The ability to identify leading and lagging trends, perform trend analysis, and differentiate noise from meaningful events provides organizations with a powerful tool for informed decision making, proactive strategy formulation, and effective risk management.

The next section presents the methodology, which consists of two subsections: trend extraction based on indexed time series and coherence analysis between two time series. These methodologies are employed to explore the applicability of the proposed approach using real data extracted from Google Search.

The first subsection focuses on trend extraction based on indexed time series. By utilizing indexed time series data, trends can be identified and analyzed. This approach allows for the examination of temporal patterns and variations in search interest over time. The indexed time series data, obtained from Google Search data, serve as a valuable resource for trend analysis and provide insights into societal interests and preferences.

The second subsection delves into coherence analysis between two time series. This analysis explores the association between two time series, considering both time and frequencies. By examining the coherence between the two series, it becomes possible to understand the degree of similarity and correlation between them. This analysis provides valuable information about the interconnectedness and potential causal relationships between different social phenomena.

To evaluate the proposed approach, real data extracted from Google searches are utilized. These data represent actual search queries made by individuals, reflecting their interests and concerns. By employing this real-world data, the applicability and effectiveness of the methodology can be assessed, providing valuable insights into social intelligence mining.

2. Methodology and Methods

The methodology section of this paper briefly describes a trend extraction approach based on indexed time series and an approach to coherence analysis between two time series. By utilizing real data from Google Search, the proposed approach can be evaluated and its effectiveness in uncovering trends and associations can be assessed. These methodologies serve as powerful tools for exploring and analyzing social phenomena, offering valuable insights into the dynamics of our ever-evolving society.

2.1. Trend Analysis

Search engine trend analysis has emerged as a valuable technique for gaining insights into user behavior, sentiment analysis, and trend identification. Among various search engines, Google Trends stands out as a prominent platform that provides a vast amount of data, which can be utilized for time series analysis and opinion mining of individuals.

By monitoring the frequency of searches related to specific keywords over time, researchers can obtain valuable insights into the popularity and dynamics of various topics. This data can be leveraged for time series analysis techniques, such as trend identification, seasonality detection, and forecasting. The data extracted from Google Trends data provides not only quantitative information but also a glimpse into public sentiment and opinions. By analyzing the content of search queries and associated search results, researchers can gain insights into the preferences, concerns, and sentiments of individuals. Opinion mining techniques, such as sentiment analysis and topic modeling, can be applied to extract meaningful insights from this data, enabling a deeper understanding of public opinion on specific subjects.

To facilitate trend analysis and comparison across different topics, the concept of creating indices based on selected keywords can be used. These indices capture the relative popularity or interest in specific topics over time. The formula for creating indices can be adjusted based on the desired characteristics and data normalization techniques. Two common types of indices are:

(a) Univariate Google Trend Index: This index represents the search interest for a single keyword or topic. It is calculated by normalizing the search volume or frequency for the chosen keyword over a specific time period. Normalization techniques, such as dividing by the maximum search volume or using z-scores, can be employed to standardize the data and make it comparable.

(b) Multivariate Google Trend Index: This index captures the comparative popularity of multiple keywords or topics. It involves selecting a set of keywords of interest and calculating the search volume or frequency for each keyword.

By utilizing these indices, researchers and practitioners can gain a comprehensive view of the relative popularity and trends associated with different keywords or topics over time. This enables them to identify emerging trends, track public sentiment, and compare the performance of various keywords or topics within their respective domains.

2.2. Lead and Lag Analysis

A wavelet transform is used to transform time series with complex periodic behavior to simplified signals, each of which has simple periodic behavior (with a single period). From a mathematical point of view, a wavelet transform is a generalization of Fourier transform. A Continuous Wavelet Transform, CWT, uses a mother wavelet function $\psi(\cdot)$ to transform a discrete-time time series $\{y_t\}_1^n$ to wavelet coefficients $W_\psi\{y\}(\tau, s)$, for the time localizing parameter τ and the scale parameter s.

2.2.1. Univariate Case

The wavelet coefficients $W_\psi\{y\}(\tau, s)$ are defined as a convolution of time series $\{y_t\}_1^n$ with the localized mother wavelet $\psi(\cdot)$ (named child wavelet), localized in time and frequency space by τ and s [34]:

$$W_\psi\{y\}(\tau, s) = \sum_{t=1}^{n} y_t \frac{1}{\sqrt{s}} \overline{\psi}\left(\frac{t-\tau}{s}\right),$$

where $\overline{\psi}(\cdot)$ is the complex conjugate of the mother wavelet $\psi(\cdot)$. The localization parameter τ exhibits periodic behavior over time, while the scale parameter s localizes the periodic behavior in the frequency domain. When the scale parameter s has larger values, this indicates long-term periodic behavior with low frequency. On the other hand, smaller values of the scale parameter s reveal details in short-term periodic patterns with higher frequencies. One commonly used choice for the mother wavelet is the Morlet wavelet [33], which is formulated as follows:

$$\psi(t) = c_\omega \pi^{-\frac{1}{4}} \exp\left\{-\frac{t^2}{2}\right\}\left(e^{i\omega t} - \kappa_\omega\right),$$

where ω is the angular frequency, and κ_ω and c_ω are constants defined as:

$$c_\omega = \left(1 + e^{-\omega^2} - 2e^{-\frac{3}{4}\omega^2}\right)^{-\frac{1}{2}}, \kappa_\omega = e^{-\frac{1}{2}\omega^2}.$$

The $\omega = 6$ is a proper choice for the angular frequency since it makes the Morlet wavelet approximately analytic. Large absolute values of $W_\psi\{y\}(\tau, s)$ indicate powerful periodic patterns in time τ and period s. The wavelet coefficients can be used to construct the wavelet power spectrum of time series $\{y_t\}_1^n$:

$$Power_\psi\{y\}(\tau, s) = \frac{1}{s}\left|W_\psi\{y\}(\tau, s)\right|^2$$

The wavelet power spectrum, denoted as $Power_\psi\{y\}$, is a valuable tool for mapping periodic patterns in a given time series over time. To assess the significance of the wavelet power spectrum, it can be compared against the white noise spectrum using either the asymptotic chi-square statistic [34] or Monte Carlo simulation [35]. The Monte Carlo simulation approach is employed for evaluating the significance of the wavelet power spectrum.

2.2.2. Bivariate Case

Let us now consider the time series $\{x_t\}_1^n$ and $\{y_t\}_1^n$ as the bivariate case. A cross-wavelet transform can be used to investigate the relationship between $\{x_t\}_1^n$ and $\{y_t\}_1^n$ [34]:

$$W_\psi\{xy\}(\tau, s) = \frac{1}{s} W_\psi\{x\}(\tau, s)\, \overline{W}_\psi\{y\}(\tau, s),$$

where $\overline{W}$ denotes a complex conjugate and $W_\psi\{x\}(\tau, s)$ and $W_\psi\{y\}(\tau, s)$ are the wavelet coefficients in CWT of $\{x_t\}_1^n$ and $\{y_t\}_1^n$, respectively. The wavelet cross power spectrum, as modulus of wavelet coefficients, can be used to map the similarities between two time series' periodic behavior:

$$Power_\psi\{xy\}(\tau, s) = \left|W_\psi\{xy\}(\tau, s)\right|.$$

The $Power_\psi\{xy\}(\tau, s)$, like covariance, depends on the underlying time series' unit of measurement and may not properly interpret the degree of association between two series. Wavelet coherence between two time series $\{x_t\}_1^n$ and $\{y_t\}_1^n$ is defined as the local cross-correlation between the series, localized at time τ and scale s:

$$W_\psi\{xy\}(\tau, s) = \frac{\left|sW_\psi\{xy\}(\tau, s)\right|^2}{sPower_\psi\{x\}(\tau, s).sPower_\psi\{y\}(\tau, s)},$$

where prefix s behind W_ψ and $Power_\psi$ indicates smoothing is required. Similar to the power spectrum, the wavelet coherence between two series can also be examined using Monte Carlo simulation [36–39]. Monte Carlo simulation provides a robust approach for testing the significance of wavelet coherence and assessing the presence of coherent relationships between the two series under investigation.

The Continuous Wavelet Transform (CWT) reveals localized periodic patterns in a given time series $\{y_t\}_1^n$. The wavelet phase indicates the local displacement of the periodic behavior relative to the localization parameter τ, which is shifted across the time domain when τ is set as the origin. The wavelet phase is typically represented as an angle within the interval $[-\pi, \pi]$.

$$Phase_\psi\{y\}(\tau, s) = \tan^{-1}\left(\frac{Im\left(W_\psi\{y\}(\tau, s)\right)}{Re\left(W_\psi\{y\}(\tau, s)\right)}\right),$$

where $Im(.)$ and $Re(.)$ are imaginary and real parts of the wavelet coefficient $W_\psi\{y\}(\tau, s)$.

Using the cross-wavelet coefficients, one can calculate the difference between wavelet phases from two time series (which is actually the difference between two phases):

$$Angle_\psi\{xy\}(\tau, s) = \tan^{-1}\left(\frac{Im\left(W_\psi\{xy\}(\tau, s)\right)}{Re\left(W_\psi\{xy\}(\tau, s)\right)}\right) = Phase_\psi\{x\}(\tau, s) - Phase_\psi\{y\}(\tau, s),$$

where $Angle_{\psi}\{xy\}(\tau, s)$ represents the phase difference between two time series $\{x_t\}_1^n$ and $\{y_t\}_1^n$. $Angle_{\psi}\{xy\}(\tau, s)$ can be used to determine which time series starts the periodic pattern first and which one is following, for a given time and frequency interval. Figure 1 shows the simplified interpretation of the phase difference between time series $\{x_t\}_1^n$ and $\{y_t\}_1^n$.

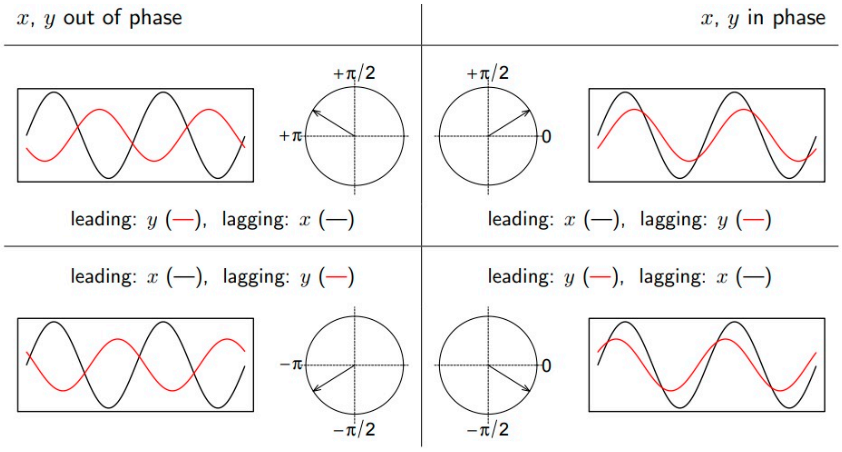

Figure 1. Interpretation of phase difference between signals x and y [32].

Various social phenomena can exhibit cyclical patterns [33]. By applying wavelet analysis to the social data, we can uncover the underlying periodic patterns in these phenomena. For example, analyzing people's interest in a subject through chat discussions or online searches can reveal if there are cycles where this subject becomes popular in society. Similarly, examining the number of participants in a social activity can expose the cycles of outbursts in that particular activity.

Furthermore, by utilizing a wavelet coherence analysis and phase difference, we can examine the correlation between two social phenomena, even if it was only for a brief period. This analysis can help determine which phenomenon had a leading role if such a relationship existed. The presence of coherency and phase difference between two social phenomena could indicate a causal relationship, where events from the leading series influence events in the lagging series. Alternatively, it could suggest that both series are influenced by another common social phenomenon. These findings serve as powerful tools for generating hypotheses about social events, trends, and their interrelations.

3. Applied Methodology: Real Data Implementation and Analysis

In this section, we focus on the application of social trend mining to several dimensions of human security including food, water, and energy security. These three dimensions of human security correspond to three UN Sustainable Development Goals (SDGs)—SDG 2, SDG 6, and SDG 7, respectively. Let us now provide a brief overview of three SDGs utilized in this paper.

Sustainable Development Goal 2 is about creating a world free of hunger by 2030. In 2020, between 720 million and 811 million persons worldwide were suffering from hunger, roughly 161 million more than in 2019. Also in 2020, a staggering 2.4 billion people, or above 30 percent of the world's population, were moderately or severely food insecure, lacking regular access to adequate food. The figure increased by nearly 320 million people in just one year. Globally, 149.2 million children under 5 years of age, or 22.0 percent, were suffering from stunting (low height for their age) in 2020, a decrease from 24.4 percent in 2015.

SDG 6 is about ensuring access to water and sanitization for all. Access to safe water, sanitation, and hygiene is the most basic human need for health and well-being. Billions of people will lack access to these basic services in 2030 unless progress quadruples. Demand for water is rising owing to rapid population growth, urbanization, and increasing water needs from the agriculture, industry, and energy sectors.

To reach universal access to drinking water, sanitation, and hygiene by 2030, the current rates of progress would need to increase fourfold. Achieving these targets would save 829,000 people annually, who die from diseases directly attributable to unsafe water, inadequate sanitation, and poor hygiene practices.

SDG 7 is about ensuring access to clean and affordable energy, which is key to the development of agriculture, business, communications, education, healthcare, and transportation. The lack of access to energy hinders economic and human development.

The latest data suggest that the world continues to advance towards sustainable energy targets. Nevertheless, the current pace of progress is insufficient to achieve Goal 7 by 2030. Huge disparities in access to modern sustainable energy persist.

It should be mentioned that significant challenges remain at the global level in terms of achieving these SDGs. This assessment is true for most of the world's major regions, while recent trends are mainly stagnating (in lower-income countries) or moderately increasing (in higher-income countries).

The actual or perceived lack of food, water, or energy security could be a source of social instability. In addition to the indicators describing the actual availability, accessibility, and affordability of food, water, and energy, such as prices and use, indicators describing people's perceptions provide important input for policy makers. Google Search data can inform such indicators which could be made available to policy makers almost in real time.

Figure 2, as an example, depicts the Google Search hits for the keywords "Food Security", "Energy Security", and "Water Security" over the past five years. These three concepts—food, energy, and water security—are important dimensions of human security. However, when comparing the search hits for the three subsets, it is evident that the search interest in food security is significantly higher than that for water security and energy security. The search interest in energy security is lower than the other two dimensions although only slightly lower than the search interest in water security.

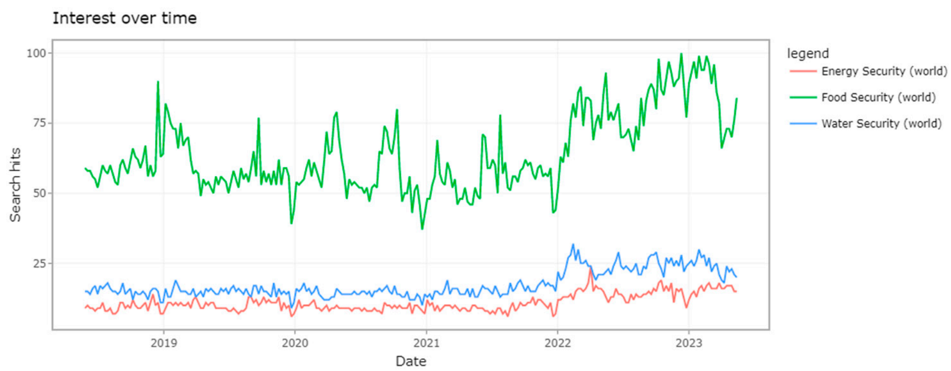

Figure 2. The Google Search hits for the keywords "Food Security", "Energy Security", and "Water Security" over the last 5 years.

Let us now explore the periodic behavior in the search interests for "Food Security" and "Water Security". Figure 3 displays the wavelet power spectrum for both series.

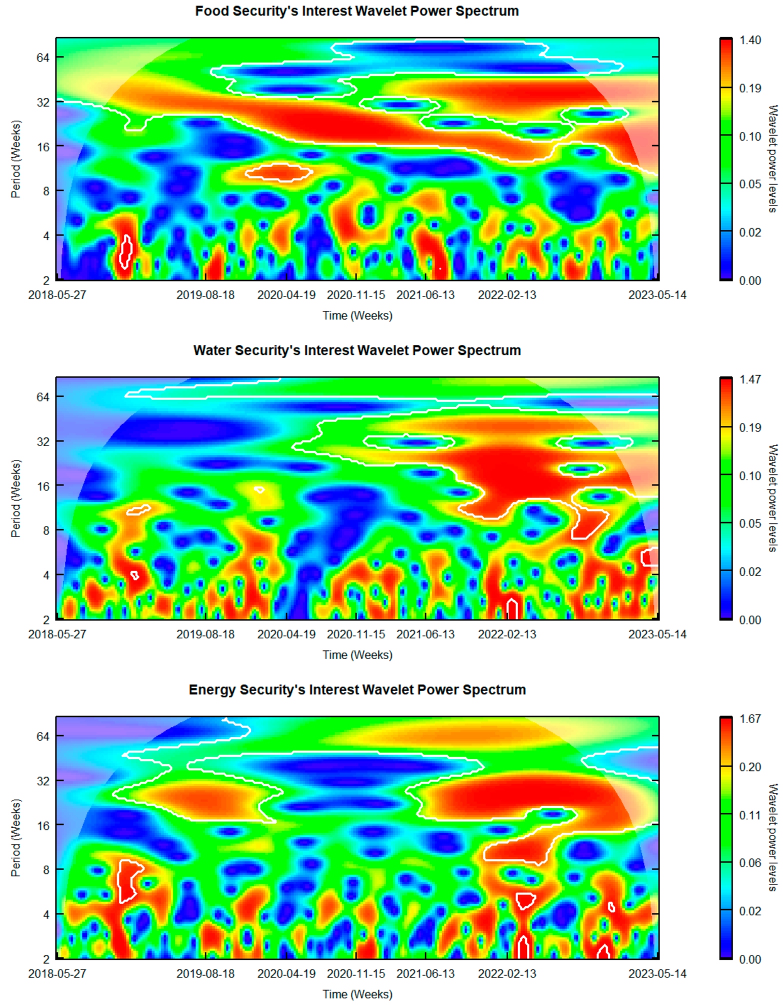

Figure 3. Wavelet power spectrum for "Food Security", "Water Security", and "Energy Security" Google Trends. White contours show significant powers at $\alpha = 0.1$ significance level.

As depicted in Figure 3 (top panel), the interest in "Food Security" has exhibited significant low and mid-frequency behaviors over the past five years. Note that low-frequency cycles are cycles with long periods, for example, longer than 32 weeks period in this data.

Mid-frequency cycles are cycles with mid-range periods, for example, around a 16-week period in this data. The significance test, conducted using Monte Carlo simulation with 5000 sample paths, confirms this observation. However, in recent years (i.e., after 19-Apr-2020), the power spectrum has shown an increase, with a focus on mid-range periods (around 16 and 32 weeks) and long-range periods (above 32 weeks). This indicates that the search frequency for the keyword "Food Security" has become more frequent over time.

In the middle panel of Figure 3, the power spectrum for "Water Security" displays significant patterns mostly concentrated on the right side of the timeline (approximately after 15-Nov-2020). The most powerful periodic patterns occur within the 16 to 32-week period range. In other words, approximately after 15-Nov-2020, there has been a periodic pattern in people's interest in the "Water Security" keyword. The length of each periodic pattern (the beginning of one surge of interest to the beginning of the next one) mostly includes periods below 16 to periods above 32 weeks.

As shown in the bottom panel, the significant "Energy Security" power spectrum also is mostly concentrated on low and mid frequencies (i.e., long periods in which the time from one surge of interest in "Energy Security" is between 32 to 64 weeks and mid-ranged periods which the time from one surge of interest in "Energy Security" is between 16 to

32 weeks). Periodic behavior of interest in the "Energy Security" keyword has become more powerful after 13-Jun-2021. Furthermore, the periodic behavior of interest in "Energy Security" includes shorter periods (higher frequency) as well. In other words, the power spectrum of interest in "Energy Security" shows that the interest in "Energy Security" has increased and the search for "Energy Security" has become more frequent.

These findings suggest that the interest in "Food Security", "Water Security", and "Energy Security" has increased in the last three years (after 14-Apr-2020), and searching for these keywords has become more frequent. Furthermore, it can be seen the increased interest in these keywords started with "Food Security" and, as the top panel shows an increased power spectrum at higher frequencies sooner. In other words, after 14-Apr-2020, the search for "Food Security" became more frequent, then the search for "Water Security", and, finally, "Energy Security".

Additionally, in recent years (especially after 13-Jun-2021) the periodic behavior of interest in these keywords demonstrates mid-range periodic patterns (with period lengths between 16 and 32 weeks.), which suggests that it takes 16 to 32 weeks (almost 4 to 8 months) form one surge of interest in these keywords to the next one.

In order to examine the relationship between interest in "Food Security" and "Water Security", the wavelet coherence analysis is applied to two series. The results are given in Figure 4.

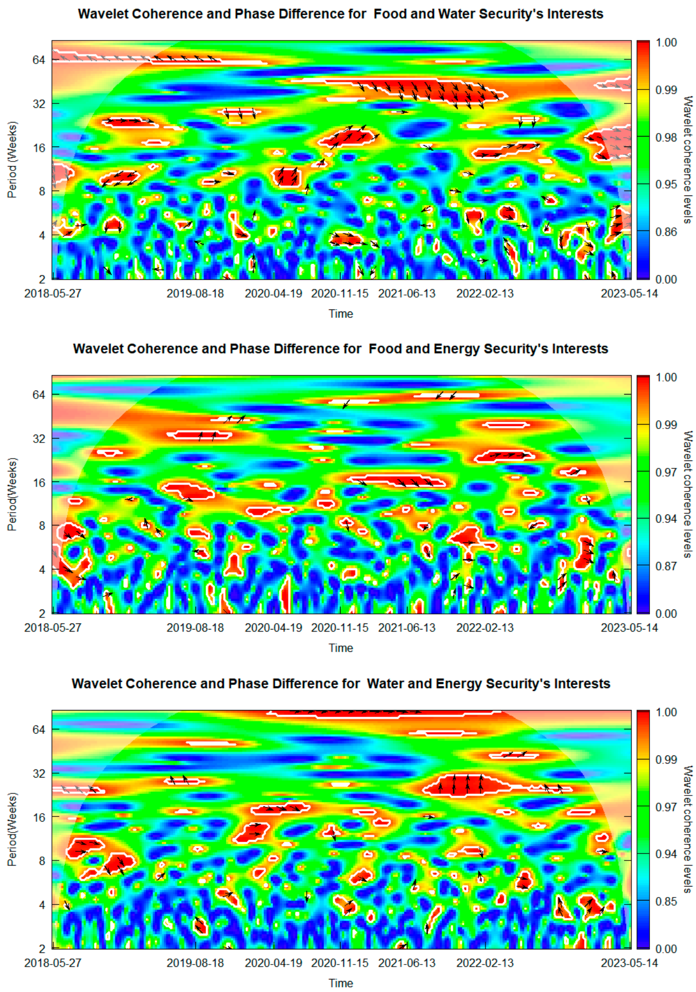

Figure 4. Wavelet coherence and phase difference angles (arrows) for "Food Security", "Water Security", and "Energy Security" interests. White contours show significant powers at $\alpha = 0.1$ significance level (90% confidence level). Phase difference angles are only presented for locations with significant coherence.

As previously mentioned, wavelet coherence and phase difference analysis are valuable tools for examining the relationship between two time series signals, such as food security and water security, in both the time and frequency domains. These techniques provide insights into the similarity, coherence, and phase relationship between the two signals at different scales or frequencies, over time.

Wavelet coherence quantifies the correlation between the two signals as a function of both time and frequency. It reveals the level of similarity or shared variability between the two time series across different frequency components. Higher coherence values indicate a stronger relationship, while lower coherence values suggest a weaker or non-existent relationship.

On the other hand, phase difference captures the phase lag or lead between the two signals. It indicates the relative timing or synchronization between the peaks and troughs of the two time series. A phase difference of zero denotes perfect synchronization, implying that the peaks and troughs of the two signals align precisely. Non-zero phase difference values indicate a lag or lead between the two signals, with the peaks and troughs occurring at different times.

By employing wavelet coherence and phase difference analysis, we can gain a deeper understanding of the relationship between food security and water security, uncovering their coherence and phase synchronization characteristics across different frequencies and over time.

In order to analyze the coherence between each two of these three time series, only the time intervals and periods in which the coherence of the two series is significant, and their power spectrum will be considered. Furthermore, in order to avoid overestimating the number of cyclical patterns, the results are presented for time intervals and periods whose length is not shorter than half of their period and at least 5 weeks apart.

The coherence analysis between “Food Security” and “Water Security” (top panel in Figure 4) reveals that the two series exhibit significant coherence mostly in mid-range periods, i.e., 15.45-week and 25.11-week periods, and long periods, i.e., 32-week, 38.1-week, 43.71-week, and 64-week periods (see Table A1 in Appendix A for more details). In other words, significant cyclical patterns are evident in both series and demonstrate a significant coherence between them, suggesting that they behave similarly, possibly with a time delay. It also can be seen that during the time, the frequencies in which two series have become coherent are increased (the length of periods is decreased). For instance, before the end of 2020, coherence between two series existed mostly at 43.71-week and 64-week periods ($\frac{1}{43.71} = 0.02287806$ and $\frac{1}{64} = 0.015625$ frequencies, respectively) while after June 2022, the coherence between the two series has occurred mostly in 25.11-week and 15.45-week periods ($\frac{1}{15.45} = 0.06472492$ and $\frac{1}{25.11} = 0.03982477$ frequencies, respectively).

The middle panel in Figure 4 shows significant coherency between “Food Security” and “Energy Security”. Coupling these results with the power spectrum results (Figure 3) reveals that the two series exhibit significant coherence mostly in mid-range periods, i.e., 18.38-week and 25.11-week periods, and longer periods, i.e., 34.3-week and 39.4-week periods (see Table A2 for more details). This means there are significant cyclical patterns in both series with these periods in which they behave similarly in a time interval, possibly with a time delay. For instance, between 13-Feb-2022 and 3-Jul-2022, both series demonstrate a significant cyclical pattern in which it would take 25.11 weeks from one surge of interest in keywords to the next one, and two series have almost the same behavior possibly with a time delay.

Significant coherence between “Water Security” and “Energy Security” is presented in the bottom panel of Figure 4. Overlapping significant coherence areas (inside white contours) with “Water Security” and “Energy Security” power spectrums (Figure 3) shows that two series have significant coherence, mostly in mid-range periods (i.e., 17.15-week and 25.11-week periods) and very long period, i.e., 84.45-week period (see Table A3 for details).

The arrows displayed in above mentioned periods indicate the angular phase difference between the two series during each period. To convert these angular phase differences into a time unit (weeks), the following formulation can be utilized.

$$Phase.diff_{\psi}\{xy\}(\tau, s) = \frac{l_p}{2\pi} Angle_{\psi}\{xy\}(\tau, s),$$

where $Phase.diff_{\psi}\{xy\}(\tau, s)$ is the phase difference between two series, measured by time unit (which is "week" in our data), l_p is the period length and $Angle_{\psi}\{xy\}(\tau, s)$ is angular phase difference measured in radians. For instance, in weekly data, the angular phase difference between two series for a 25.11-week period converts to phase difference in weeks as:

$$Phase.diff_{\psi}\{xy\}(\tau, s) = \frac{25.11}{2\pi} Angle_{\psi}\{xy\}(\tau, s)$$

Tables A1–A3 in Appendix A illustrate the phase difference and leading time series in each of the time intervals and periods discussed above. According to Tables A1–A3, all three time series have significant cyclical behavior with a 25.11-week period at some point over the time and each time series has significant coherence with another one. For instance, between 15-Apr-2022 and 3-Jul-2022, there is significant coherence between all pairs of time series, i.e., in the "Food Security"–"Water Security" pair, in the "Food Security"–"Energy Security" pair, and in "Water Security–Energy Security". In other words, in this short time interval, all three time series have a cyclical pattern in which the surge of interest in any one keyword to the next surge of interest in that keyword takes almost 25.11 weeks. Furthermore, the cyclical pattern is similar in all three time series, except for possible time delay. However, the cyclical pattern and coherence for each pair of time series may exceed this time interval differently. Phase difference analysis shows that between 15-Apr-2022 and 3-Jul-2022, in a cyclical pattern with a 25.11-week period, interest in "Food Security" leads both "Water Security" and "Energy Security" (with different phase difference values) and interest in "Energy Security" leads interest in "Water Security". These results imply that there is a cyclical pattern with a 25.11-week period length, between 15-Apr-2022 and 3-Jul-2022, in which the surge of interest in keywords first comes to "Food Security" and then "Energy Security" and, finally, "Water Security".

4. Search Engine: Comparative Analysis

Table 1 presents a comparative analysis of the trend extraction features offered by three prominent search engines: Google, Bing, and Yahoo. It serves as a valuable reference for users and decision makers seeking to understand the capabilities of these search engines in extracting and analyzing trending data.

In the table, various key features are assessed, including data accessibility, trend analysis tools, real-time data availability, geographic specificity, data visualization options, API support, and customization capabilities.

Google stands out with its extensive data accessibility, strong trend analysis tools, and real-time data availability, making it a robust choice for users interested in tracking and analyzing trends. Bing offers decent trend analysis capabilities and some customization options, making it a suitable alternative. Yahoo, on the other hand, offers limited data accessibility and trend analysis tools, making it less suited for in-depth trend extraction and analysis tasks.

Overall, this comparative analysis provides insights into the strengths and weaknesses of these search engines concerning trend extraction, enabling users to make informed choices based on their specific data analysis needs and preferences.

Table 1. Comparison of trend extraction features in popular search engines.

Feature	Google	Bing	Yahoo
Data Accessibility	Extensive data availability	Good data accessibility	Limited data accessibility
Trend Analysis	Strong trend analysis tools	Decent trend analysis	Limited trend analysis
Real-time Data	Provides real-time data	Offers real-time data	Limited real-time data
Geographic Specificity	Offers precise location data	Provides location-based results	Limited location data
Data Visualization	Offers data visualization tools	Basic data visualization	Limited data visualization
API Support	Robust API for data access	API support available	Limited API support
Customization	Customizable search parameters	Some customization options	Limited customization

5. Discussion

This paper delves into the concept of Social Intelligence Mining, highlighting the importance of leveraging open access data and Google Search engine data for trend analysis. This approach offers several notable advantages for both researchers and practitioners.

Firstly, the analysis of Google Search data as a time series provides a powerful tool for trend identification. By examining search queries over time, researchers can pinpoint emerging trends, recognize seasonality patterns, and even make predictions about future developments. This temporal perspective is invaluable for staying ahead in rapidly evolving fields and industries.

Furthermore, the application of opinion mining techniques to search queries offers a more profound understanding of public sentiment and preferences. This sentiment analysis adds a layer of nuance to the data, enabling decision makers to make informed choices regarding strategy formulation and risk management. In sum, Social Intelligence Mining, driven by open access data and Google Search engine data, equips organizations with comprehensive insights into user behavior, sentiment analysis, and trend identification.

This approach facilitates competitive advantages, informed decision making, and meaningful engagement with target audiences. As technology and data continue to evolve, the potential of Social Intelligence Mining for shaping strategies, driving innovation, and creating value across diverse domains remains substantial.

Additionally, the paper highlights the utility of wavelet coherence analysis and phase difference in uncovering hidden relationships and patterns within social data. These techniques offer a more profound understanding of the dynamics between social phenomena. By identifying leading and lagging trends, researchers and practitioners can make well-informed decisions based on a more comprehensive view of the data.

The specific case study presented in the paper on “Food Security”, “Energy Security”, and “Water Security” serves as an illustrative example. However, the methodology outlined can be applied to a wide range of domains and topics. Open access data sources like Google Trends offer valuable insights into public sentiment, emerging trends, and proactive strategy development.

Looking ahead, further research in this field should consider expanding the analysis to encompass additional relevant social phenomena. This expansion will allow for the exploration of more complex relationships and patterns. Additionally, incorporating data from social media and news sources can provide a more comprehensive understanding of social dynamics.

Addressing the challenges associated with data quality, privacy, and bias is also crucial for ensuring the reliability and validity of results in Social Intelligence Mining. As this field continues to evolve, these challenges must be carefully addressed to maintain the integrity of the research and its practical applications.

6. Conclusions

In conclusion, this paper underscores the pivotal role of Social Intelligence Mining, accentuating the utility of open access data and Google Search engine data for in-depth trend analysis. Harnessing these resources, coupled with sophisticated analytical methods, empowers organizations to secure a competitive advantage, make evidence-based decisions, and more effectively engage their target demographics.

Our findings spotlight the efficacy of wavelet coherence analysis and phase difference in elucidating concealed relationships and patterns within social datasets. Such techniques facilitate a more profound grasp of social phenomena dynamics, subsequently refining decision-making protocols.

However, this research is not without its limitations. The focus on a singular case study, albeit comprehensive, may not capture the entire spectrum of possibilities within Social Intelligence Mining. Looking forward, the versatility of the presented methodology suggests its applicability across diverse domains and subjects. Still, future research should venture into investigating intricate relationships and broaden its analytical scope to encapsulate various social phenomena. Integrating data from diverse platforms, such as social media and news outlets, will enrich the analysis. Addressing pressing concerns of data integrity, privacy, and potential biases will be paramount to buttress the dependability of subsequent Social Intelligence Mining endeavors.

To encapsulate, Social Intelligence Mining stands poised to redefine strategy formulation, spur innovation, and offer unparalleled value across sectors. Its sustained evolution augurs well for refining both decision-making paradigms and the comprehension of intricate social dynamics.

Author Contributions: H.H., N.K., E.R. and M.R.Y. conceptualied and designed the study and methodology. H.H. and M.R.Y. developed the software code and conducted formal data analysis. H.H. prepared the original draft. E.R., M.R.Y. and N.K. reviewed and edited the paper. All authors have read and agreed to the published version of the manuscript.

Funding: IIASA internal funding.

Data Availability Statement: Data are available upon request.

Acknowledgments: We extend our sincere gratitude to the referees and the editor, whose insightful comments and suggestions significantly contributed to the enhancement of our paper.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. The phase difference and leading time series for "Food Security"–" Water Security" pair.

Date	Coherence	Phase Diff. (Angular)	Phase Diff. (Temporal)	Leading Series	Date	Coherence	Phase Diff. (Angular)	Phase Diff. (Temporal)	Leading Series
15.45-week period									
23-Jan-22	0.9958	0.0343	0.0844	Food Security	17-Apr-22	0.9966	0.2759	0.6786	Food Security
30-Jan-22	0.9963	0.0468	0.1151	Food Security	24-Apr-22	0.9966	0.3023	0.7436	Food Security
6-Feb-22	0.9966	0.0607	0.1493	Food Security	1-May-22	0.9966	0.3285	0.808	Food Security

Table A1. *Cont.*

Date	Coherence	Phase Diff. (Angular)	Phase Diff. (Temporal)	Leading Series	Date	Coherence	Phase Diff. (Angular)	Phase Diff. (Temporal)	Leading Series
13-Feb-22	0.9969	0.0761	0.1872	Food Security	8-May-22	0.9967	0.3543	0.8715	Food Security
20-Feb-22	0.997	0.093	0.2288	Food Security	15-May-22	0.9968	0.3793	0.933	Food Security
27-Feb-22	0.9971	0.1115	0.2743	Food Security	22-May-22	0.9969	0.4032	0.9918	Food Security
6-Mar-22	0.9971	0.1314	0.3232	Food Security	29-May-22	0.9971	0.4255	1.0466	Food Security
13-Mar-22	0.997	0.1528	0.3758	Food Security	5-Jun-22	0.9973	0.4458	1.0966	Food Security
20-Mar-22	0.997	0.1755	0.4317	Food Security	12-Jun-22	0.9974	0.4639	1.1411	Food Security
27-Mar-22	0.9969	0.1994	0.4905	Food Security	19-Jun-22	0.9975	0.4793	1.179	Food Security
3-Apr-22	0.9968	0.2242	0.5515	Food Security	26-Jun-22	0.9975	0.4916	1.2092	Food Security
10-Apr-22	0.9967	0.2498	0.6144	Food Security	3-Jul-22	0.9974	0.5004	1.2309	Food Security
25.11-week period									
15-May-22	0.9966	−1.6031	−6.4058	Food Security	26-Jun-22	0.9993	−1.6985	−6.787	Food Security
22-May-22	0.9971	−1.6216	−6.4797	Food Security	3-Jul-22	0.9994	−1.7098	−6.8321	Food Security
29-May-22	0.9977	−1.6392	−6.55	Food Security	10-Jul-22	0.9993	−1.7194	−6.8705	Food Security
5-Jun-22	0.9981	−1.6558	−6.6163	Food Security	17-Jul-22	0.999	−1.7269	−6.9004	Food Security
12-Jun-22	0.9986	−1.6713	−6.6783	Food Security	24-Jul-22	0.9983	−1.7322	−6.9216	Food Security
19-Jun-22	0.999	−1.6856	−6.7354	Food Security	31-Jul-22	0.9972	−1.7347	−6.9316	Food Security
32-week period									
24-Oct-21	0.9963	−1.0047	−5.1169	Water Security	19-Dec-21	0.9974	−1.0521	−5.3583	Water Security
31-Oct-21	0.9966	−1.0097	−5.1424	Water Security	26-Dec-21	0.9973	−1.059	−5.3934	Water Security
7-Nov-21	0.9968	−1.015	−5.1694	Water Security	2-Jan-22	0.9973	−1.0661	−5.4296	Water Security
14-Nov-21	0.9971	−1.0206	−5.1979	Water Security	9-Jan-22	0.9972	−1.0733	−5.4663	Water Security
21-Nov-21	0.9972	−1.0265	−5.2279	Water Security	16-Jan-22	0.997	−1.0806	−5.5035	Water Security
28-Nov-21	0.9973	−1.0326	−5.259	Water Security	23-Jan-22	0.9968	−1.0881	−5.5416	Water Security
5-Dec-21	0.9974	−1.0389	−5.2911	Water Security	30-Jan-22	0.9966	−1.0957	−5.5804	Water Security
12-Dec-21	0.9974	−1.0454	−5.3242	Water Security	6-Feb-22	0.9964	−1.1034	−5.6196	Water Security
38.1-week period									
11-Apr-21	0.9963	−1.2271	−7.432	Water Security	17-Oct-21	0.9979	−1.0351	−6.2692	Water Security

Table A1. *Cont.*

Date	Coherence	Phase Diff. (Angular)	Phase Diff. (Temporal)	Leading Series	Date	Coherence	Phase Diff. (Angular)	Phase Diff. (Temporal)	Leading Series
38.1-week period									
18-Apr-21	0.9965	−1.2208	−7.3939	Water Security	24-Oct-21	0.9979	−1.0271	−6.2207	Water Security
25-Apr-21	0.9966	−1.2145	−7.3557	Water Security	31-Oct-21	0.9979	−1.0191	−6.1723	Water Security
2-May-21	0.9967	−1.2081	−7.317	Water Security	7-Nov-21	0.9979	−1.0109	−6.1226	Water Security
9-May-21	0.9969	−1.2017	−7.2782	Water Security	14-Nov-21	0.9979	−1.0027	−6.0729	Water Security
16-May-21	0.997	−1.1952	−7.2388	Water Security	21-Nov-21	0.9978	−0.9945	−6.0233	Water Security
23-May-21	0.9971	−1.1886	−7.1989	Water Security	28-Nov-21	0.9978	−0.9862	−5.973	Water Security
30-May-21	0.9972	−1.182	−7.1589	Water Security	5-Dec-21	0.9978	−0.9778	−5.9221	Water Security
6-Jun-21	0.9972	−1.1753	−7.1183	Water Security	12-Dec-21	0.9978	−0.9693	−5.8706	Water Security
13-Jun-21	0.9973	−1.1685	−7.0771	Water Security	19-Dec-21	0.9977	−0.9608	−5.8192	Water Security
20-Jun-21	0.9974	−1.1617	−7.0359	Water Security	26-Dec-21	0.9977	−0.9521	−5.7665	Water Security
27-Jun-21	0.9975	−1.1547	−6.9935	Water Security	2-Jan-22	0.9976	−0.9435	−5.7144	Water Security
4-Jul-21	0.9975	−1.1477	−6.9511	Water Security	9-Jan-22	0.9976	−0.9347	−5.6611	Water Security
11-Jul-21	0.9976	−1.1407	−6.9087	Water Security	16-Jan-22	0.9975	−0.9259	−5.6078	Water Security
18-Jul-21	0.9976	−1.1336	−6.8657	Water Security	23-Jan-22	0.9975	−0.917	−5.5539	Water Security
25-Jul-21	0.9977	−1.1264	−6.8221	Water Security	30-Jan-22	0.9974	−0.908	−5.4994	Water Security
1-Aug-21	0.9977	−1.1191	−6.7779	Water Security	6-Feb-22	0.9973	−0.8989	−5.4443	Water Security
8-Aug-21	0.9978	−1.1118	−6.7337	Water Security	13-Feb-22	0.9973	−0.8897	−5.3885	Water Security
15-Aug-21	0.9978	−1.1044	−6.6889	Water Security	20-Feb-22	0.9972	−0.8805	−5.3328	Water Security
22-Aug-21	0.9978	−1.097	−6.6441	Water Security	27-Feb-22	0.9971	−0.8712	−5.2765	Water Security
29-Aug-21	0.9978	−1.0895	−6.5986	Water Security	6-Mar-22	0.9971	−0.8618	−5.2196	Water Security
5-Sep-21	0.9979	−1.0819	−6.5526	Water Security	13-Mar-22	0.997	−0.8523	−5.162	Water Security
12-Sep-21	0.9979	−1.0742	−6.506	Water Security	20-Mar-22	0.9969	−0.8427	−5.1039	Water Security
19-Sep-21	0.9979	−1.0665	−6.4593	Water Security	27-Mar-22	0.9968	−0.833	−5.0451	Water Security
26-Sep-21	0.9979	−1.0588	−6.4127	Water Security	3-Apr-22	0.9967	−0.8232	−4.9858	Water Security
3-Oct-21	0.9979	−1.051	−6.3655	Water Security	10-Apr-22	0.9967	−0.8134	−4.9264	Water Security
10-Oct-21	0.9979	−1.0431	−6.3176	Water Security					

Table A1. *Cont.*

Date	Coherence	Phase Diff. (Angular)	Phase Diff. (Temporal)	Leading Series	Date	Coherence	Phase Diff. (Angular)	Phase Diff. (Temporal)	Leading Series
43.71-week period									
4-Oct-20	0.996	−0.8364	−5.819	Water Security	23-May-21	0.9998	−0.9986	−6.9474	Water Security
11-Oct-20	0.9961	−0.8437	−5.8698	Water Security	30-May-21	0.9998	−0.9982	−6.9447	Water Security
18-Oct-20	0.9962	−0.8512	−5.922	Water Security	6-Jun-21	0.9997	−0.9975	−6.9398	Water Security
25-Oct-20	0.9963	−0.8587	−5.9741	Water Security	13-Jun-21	0.9997	−0.9964	−6.9321	Water Security
1-Nov-20	0.9964	−0.8662	−6.0263	Water Security	20-Jun-21	0.9996	−0.995	−6.9224	Water Security
8-Nov-20	0.9965	−0.8738	−6.0792	Water Security	27-Jun-21	0.9996	−0.9932	−6.9099	Water Security
15-Nov-20	0.9967	−0.8813	−6.1314	Water Security	4-Jul-21	0.9995	−0.9911	−6.8953	Water Security
22-Nov-20	0.9969	−0.8887	−6.1829	Water Security	11-Jul-21	0.9994	−0.9885	−6.8772	Water Security
29-Nov-20	0.997	−0.8961	−6.2343	Water Security	18-Jul-21	0.9993	−0.9857	−6.8577	Water Security
6-Dec-20	0.9972	−0.9033	−6.2844	Water Security	25-Jul-21	0.9993	−0.9825	−6.8354	Water Security
13-Dec-20	0.9974	−0.9104	−6.3338	Water Security	1-Aug-21	0.9992	−0.9789	−6.8104	Water Security
20-Dec-20	0.9976	−0.9174	−6.3825	Water Security	8-Aug-21	0.9991	−0.975	−6.7833	Water Security
27-Dec-20	0.9978	−0.9241	−6.4291	Water Security	15-Aug-21	0.9989	−0.9708	−6.754	Water Security
3-Jan-21	0.9979	−0.9307	−6.4751	Water Security	22-Aug-21	0.9988	−0.9662	−6.722	Water Security
10-Jan-21	0.9981	−0.937	−6.5189	Water Security	29-Aug-21	0.9987	−0.9613	−6.6879	Water Security
17-Jan-21	0.9983	−0.9431	−6.5613	Water Security	5-Sep-21	0.9986	−0.9561	−6.6518	Water Security
24-Jan-21	0.9985	−0.949	−6.6024	Water Security	12-Sep-21	0.9985	−0.9506	−6.6135	Water Security
31-Jan-21	0.9986	−0.9545	−6.6406	Water Security	19-Sep-21	0.9983	−0.9448	−6.5731	Water Security
7-Feb-21	0.9988	−0.9598	−6.6775	Water Security	26-Sep-21	0.9982	−0.9386	−6.53	Water Security
14-Feb-21	0.9989	−0.9648	−6.7123	Water Security	3-Oct-21	0.9981	−0.9322	−6.4855	Water Security
21-Feb-21	0.9991	−0.9695	−6.745	Water Security	10-Oct-21	0.9979	−0.9255	−6.4389	Water Security
28-Feb-21	0.9992	−0.9738	−6.7749	Water Security	17-Oct-21	0.9978	−0.9185	−6.3902	Water Security
7-Mar-21	0.9993	−0.9778	−6.8027	Water Security	24-Oct-21	0.9976	−0.9113	−6.3401	Water Security
14-Mar-21	0.9994	−0.9815	−6.8285	Water Security	31-Oct-21	0.9975	−0.9038	−6.2879	Water Security
21-Mar-21	0.9995	−0.9849	−6.8521	Water Security	7-Nov-21	0.9974	−0.896	−6.2336	Water Security
28-Mar-21	0.9996	−0.9879	−6.873	Water Security	14-Nov-21	0.9972	−0.8879	−6.1773	Water Security

Table A1. *Cont.*

Date	Coherence	Phase Diff. (Angular)	Phase Diff. (Temporal)	Leading Series	Date	Coherence	Phase Diff. (Angular)	Phase Diff. (Temporal)	Leading Series
43.71-week period									
4-Apr-21	0.9997	−0.9905	−6.8911	Water Security	21-Nov-21	0.9971	−0.8796	−6.1195	Water Security
11-Apr-21	0.9997	−0.9927	−6.9064	Water Security	28-Nov-21	0.9969	−0.8711	−6.0604	Water Security
18-Apr-21	0.9998	−0.9946	−6.9196	Water Security	5-Dec-21	0.9968	−0.8624	−5.9999	Water Security
25-Apr-21	0.9998	−0.9962	−6.9307	Water Security	12-Dec-21	0.9966	−0.8534	−5.9373	Water Security
2-May-21	0.9998	−0.9973	−6.9384	Water Security	19-Dec-21	0.9965	−0.8442	−5.8733	Water Security
9-May-21	0.9998	−0.9981	−6.944	Water Security	26-Dec-21	0.9963	−0.8348	−5.8079	Water Security
16-May-21	0.9998	−0.9985	−6.9468	Water Security	2-Jan-22	0.9962	−0.8253	−5.7418	Water Security
64-week period									
16-Dec-18	0.9983	2.6076	26.5608	Water Security	2-Jun-19	0.998	2.5975	26.4579	Water Security
23-Dec-18	0.9983	2.607	26.5547	Water Security	9-Jun-19	0.998	2.5975	26.4579	Water Security
30-Dec-18	0.9983	2.6065	26.5496	Water Security	16-Jun-19	0.998	2.5975	26.4579	Water Security
6-Jan-19	0.9983	2.6059	26.5435	Water Security	23-Jun-19	0.998	2.5976	26.4589	Water Security
13-Jan-19	0.9983	2.6054	26.5384	Water Security	30-Jun-19	0.9979	2.5978	26.461	Water Security
20-Jan-19	0.9982	2.6048	26.5323	Water Security	7-Jul-19	0.9979	2.598	26.463	Water Security
27-Jan-19	0.9982	2.6043	26.5272	Water Security	14-Jul-19	0.9979	2.5983	26.4661	Water Security
3-Feb-19	0.9982	2.6037	26.5211	Water Security	21-Jul-19	0.9979	2.5987	26.4701	Water Security
10-Feb-19	0.9982	2.6032	26.516	Water Security	28-Jul-19	0.9979	2.5992	26.4752	Water Security
17-Feb-19	0.9982	2.6027	26.5109	Water Security	4-Aug-19	0.9978	2.5997	26.4803	Water Security
24-Feb-19	0.9982	2.6022	26.5058	Water Security	11-Aug-19	0.9978	2.6004	26.4875	Water Security
3-Mar-19	0.9982	2.6017	26.5007	Water Security	18-Aug-19	0.9978	2.6011	26.4946	Water Security
10-Mar-19	0.9982	2.6012	26.4956	Water Security	25-Aug-19	0.9977	2.602	26.5038	Water Security
17-Mar-19	0.9981	2.6007	26.4905	Water Security	1-Sep-19	0.9977	2.6029	26.5129	Water Security
24-Mar-19	0.9981	2.6003	26.4864	Water Security	8-Sep-19	0.9977	2.604	26.5241	Water Security
31-Mar-19	0.9981	2.5998	26.4813	Water Security	15-Sep-19	0.9976	2.6052	26.5363	Water Security
7-Apr-19	0.9981	2.5994	26.4773	Water Security	22-Sep-19	0.9976	2.6065	26.5496	Water Security
14-Apr-19	0.9981	2.5991	26.4742	Water Security	29-Sep-19	0.9975	2.6079	26.5639	Water Security

Table A1. *Cont.*

Date	Coherence	Phase Diff. (Angular)	Phase Diff. (Temporal)	Leading Series	Date	Coherence	Phase Diff. (Angular)	Phase Diff. (Temporal)	Leading Series
64-week period									
21-Apr-19	0.9981	2.5987	26.4701	Water Security	6-Oct-19	0.9975	2.6094	26.5791	Water Security
28-Apr-19	0.9981	2.5984	26.4671	Water Security	13-Oct-19	0.9974	2.6111	26.5964	Water Security
5-May-19	0.9981	2.5981	26.464	Water Security	20-Oct-19	0.9973	2.6129	26.6148	Water Security
12-May-19	0.998	2.5979	26.462	Water Security	27-Oct-19	0.9972	2.6149	26.6352	Water Security
19-May-19	0.998	2.5977	26.46	Water Security	3-Nov-19	0.9972	2.617	26.6565	Water Security
26-May-19	0.998	2.5976	26.4589	Water Security					

Table A2. The phase difference and leading time series for "Food Security"–"Energy Security" pair.

Date	Coherence	Phase Diff. (Angular)	Phase Diff. (Temporal)	Leading Series	Date	Coherence	Phase Diff. (Angular)	Phase Diff. (Temporal)	Leading Series
18.38-week period									
9-Oct-22	0.9969	0.4942	1.4456	Food Security	20-Nov-22	0.9993	0.5193	1.519	Food Security
16-Oct-22	0.998	0.4976	1.4555	Food Security	27-Nov-22	0.999	0.5243	1.5336	Food Security
23-Oct-22	0.9988	0.5014	1.4667	Food Security	4-Dec-22	0.9986	0.5296	1.5492	Food Security
30-Oct-22	0.9992	0.5055	1.4787	Food Security	11-Dec-22	0.9981	0.5351	1.5652	Food Security
6-Nov-22	0.9994	0.5099	1.4915	Food Security	18-Dec-22	0.9976	0.5407	1.5816	Food Security
13-Nov-22	0.9994	0.5145	1.505	Food Security	25-Dec-22	0.9971	0.5466	1.5989	Food Security
25.11-week period									
13-Feb-22	0.9966	0.3524	1.4081	Food Security	1-May-22	0.9996	0.1925	0.7692	Food Security
20-Feb-22	0.9971	0.3329	1.3302	Food Security	8-May-22	0.9997	0.1838	0.7344	Food Security
27-Feb-22	0.9976	0.3144	1.2563	Food Security	15-May-22	0.9997	0.1763	0.7045	Food Security
6-Mar-22	0.9979	0.297	1.1868	Food Security	22-May-22	0.9996	0.1698	0.6785	Food Security
13-Mar-22	0.9983	0.2806	1.1212	Food Security	29-May-22	0.9994	0.1645	0.6573	Food Security
20-Mar-22	0.9986	0.2652	1.0597	Food Security	5-Jun-22	0.9992	0.1605	0.6413	Food Security
27-Mar-22	0.9988	0.2507	1.0018	Food Security	12-Jun-22	0.9989	0.1579	0.6309	Food Security
3-Apr-22	0.9991	0.2371	0.9474	Food Security	19-Jun-22	0.9985	0.1567	0.6262	Food Security
10-Apr-22	0.9993	0.2245	0.8971	Food Security	26-Jun-22	0.9979	0.1572	0.6281	Food Security
17-Apr-22	0.9994	0.2129	0.8507	Food Security	3-Jul-22	0.9971	0.1594	0.6369	Food Security

Table A2. *Cont.*

Date	Coherence	Phase Diff. (Angular)	Phase Diff. (Temporal)	Leading Series	Date	Coherence	Phase Diff. (Angular)	Phase Diff. (Temporal)	Leading Series
25.11-week period									
24-Apr-22	0.9995	0.2022	0.808	Food Security					
34.3-week period									
19-May-19	0.9962	1.2155	6.6348	Food Security	1-Sep-19	0.9994	1.2373	6.7538	Food Security
26-May-19	0.9966	1.214	6.6266	Food Security	8-Sep-19	0.9994	1.2425	6.7822	Food Security
2-Jun-19	0.9969	1.2129	6.6206	Food Security	15-Sep-19	0.9994	1.2482	6.8133	Food Security
9-Jun-19	0.9972	1.2121	6.6162	Food Security	22-Sep-19	0.9994	1.2545	6.8477	Food Security
16-Jun-19	0.9975	1.2118	6.6146	Food Security	29-Sep-19	0.9994	1.2614	6.8853	Food Security
23-Jun-19	0.9978	1.2118	6.6146	Food Security	6-Oct-19	0.9993	1.2687	6.9252	Food Security
30-Jun-19	0.9981	1.2123	6.6173	Food Security	13-Oct-19	0.9991	1.2767	6.9689	Food Security
7-Jul-19	0.9983	1.2132	6.6222	Food Security	20-Oct-19	0.9989	1.2852	7.0153	Food Security
14-Jul-19	0.9985	1.2146	6.6299	Food Security	27-Oct-19	0.9987	1.2943	7.0649	Food Security
21-Jul-19	0.9987	1.2164	6.6397	Food Security	3-Nov-19	0.9985	1.304	7.1179	Food Security
28-Jul-19	0.9989	1.2187	6.6523	Food Security	10-Nov-19	0.9982	1.3143	7.1741	Food Security
4-Aug-19	0.999	1.2214	6.667	Food Security	17-Nov-19	0.9978	1.3252	7.2336	Food Security
11-Aug-19	0.9992	1.2246	6.6845	Food Security	24-Nov-19	0.9974	1.3367	7.2964	Food Security
18-Aug-19	0.9993	1.2283	6.7047	Food Security	1-Dec-19	0.9969	1.3488	7.3624	Food Security
25-Aug-19	0.9994	1.2325	6.7276	Food Security	8-Dec-19	0.9964	1.3615	7.4317	Food Security
39.4-week period									
6-Feb-22	0.9967	−0.2142	−1.3431	Energy Security	24-Apr-22	0.9997	−0.1654	−1.0371	Energy Security
13-Feb-22	0.9972	−0.2095	−1.3136	Energy Security	1-May-22	0.9997	−0.1615	−1.0126	Energy Security
20-Feb-22	0.9978	−0.2049	−1.2848	Energy Security	8-May-22	0.9996	−0.1577	−0.9888	Energy Security
27-Feb-22	0.9982	−0.2002	−1.2553	Energy Security	15-May-22	0.9995	−0.1541	−0.9662	Energy Security
6-Mar-22	0.9986	−0.1956	−1.2264	Energy Security	22-May-22	0.9993	−0.1506	−0.9443	Energy Security
13-Mar-22	0.9989	−0.1911	−1.1982	Energy Security	29-May-22	0.9991	−0.1473	−0.9236	Energy Security
20-Mar-22	0.9992	−0.1866	−1.17	Energy Security	5-Jun-22	0.9988	−0.1442	−0.9042	Energy Security
27-Mar-22	0.9994	−0.1822	−1.1424	Energy Security	12-Jun-22	0.9985	−0.1413	−0.886	Energy Security
3-Apr-22	0.9995	−0.1778	−1.1148	Energy Security	19-Jun-22	0.9982	−0.1386	−0.869	Energy Security

Table A2. *Cont.*

Date	Coherence	Phase Diff. (Angular)	Phase Diff. (Temporal)	Leading Series	Date	Coherence	Phase Diff. (Angular)	Phase Diff. (Temporal)	Leading Series
39.4-week period									
10-Apr-22	0.9997	−0.1736	−1.0885	Energy Security	26-Jun-22	0.9978	−0.1361	−0.8534	Energy Security
17-Apr-22	0.9997	−0.1694	−1.0622	Energy Security	3-Jul-22	0.9974	−0.1339	−0.8396	Energy Security

Table A3. The phase difference and leading time series for "Water Security"–"Energy Security" pair.

Date	Coherence	Phase Diff. (Angular)	Phase Diff. (Temporal)	Leading Series	Date	Coherence	Phase Diff. (Angular)	Phase Diff. (Temporal)	Leading Series
17.14-week period									
30-Oct-22	0.9968	0.641	1.7494	Water Security	18-Dec-22	0.9995	0.714	1.9487	Water Security
6-Nov-22	0.998	0.6543	1.7857	Water Security	25-Dec-22	0.9992	0.7201	1.9653	Water Security
13-Nov-22	0.9988	0.6669	1.8201	Water Security	1-Jan-23	0.9988	0.7252	1.9793	Water Security
20-Nov-22	0.9994	0.6786	1.8521	Water Security	8-Jan-23	0.9983	0.7295	1.991	Water Security
27-Nov-22	0.9997	0.6891	1.8807	Water Security	15-Jan-23	0.9979	0.7329	2.0003	Water Security
4-Dec-22	0.9998	0.6986	1.9067	Water Security	22-Jan-23	0.9975	0.7357	2.0079	Water Security
11-Dec-22	0.9997	0.7068	1.929	Water Security					
25.11-week period									
8-Aug-21	0.9967	1.4767	5.9007	Water Security	27-Mar-22	0.9974	1.7032	6.8057	Energy Security
15-Aug-21	0.9972	1.4849	5.9334	Water Security	3-Apr-22	0.9972	1.7131	6.8453	Energy Security
22-Aug-21	0.9976	1.4928	5.965	Water Security	10-Apr-22	0.9971	1.7234	6.8865	Energy Security
29-Aug-21	0.998	1.5003	5.995	Water Security	17-Apr-22	0.997	1.734	6.9288	Energy Security
5-Sep-21	0.9983	1.5075	6.0237	Water Security	24-Apr-22	0.9968	1.7448	6.972	Energy Security
12-Sep-21	0.9985	1.5143	6.0509	Water Security	1-May-22	0.9967	1.756	7.0167	Energy Security
19-Sep-21	0.9987	1.5209	6.0773	Water Security	8-May-22	0.9966	1.7675	7.0627	Energy Security
26-Sep-21	0.9989	1.5272	6.1025	Water Security	15-May-22	0.9966	1.7793	7.1098	Energy Security
3-Oct-21	0.999	1.5334	6.1272	Water Security	22-May-22	0.9965	1.7914	7.1582	Energy Security
10-Oct-21	0.9991	1.5393	6.1508	Water Security	29-May-22	0.9965	1.8037	7.2073	Energy Security
17-Oct-21	0.9992	1.545	6.1736	Water Security	5-Jun-22	0.9965	1.8163	7.2577	Energy Security
24-Oct-21	0.9992	1.5507	6.1964	Water Security	12-Jun-22	0.9966	1.8292	7.3092	Energy Security
31-Oct-21	0.9992	1.5563	6.2187	Water Security	19-Jun-22	0.9967	1.8423	7.3616	Energy Security

Table A3. *Cont.*

Date	Coherence	Phase Diff. (Angular)	Phase Diff. (Temporal)	Leading Series	Date	Coherence	Phase Diff. (Angular)	Phase Diff. (Temporal)	Leading Series
25.11-week period									
7-Nov-21	0.9993	1.5618	6.2407	Water Security	26-Jun-22	0.9968	1.8557	7.4151	Energy Security
14-Nov-21	0.9993	1.5673	6.2627	Water Security	3-Jul-22	0.9969	1.8692	7.469	Energy Security
21-Nov-21	0.9992	1.5728	6.2847	Energy Security	10-Jul-22	0.9971	1.883	7.5242	Energy Security
28-Nov-21	0.9992	1.5783	6.3067	Energy Security	17-Jul-22	0.9973	1.897	7.5801	Energy Security
5-Dec-21	0.9992	1.584	6.3294	Energy Security	24-Jul-22	0.9975	1.9111	7.6365	Energy Security
12-Dec-21	0.9991	1.5897	6.3522	Energy Security	31-Jul-22	0.9977	1.9253	7.6932	Energy Security
19-Dec-21	0.9991	1.5956	6.3758	Energy Security	7-Aug-22	0.998	1.9397	7.7508	Energy Security
26-Dec-21	0.999	1.6016	6.3998	Energy Security	14-Aug-22	0.9982	1.9542	7.8087	Energy Security
2-Jan-22	0.9989	1.6079	6.4249	Energy Security	21-Aug-22	0.9985	1.9687	7.8666	Energy Security
9-Jan-22	0.9988	1.6143	6.4505	Energy Security	28-Aug-22	0.9987	1.9832	7.9246	Energy Security
16-Jan-22	0.9987	1.621	6.4773	Energy Security	4-Sep-22	0.9988	1.9977	7.9825	Energy Security
23-Jan-22	0.9986	1.6279	6.5049	Energy Security	11-Sep-22	0.999	2.0121	8.0401	Energy Security
30-Jan-22	0.9985	1.6351	6.5336	Energy Security	18-Sep-22	0.999	2.0264	8.0972	Energy Security
6-Feb-22	0.9984	1.6425	6.5632	Energy Security	25-Sep-22	0.999	2.0405	8.1535	Energy Security
13-Feb-22	0.9982	1.6503	6.5944	Energy Security	2-Oct-22	0.9989	2.0544	8.2091	Energy Security
20-Feb-22	0.9981	1.6583	6.6263	Energy Security	9-Oct-22	0.9988	2.068	8.2634	Energy Security
27-Feb-22	0.998	1.6666	6.6595	Energy Security	16-Oct-22	0.9985	2.0813	8.3166	Energy Security
6-Mar-22	0.9978	1.6753	6.6943	Energy Security	23-Oct-22	0.9982	2.0941	8.3677	Energy Security
13-Mar-22	0.9977	1.6843	6.7302	Energy Security	30-Oct-22	0.9978	2.1065	8.4173	Energy Security
20-Mar-22	0.9975	1.6936	6.7674	Energy Security	6-Nov-22	0.9973	2.1184	8.4648	Energy Security
12-Apr-20	0.9987	−0.0654	−0.879	Energy Security	11-Apr-21	0.9997	−0.0594	−0.7984	Energy Security
19-Apr-20	0.9989	−0.0616	−0.8279	Energy Security	18-Apr-21	0.9997	−0.0616	−0.8279	Energy Security
26-Apr-20	0.999	−0.0581	−0.7809	Energy Security	25-Apr-21	0.9997	−0.0638	−0.8575	Energy Security
3-May-20	0.9991	−0.0548	−0.7365	Energy Security	2-May-21	0.9996	−0.0661	−0.8884	Energy Security
10-May-20	0.9992	−0.0517	−0.6949	Energy Security	9-May-21	0.9996	−0.0685	−0.9207	Energy Security
17-May-20	0.9992	−0.0488	−0.6559	Energy Security	16-May-21	0.9996	−0.0708	−0.9516	Energy Security

Table A3. *Cont.*

Date	Coherence	Phase Diff. (Angular)	Phase Diff. (Temporal)	Leading Series	Date	Coherence	Phase Diff. (Angular)	Phase Diff. (Temporal)	Leading Series
25.11-week period									
24-May-20	0.9993	−0.0461	−0.6196	Energy Security	23-May-21	0.9996	−0.0732	−0.9838	Energy Security
31-May-20	0.9994	−0.0436	−0.586	Energy Security	30-May-21	0.9996	−0.0757	−1.0174	Energy Security
7-Jun-20	0.9995	−0.0412	−0.5537	Energy Security	6-Jun-21	0.9996	−0.0782	−1.051	Energy Security
14-Jun-20	0.9995	−0.0391	−0.5255	Energy Security	13-Jun-21	0.9995	−0.0807	−1.0846	Energy Security
21-Jun-20	0.9996	−0.0371	−0.4986	Energy Security	20-Jun-21	0.9995	−0.0833	−1.1196	Energy Security
28-Jun-20	0.9996	−0.0353	−0.4744	Energy Security	27-Jun-21	0.9995	−0.0859	−1.1545	Energy Security
5-Jul-20	0.9997	−0.0336	−0.4516	Energy Security	4-Jul-21	0.9995	−0.0886	−1.1908	Energy Security
12-Jul-20	0.9997	−0.0321	−0.4314	Energy Security	11-Jul-21	0.9995	−0.0913	−1.2271	Energy Security
19-Jul-20	0.9998	−0.0308	−0.414	Energy Security	18-Jul-21	0.9995	−0.094	−1.2634	Energy Security
26-Jul-20	0.9998	−0.0296	−0.3978	Energy Security	25-Jul-21	0.9994	−0.0968	−1.301	Energy Security
2-Aug-20	0.9998	−0.0286	−0.3844	Energy Security	1-Aug-21	0.9994	−0.0996	−1.3387	Energy Security
9-Aug-20	0.9999	−0.0276	−0.371	Energy Security	8-Aug-21	0.9994	−0.1024	−1.3763	Energy Security
16-Aug-20	0.9999	−0.0269	−0.3615	Energy Security	15-Aug-21	0.9994	−0.1052	−1.4139	Energy Security
23-Aug-20	0.9999	−0.0262	−0.3521	Energy Security	22-Aug-21	0.9994	−0.1081	−1.4529	Energy Security
30-Aug-20	0.9999	−0.0257	−0.3454	Energy Security	29-Aug-21	0.9994	−0.111	−1.4919	Energy Security
6-Sep-20	0.9999	−0.0253	−0.34	Energy Security	5-Sep-21	0.9993	−0.114	−1.5322	Energy Security
13-Sep-20	0.9999	−0.0251	−0.3374	Energy Security	12-Sep-21	0.9993	−0.117	−1.5725	Energy Security
20-Sep-20	1	−0.0249	−0.3347	Energy Security	19-Sep-21	0.9993	−0.12	−1.6128	Energy Security
27-Sep-20	1	−0.0249	−0.3347	Energy Security	26-Sep-21	0.9993	−0.123	−1.6532	Energy Security
4-Oct-20	1	−0.025	−0.336	Energy Security	3-Oct-21	0.9993	−0.1261	−1.6948	Energy Security
11-Oct-20	1	−0.0252	−0.3387	Energy Security	10-Oct-21	0.9993	−0.1291	−1.7352	Energy Security
18-Oct-20	1	−0.0255	−0.3427	Energy Security	17-Oct-21	0.9993	−0.1322	−1.7768	Energy Security
25-Oct-20	1	−0.0259	−0.3481	Energy Security	24-Oct-21	0.9992	−0.1354	−1.8198	Energy Security
1-Nov-20	1	−0.0264	−0.3548	Energy Security	31-Oct-21	0.9992	−0.1385	−1.8615	Energy Security
8-Nov-20	1	−0.027	−0.3629	Energy Security	7-Nov-21	0.9992	−0.1417	−1.9045	Energy Security
15-Nov-20	1	−0.0276	−0.371	Energy Security	14-Nov-21	0.9992	−0.1449	−1.9475	Energy Security

Table A3. *Cont.*

Date	Coherence	Phase Diff. (Angular)	Phase Diff. (Temporal)	Leading Series	Date	Coherence	Phase Diff. (Angular)	Phase Diff. (Temporal)	Leading Series
84.45-week period									
22-Nov-20	1	−0.0284	−0.3817	Energy Security	21-Nov-21	0.9992	−0.1481	−1.9905	Energy Security
29-Nov-20	0.9999	−0.0293	−0.3938	Energy Security	28-Nov-21	0.9992	−0.1514	−2.0349	Energy Security
6-Dec-20	0.9999	−0.0302	−0.4059	Energy Security	5-Dec-21	0.9992	−0.1546	−2.0779	Energy Security
13-Dec-20	0.9999	−0.0313	−0.4207	Energy Security	12-Dec-21	0.9991	−0.1579	−2.1222	Energy Security
20-Dec-20	0.9999	−0.0324	−0.4355	Energy Security	19-Dec-21	0.9991	−0.1612	−2.1666	Energy Security
27-Dec-20	0.9999	−0.0336	−0.4516	Energy Security	26-Dec-21	0.9991	−0.1645	−2.2109	Energy Security
3-Jan-21	0.9999	−0.0348	−0.4677	Energy Security	2-Jan-22	0.9991	−0.1679	−2.2566	Energy Security
10-Jan-21	0.9999	−0.0362	−0.4865	Energy Security	9-Jan-22	0.9991	−0.1712	−2.301	Energy Security
17-Jan-21	0.9999	−0.0376	−0.5054	Energy Security	16-Jan-22	0.9991	−0.1746	−2.3467	Energy Security
24-Jan-21	0.9999	−0.039	−0.5242	Energy Security	23-Jan-22	0.9991	−0.178	−2.3924	Energy Security
31-Jan-21	0.9998	−0.0406	−0.5457	Energy Security	30-Jan-22	0.9991	−0.1814	−2.4381	Energy Security
7-Feb-21	0.9998	−0.0422	−0.5672	Energy Security	6-Feb-22	0.999	−0.1848	−2.4838	Energy Security
14-Feb-21	0.9998	−0.0439	−0.59	Energy Security	13-Feb-22	0.999	−0.1882	−2.5295	Energy Security
21-Feb-21	0.9998	−0.0456	−0.6129	Energy Security	20-Feb-22	0.999	−0.1917	−2.5765	Energy Security
28-Feb-21	0.9998	−0.0474	−0.6371	Energy Security	27-Feb-22	0.999	−0.1951	−2.6222	Energy Security
7-Mar-21	0.9998	−0.0493	−0.6626	Energy Security	6-Mar-22	0.999	−0.1986	−2.6693	Energy Security
14-Mar-21	0.9998	−0.0512	−0.6881	Energy Security	13-Mar-22	0.999	−0.2021	−2.7163	Energy Security
21-Mar-21	0.9997	−0.0532	−0.715	Energy Security	20-Mar-22	0.999	−0.2056	−2.7633	Energy Security
28-Mar-21	0.9997	−0.0552	−0.7419	Energy Security	27-Mar-22	0.999	−0.2091	−2.8104	Energy Security
4-Apr-21	0.9997	−0.0573	−0.7701	Energy Security	3-Apr-22	0.999	−0.2126	−2.8574	Energy Security

References

1. Hassani, H.; Huang, X.; MacFeely, S.; Entezarian, M.R. Big Data and the United Nations Sustainable Development Goals (UN SDGs) at a Glance. *Big Data Cogn. Comput.* **2021**, *5*, 28. [CrossRef]
2. Hassani, H.; Huang, X.; Silva, E. Big Data and Climate Change. *Big Data Cogn. Comput.* **2019**, *3*, 12. [CrossRef]
3. Google Trend. Available online: Https://trends.google.com/ (accessed on 15 September 2023).
4. McCracken, J.T. Google Trends as a leading indicator of the real economy. *J. Monet. Econ.* **2016**, *82*, 1–14.
5. Li, J.Y.; Wang, Q. Google Trends as a proxy for tourism demand: An empirical study. *Tour. Manag.* **2016**, *52*, 190–199.
6. Wang, Y.; Chen, X. Using Google Trends to predict stock market returns: Evidence from China. *J. Bus. Res.* **2018**, *89*, 193–201.
7. Polgreen, P.M.; Brandt, A.L.; Janelle, J.M.; Lederberg, E.J. Predicting the spread of infectious diseases using Google Trends data. *J. Infect. Dis.* **2008**, *198*, 962–967.
8. Choi, H.; Varian, H. Predicting the present with Google Trends. *Econ. Rec.* **2012**, *88*, 2–9. [CrossRef]

9. Carneiro, H.A.; Mylonakis, E.; Google Trends Team. Google Trends: A web-based tool for real-time surveillance of disease outbreaks. *Clin. Infect. Dis.* **2009**, *49*, 1557–1564. [CrossRef] [PubMed]
10. Eysenbach, G. Infodemiology: Tracking flu-related searches on the web for syndromic surveillance. *AMIA Annu. Symp. Proc.* **2006**, *2006*, 244–248.
11. Nuti, S.V.; Wayda, B.; Ranasinghe, I.; Wang, S.; Dreyer, R.P.; Chen, S.I.; Krumholz, H.M. The use of Google Trends in health care research: A systematic review. *PLoS ONE* **2014**, *9*, e109583. [CrossRef] [PubMed]
12. Yang, A.C.; Tsai, S.J.; Huang, N.E.; Peng, C.K. Association of Internet search trends with suicide death in Taipei City, Taiwan, 2004–2009. *J. Affect. Disord.* **2010**, *124*, 307–311. [CrossRef]
13. Ginsberg, J.; Mohebbi, M.H.; Patel, R.S.; Brammer, L.; Smolinski, M.S.; Brilliant, L. Detecting influenza epidemics using search engine query data. *Nature* **2009**, *457*, 1012–1014. [CrossRef]
14. Pervaiz, F.; Pervaiz, M.K. Investigating the role of Google search on tourism demand in Australia: An econometric approach. *J. Travel Res.* **2012**, *51*, 470–480.
15. Haim, M.; Graefe, A.; Vogt, C.A. Investigating the use of destination-related online media in travel planning. *J. Travel Res.* **2011**, *50*, 571–582.
16. Marquet, O.; Alberico, C.; Miranda-Moreno, L.F. Disentangling the effects of accessibility on mode choice using Google Maps: Evidence from Santiago de Chile. *Transp. Res. Part A Policy Pract.* **2016**, *94*, 450–465.
17. Wang, Q.; Chen, J. Internet search behavior and tourism destination choice: A case study of Hainan Island, China. *J. Destin. Mark. Manag.* **2019**, *11*, 41–50.
18. Killworth, P.D.; Bernard, H.R. The reversal small-world experiment. *Soc. Netw.* **1978**, *1*, 159–192. [CrossRef]
19. Killworth, P.D.; McCarty, C.; Bernard, H.R.; House, M. The accuracy of small world chains in social networks. *Soc. Netw.* **2006**, *28*, 85–96. [CrossRef]
20. Kleinberg, J. The small-world phenomenon: An algorithmic perspective. In Proceedings of the Thirty-Second Annual ACM Symposium on Theory of Computing, Portland, OR, USA, 21–23 May 2000; ACM: New York, NY, USA, 2000; pp. 163–170.
21. Kleinberg, J. Small-world phenomena and the dynamics of information. In *Advances in Neural Information Processing Systems*; NeurIPS: Vancouver, BC, Canada, 2002; pp. 431–438.
22. Kleinfeld, J. Could it be a big world after all? The six degrees of separation myth. *Society* **2002**, *12*, 5-2.
23. Korte, C.; Milgram, S. Acquaintance networks between racial groups: Application of the small world method. *J. Personal. Soc. Psychol.* **1970**, *15*, 101. [CrossRef]
24. Badi, I.; Elghoul, E.M. Using Grey-ARAS Approach to Investigate the Role of Social Media Platforms in Spreading Fake News During COVID-19 Pandemic. *J. Intell. Manag. Decis.* **2023**, *2*, 66–73. [CrossRef]
25. Dong, K.; Tse, Y.K. Examining Public Perceptions of UK Rail Strikes: A Text Analytics Approach Using Twitter Data. *Inf. Dyn. Appl.* **2023**, *2*, 101–114. [CrossRef]
26. Thakur, N. Social Media Mining and Analysis: A Brief Review of Recent Challenges. *Information* **2023**, *14*, 484. [CrossRef]
27. Gundecha, P.; Liu, H. Mining Social Media: A Brief Introduction. In *2012 TutORials in Operations Research*; INFORMS: Catonsville, MD, USA, 2012; pp. 1–17.
28. Bhattacharya, A. A Multi-Agent Model to Study the Effects of Crowdsourcing on the Spread of Misinformation in Social Networks. Master's Thesis, University of Cincinnati, Cincinnati, OH, USA, 2023. Available online: http://rave.ohiolink.edu/etdc/view?acc_num=ucin1684770124758418 (accessed on 14 August 2023).
29. Belle Wong, J.D. Top Social Media Statistics and Trends of 2023. Available online: https://www.forbes.com/advisor/business/social-media-statistics/ (accessed on 14 August 2023).
30. Jones, I.; Liu, H. Mining Social Media: Challenges and Opportunities. In Proceedings of the 2013 International Conference on Social Intelligence and Technology, State College, PA, USA, 8–10 May 2013; pp. 90–99.
31. Thakur, N. Sentiment Analysis and Text Analysis of the Public Discourse on Twitter about COVID-19 and MPox. *Big Data Cogn. Comput.* **2023**, *7*, 116. [CrossRef]
32. Thakur, N. A Large-Scale Dataset of Twitter Chatter about Online Learning during the Current COVID-19 Omicron Wave. *Data* **2022**, *7*, 109. [CrossRef]
33. Thakur, N.; Han, C.Y. A Multimodal Approach for Early Detection of Cognitive Impairment from Tweets. In *Human Interaction, Emerging Technologies and Future Systems V*; Springer International Publishing: Cham, Switzerland, 2022; pp. 11–19. ISBN 9783030855390.
34. Carmona, R.; Hwang, W.L.; Torresani, B. *Practical Time Frequency Analysis: Gabor and Wavelet Transforms with an Implementation in S*; Academic Press: San Diego, CA, USA, 1998.
35. Morlet, J.; Arens, G.; Fourgeau, E.; Giard, D. Wave propagation and sampling theory—Part I: Complex signal and scattering in multilayered media. *Geophysics* **1982**, *47*, 203–221. [CrossRef]
36. Torrence, C.; Compo, G.P. A practical guide to wavelet analysis. *Bull. Am. Meteorol. Soc.* **1998**, *79*, 61–78. [CrossRef]
37. Ge, Z. Significance tests for the wavelet power and the wavelet power spectrum. *Ann. Geophys.* **2007**, *25*, 2259–2269. [CrossRef]

38. Maraun, D.; Kurths, J. Cross wavelet analysis: Significance testing and pitfalls. *Nonlinear Process. Geophys.* **2004**, *11*, 505–514. [CrossRef]
39. Ge, Z. Significance tests for the wavelet cross spectrum and wavelet linear coherence. *Ann. Geophys.* **2008**, *26*, 3819–3829. [CrossRef]