Why are events important and how to compute them in geospatial research?

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Abstract: Geospatial research has long centered around objects. While attention to events is growing rapidly, events remain objectified in spatial databases. This paper aims to highlight the importance of events in scientific inquiries and overview general event-based approaches to data modeling and computing. As machine learning algorithms and big data become popular in geospatial research, many studies appear to be the products of convenience with readily adaptable data and codes rather than curiosity. By asking why events are important and how to compute events in geospatial research, the author intends to provoke thinking into the rationale and conceptual basis of event-based modeling and to emphasize the epistemological role of events in geospatial information science. Events are essential to understanding the world and communicating the understanding, events provide points of entry for knowledge inquiries and the inquiry processes, and events mediate objects and scaffold causality. We compute events to improve understanding, but event computing and computability depend on event representation. The paper briefly reviews event-based data models in spatial databases and methods to compute events for site understanding and prediction, for spatial impact assessment, and for discovering events' dynamic structures. Concluding remarks summarize key arguments and comment on opportunities to extend event computability.

Keywords: object, endurant, event, occurrent, partonomy, event-based modeling, event computing, epistemology

1 Introduction

Events are at the heart of grand challenges we face locally, regionally, and globally. From global climate change and regional economic development to local elections, events trans-

form our lives and livelihoods. The coronavirus pandemic has devastated all aspects of our society and charted many unprecedented courses of actions and counter-actions in responses. Events are triggers, drivers, and consequences of these challenges. Addressing these grand challenges depends on our abilities to model and compute events to decipher how events work, what entail, and when and what to expect in space over time. According to the Basic Formal Ontology (BFO) developed at the Institute for Formal Ontology and Medical Information Science, the basic structure of reality constitutes two modes of existence: (1) endurants (or continuants) capable of persistent self-identity through time even with changes, and (2) occurrents unfolding themselves in space-time [15]. Endurants are people, fields, or objects (henceforth all inclusive as objects for simplicity) that exist in full in any instant of time. A book may change its cover but remains the same book. A person is the same person in every time instant of their life. In contrast, occurents are activities, events, or processes that develop as 4-dimensional space-time beings with temporal parts over time. Neuroscience research echoes the ontological distinction of endurants and occurrents with differentiating cognitive processes between the two modes of existence: objects and events [17]. Object categorization depends on perceptual and functional qualities of objects, whereas event categorization involves parsing action streams into discrete, meaningful units detected by changes. "(E)vents occur when objects change or interact" [43, p. 4].

Conventional spatial databases record spatially referenced objects in the human and physical environments and allow us to inquire where things are and compute their relationships and patterns in space and time. Event databases with spatial references also exist. Spatial databases for hazardous events, such as tornadoes, hail storms, earthquakes, avalanches, landslides, wildfires, droughts, floods, hurricanes, and storm surges, are common in many countries. Examples of large spatial databases for social events include criminal events (FBI NIBRS[1] data in the US), global terrorist events (GTD[2] for world terrorist attacks), news events (GDELT and Phoenix RT of news from print, broadcast, and web news media), social, political, and economic events (SPEED[3] for post-WWII global news reports, USD[4] for urban social disorder events from 1960-2014, GEO-SVAC[5] for incidents of sexual violence, ACLED[6] for armed conflict events, and SCAD[7] for social conflict and political unrest in Africa). Their spatial references are highly abstract in forms of time-stamped points or polygons, without temporal parts nor discrete, meaningful units; in other words, these databases objectify events. These highly abstract representations of objectified events confine what we can learn from events. Popular studies are limited to identifying event clusters, their patterns over space and time, and their correlations to other objects or events. Exceptions are trajectories with time-stamped locations over the course of a movement, such as taxi-and-limousine trip record data in New York City, USA[8] plus intermediate stops (e.g., hurricane tracks[9] and GeoLife GPS trajectories[10]).

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[1]https://www.fbi.gov/services/cjis/ucr/nibrs
[2]https://www.start.umd.edu/data-tools/global-terrorism-database-gtd
[3]https://clinecenter.illinois.edu/project/human-loop-event-data-projects/SPEED
[4]https://www.prio.org/Data/Armed-Conflict/Urban-Social-Disorder/
[5]https://www.prio.org/Data/Armed-Conflict/GEO-SVAC/
[6]https://acleddata.com/#/dashboard
[7]https://www.strausscenter.org/ccaps-research-areas/social-conflict/database/
[8]https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page
[9]https://oceanservice.noaa.gov/news/historical-hurricanes/
[10]https://www.microsoft.com/en-us/download/details.aspx?id=52367

Given big data and prevalent libraries of codes, the temptation to compute is powerful. Research that is heavy on computing and light on thinking proliferates. An inattention to knowledge and theory leads to ineffective use of these vast resources and shallow findings with little intellectual contributions to advancing knowledge. Computing without understanding distracts us from thinking and imperils scientific progress, despite impressive advances in machine learning. In July 2020, the beta testing of Generative Pre-trained Transformer 3 (GPT-3) set a new milestone in artificial intelligence capable of producing text mimicking human writing. GPT-3 is a gigantic neural network with 175 billion input parameters and 96 layers of transformer decoders, each of which has 1.8 billion parameters, and is pre-trained with 45TB (499 billion tokens) compressed data from five datasets: Common Crawl, WebText, two Internet-based book corpora (Books1 and Books2), and English-language Wikipedia [7]. Essentially, GPT-3 is trained on the entire Internet. Therefore, GPT-3 can perform domain specific tasks without training for domain-specific knowledge, such as taking the SAT, translating languages, and coding in CSS, Javascript XML (JSX), and Python, given human instructions on the desired functions or products (e.g., a website). However, tests suggest that GPT-3 relates words without an understanding of the meaning behind each word, leading to poor reasoning and, subsequently, unreliable conclusions [26].

Understanding is at the heart of human learning, distinguished from machine learning. When machines are efficient in crawling, filtering, and algorithmically processing information to produce answers, humans, more important than before, are responsible for asking and framing questions that enhance our comprehension of how the world works. Events are important because events hold the key to understanding why and how, and, furthermore, to predicting where and when. This paper aims to highlight the importance of events and general approaches to event computing from a geospatial perspective to spotlight the pathways that produce knowledge about how the world works. The use of the term "geospatial" attempts to broadly cover geographic and spatial information sciences. Discussions synthesize the recent geospatial literature with my take on key research developments, challenges and opportunities. A comprehensive review of events in geospatial research, however, is beyond the scope of this paper.

2   Why are events important in geospatial research?

For simplicity, this paper considers events for all kinds of occurrents, including activities, actions, interactions, events, and processes. While objects constitute the substances that the world is made of, events are the drivers that form the world and subsequently bring changes, movements, interactions, and dynamics to the world. The importance of events is multifaceted across disciplines. Geological events play distinct roles from political events in shaping the world, but devious tactics can intersect them with propaganda. Similar manipulations can amplify the list of importance of events with ideological or political intent, which is unhelpful to identifying the pathways in geospatial research for knowledge production. Instead, the following three assertions inform the importance of events in finding and framing geospatial research questions.

2.1 Events are essential to understanding the world and communicating the understanding

A comprehensive understanding of the dynamic world relies upon our ability to decipher what has happened where and when, why it happens, how it may develop, what objects and events it may interact with and how, what its consequences invoke, and how to predict and manage the happening in the future. Events connect people, make histories, discover sciences, and shape landscapes. Events form building blocks of our conscious experiences and episodic memories, which nurture culture development and culminate in knowledge production. Our daily life runs through events, and over time, the events we experience shape our characters, influence our decisions and outlooks, and make us who we are.

Cognitive experiments show that infants, some as young as 2 months old, can perceive auditory and visual events [22]. Some six-month old infants, the youngest tested, can remember short events, and most children by 24 months years old can remember long, temporally complex event sequences [2]. Children aged 7 or older are able to chain events sequentially to form a plot for storytelling [3]. Stories stimulate human imagination, convey experiences, and teach life lessons, which form oral histories in many indigenous cultures.

Similarly, narratives organize a sequence of events to form a coherent message that conveys the meaning of each event in relation to other events [11] and relate to what surrounds us. As such, historians develop narratives to trace the past [12] and interpret the processes that produce the landscape structure [13]. A scientific exercise or report is essentially a narrative with systematic events (e.g., tasks, processes, responses, etc.) to answer a research question. Narratives are one of the most powerful ways of world-making [35] and provide rich information for knowledge production [54].

2.2 Events provide points of entry for knowledge inquiries and the inquiry processes

Events drive scientific discoveries. A drop of an apple on Newton leading to the discovery of gravity theory is an old story how a seemly ordinary event can trigger outstanding scientific inquiry. Scientists study events and seek evidence to identify past events or project future events. Hurricanes, elections, or recessions serve the topics of many studies in physical and social sciences. An event takes place where site, environment, and situation provide the necessary support, which drives numerous studies in site modeling to identify spatial correlates and predict occurrences. Landslide risks, archaeological sites, species habitats, disease infections, or traffic accidents are examples of studies that inquire into the site characteristics, environmental constraints, and situational context of occurrences.

While events may be countable, an event's dynamic structure is difficult or impossible to observe directly. Event modeling often objectifies events as points or intervals and ignores the event's dynamic structure. Discrete event modeling that assesses time to the next event, for example, is primarily concerned with between-event time (spacing time) but neglects where events occur (timing space) [53]. Geospatial research of events considers both spatial and temporal manifestation of events. Events induce change and movement. In turn, change and movement can serve as surrogates to measure the mechanism, intensity, and consequences of the events. Inferencing event characteristics from measurements of change and movement, however, is complicated because of equifinality and multifinality; that is, many events may lead to the same change, and an event may generate many

changes. With sound logic and firm grounding in domain knowledge, such inferencing, nevertheless, can draw novel insights. For example, movement analysis of isotherms reveals warming and cooling processes embedded in general circulation models [6], and aggregate characteristics of movements inform one's routine activities [55].

Change and movement attract (or detract) events. Positive feedback pushes changes to site, environment, and situation more inviting to events of the same or different types, leading to more frequent or accelerated happenings of the same events or cascading events of different types. Carbon emission on climate change is an example with positive feedback. In contrast, negative feedback suppresses occurrences, such that vaccination reduces the spread of infections. An event can foreground latent properties (e.g., fragile infrastructure) or hidden issues (e.g., racial segregation). For example, the COVID-19 pandemic accentuates social inequity in the United States [57].

2.3   Events mediate objects and scaffold causality

Events must involve some objects. Linguistically, events commonly involve verbs that refer to relations among objects. Children acquire the concepts of events after they have developed some grasps for objects and often use terms for spatial relations (e.g., up, out, etc.) in lieu of action verbs [24]. Agents (i.e., a type of objects) carry out events. Water, air, humans, animals, and machines are examples of agents. Events operate on objects, spatial or aspatial, as events take place and need objects to provide the ingredients and functions for execution. A wildfire needs fuel and fire, and a game needs players and settings, for example. Relations among objects set the situation in which an event can take place. The event, in turn, change the objects involved (e.g., remove or modify existing ones or introduce new) and their relationships. An event of road construction creates a new road and connect two locations. A youth soccer game brings families from communities and extends social networks. As such, events are logical particulars that bind variables in the first-order predicate calculus, for instance, "Meyer climbed Kibo" as "$(\exists x)(climbed(Kibo, Meyer, x))$" [10].

Events populate and operate ubiquitously across multiple scales in space and time. Humans perceive discrete events to assume order to otherwise continuous fluxes of chaos in reality. Such perceptual experiences promote the idea of events as dynamic objects, distinguished from concrete objects for things [40]. Event perception is thus regarded as the temporal extended analog of object perception in the manifold of space-time, a.k.a dynamically molded spatiotemporal objects [4]. The added temporal dimension with the assumed orderly relations among events guides our anticipation of the coming situation, decision to actions, and our recollection afterwards. Hume's temporal priority principle states that all causes must preceded their effects [20]. Temporal relations among dynamic objects (i.e., events) are prerequisites for causation, but spatial juxtaposition of objects do not.

Events have parts that are events, which may be discontinuous temporally or spatially [10]. Such part-of relationships form a hierarchy of event partonomies. For natural and social events (e.g., hurricanes or recessions), partonomic hierarchies of events describe development phases from initiation to conclusion based on event's dynamic structure that reflects the physical dynamics in a life cycle (e.g., transitioning from tropical disturbance, tropical depression, tropical storm, hurricane, extratropical cyclone, to remnant low). For events driven by human actions, event partonomies have a privileged level of behavior episodes that are discernible easily by vision, such as talking or fighting [56]. Behavioral settings or scenes, such as restaurants or living rooms, can characterize the privi-

leged partonomic level for events, too, under the assumed agreement between activities and places. While natural events follow physical or ecological laws, events of individual activities (e.g., walking or running) inherit event-specific dynamic structure reflecting the physical dynamics responsible for generating *kinematic specification of dynamics* for event perception [42] (e.g., the path shape and speed profiles of spatiotemporal trajectories can be used to differentiate walking from running). More broadly, the essence of an event is its dynamic structure that drives drive changes to its participating objects and their relations over a perceived temporal order.

3 How to compute events in geospatial research?

Endurant objects have long enjoyed the spotlight in geospatial research. As such, the digital representations of spatial objects share common foundations in terms of geometry and structures across database systems and development platforms. Typical representations for event data in GIS remain lacking. The main challenges continue: how GIS represents reality and how the representations constrain event computing and computability.

3.1 Geospatial representation for events

The conventional static, map-centric GIS data models are incapable of representing an event's dynamic structure. Increasingly, GIS data models incorporate object-oriented concepts to organize feature classes, but the relational tables continue to restrict the static geometry of a spatial feature and a single value for each of the feature's attribute. As such, the model allows no change to the geometry or attributes of a spatial feature. However, an event's dynamic structure may involve complex changes to geometry, internal structure, and locations, individually or in any combination [14]. These changes demand multiple geometries in the spatial representation of an event and multiple values for individual attributes to allow tracking the event and tracing its changes over space and time.

The foundation for tracking or tracing an event is the ability to recognize and maintain the event's identity so that we can distinguish the event from others based on its unique characteristics [19]. Nevertheless, one's identity is challenging to determine when time is involved. If we replace parts of an object (Object A) over time to the point that all parts of the object have been updated (Object B), are Object A and Object B the same object? If we reassemble old parts of Object A to form an object (Object C), are Object A and Object C the same object? Most people are likely to agree that Object B is not Object C. However, if one considers Objects A and B are the same and Objects A and C are the same, then one shall paradoxically conclude that Objects B and C share the same identity. Determining event identity accounts for additional challenges because events are dynamic objects with four-dimensional space-time that may be discontinuous spatially or temporally. A wildfire jumps over a distance and then merges with the main fire. Do we consider one, two, or three fire events?

Since early 1990, many researchers have explored ways to represent events in GIS databases; that is, data models that use events as the primary principle to organize geospatial data. Examples include event-oriented approach to managing time in GIS [9], event-based spatio-temporal data model (ESTDM) [38], object-oriented geomorphological processes (OOgeomorph) [41], events with three domains [51], events as field-objects [52],

geospatial event objects [49], event calculus [48], event hierarchy of space-time sequences [30], events as fluid kinematics [5], and events as spatial narratives [54].

Our abilities to qualify and measure events are prerequisites for any successful implementation of event data models and use of events as the principles to organize GIS data. As discussed earlier in section 2, events may not be directly visible; instead, they generate change or movement that is measurable from observations, remote sensing, surveys, crowd-sourcing, digitization of maps or documents, or volunteered geographic sources. Therefore, before we can organize GIS data based on events, we need to define and detect events from GIS data based on probable event-induced changes or movements in space over time. By spatially and temporally assembling these changes or movements in a GIS database, we can construct the dynamic structure within an event and organize events in a partonomic hierarchy [52]. Detecting spatiotemporal events from observations of various sources continues to be an active area of research [50].

3.2 Event computing in geospatial research

As events are essential to advancing our knowledge about the world, events commonly serve as the entry points for or at the center of scientific inquiries. Edward Ullman (1980) advocates geography as spatial interactions [45]. Geographic events drive spatial interactions that shape and reshape geography. Ullman focuses on economic activities that drive the dynamics of flows of people, goods, services, energy or information between locations. Broader examples are plentiful. Natural and anthropogenic events transform our landscape. Political, social, and cultural events mold human relations. We use "event computing" here to communicate the ways in which we reckon or calculate events to make sense of our observations. There are three general approaches to event computing in geospatial research: (1) compute events as discrete occurrences to understand site and situation of event occurrences and based on the understanding to predict the spatial distribution of event likelihoods; (2) compute events to assess spatial impacts in an aftermath; and (3) compute events to uncover the event's development and predict how events will continue evolve.

3.2.1 Compute events for site understanding and prediction

The first approach that computes events as discrete occurrences has two aims. The first aim is to analyze the spatial pattern of event locations, how the pattern changes over time, and the site characteristics of event occurrences. The first aim subserves the second aim: spatial prediction of previously unknown event locations. Popular research subjects include criminal offenses, species occurrences, archaeological sites, landslide activities, traffic accidents, disease infection, and many more. Spatial representations of these events are often points. Popular tools for point pattern analysis help identify clusters of events or areas of high or low event-density. Environmental or social characteristics at event locations give rise to potential explanations for the event-occurrences and suggest explanatory variables for spatial prediction modeling. Popular examples of geospatial methods for computing discrete events include spatial multicriteria analysis [25], species distribution modeling [33] (or niche modeling [44]), spatial Bayesian modeling [1], or an array of regression-based approaches [59] to statistically relate site characteristics to event occurrences.

Since machine learning methods has gained attention in geospatial research, computing events as discrete occurrences takes advantage of its compatibility with supervised learning. Existing occurrences and their site characteristics offer training samples for algorithms (e.g., MaxEnt, support vector machine) to classify locations into binary groups of positive and negative sites or suggest the likelihood of being a positive site. There are many excellent review papers on computing events as discrete occurrences on various kinds of events, such as traffic accidents [59], species distribution [27, 33], and disease incidence [21, 46]. Events with geometries of higher dimension, like lines, areas, or volumes, are possible, such as tornado tracks, droughts, snow avalanches, and sinkholes. However, events with spatial extents inherit spatial variances of site characteristics and, therefore, need to consider additional assumptions on representative site characteristics for pattern analysis and spatial prediction.

3.2.2   Compute events for spatial impact assessment

The second approach that computes events to identify event-driven changes in space is useful for damage assessment of a natural hazard, analysis of societal consequences of a policy or a construction, evaluation of the effects from a mitigation strategy, or examination of social and economic impacts of human activities, for example. Computing event-driven changes compares spatial measures and spatial patterns before and after an event and based on the comparison to relate the changes to the working of the event: how a storm surge devastates a coastal community, how a road construction cuts off animal movements between habitats, how adding a new bus route enhances the accessibility to healthcare for a low-income neighborhood, how a music festival attracts visitors and business to a city, how a bingo night connects seniors in a neighborhood, and many other examples. For environmental, ecological, and landuse landcover studies, remotely sensed imagery is an important source of data for computing event-driven changes [23, 58]. Social or economic changes rely on area-based longitudinal data, such as census data or parcel data. The rise of natural language processing and social media sources affords geospatial researchers to detect changes in sentiments after a disaster or a social event [34, 47].

3.2.3   Compute events for discovering an event's dynamic structure

The third approach that computes an event's life-course aims to uncover the dynamic structure of an event. For physical scientists, recognizing different developmental stages of an event (including a process) is essential for understanding, modeling, and prediction. Physical geographers have a long history of adopting the life-course analysis. William Morris Davis' (1899) geographical cycle interprets how geomorphological processes operate on geological structures over time to produce landforms through stages of youth, maturity, and old-age [10]. Similar modeling efforts attempt to decipher the development of hurricanes, rain forests, and many physical and ecological processes. For social scientists, event history analysis applies discrete-state continuous-time stochastic models to elicit temporal structures of life course and social change in the occurrence of transitions and events over time [28]. A suite of statistical and computational methods (e.g., survival analysis, sequence analysis, and hidden Markov chain) focuses on frequencies, trajectories and transitions to elicit the states and dynamics of life courses [39] or life course complexity [37]. Transitions and trajectories are two key emphases in life-course analysis.

In GIS, popular approaches to delve into transitions include cellular automata and agent-based modeling to simulate geographic processes, such as land use change, urban sprawl, disease transmission, wildfire spread, or insect infestation. These spatial simulation models take an individual-based, bottom-up approach to embrace spatial heterogeneity of resources as well as the rules that guide individuals' behaviors, decisions, and interactions. Instead of testing hypotheses, spatial simulation helps generate hypotheses on how these rules may drive emergent spatial patterns and transitions of these patterns. There are numerous reviews on these methods. The book by O'Sullivan and Perry [36] guides systematic learning on conceptual, mathematical, and practical issues in spatial simulation, and Heppenstall, et al. [18] provides the latest comprehensive review.

While transitions examine changes from one state to another, trajectories follow movements. For instance, a landscape transitions from cropland to bare soil when a drought shifts east. There is a long history of environmental records tracking meteorological events, hurricanes, tornadoes, wildfires, or pollutants. The rise of location-aware technologies popularizes tracking humans and animals and leads to the call for a new integrated science of movement [32]. Trajectories, as the basic unit of spatial analysis, free geospatial researchers from the static-location confinement for insights into the temporally connected locations to inform patterns of life and human dynamics [55]. Trajectory mining has gained popularity in geospatial research with a rich suite of methods and applications [29] and continues to enjoy fast development of new methods in recent years, especially on semantic trajectory modeling that relates trajectories to travel modes, purposes, or social implications [31] and on group movements [8] and spatial community structures [16].

4   Concluding remarks and research opportunities

Events drive geographic dynamics. Understanding events is the key to knowing and communicating the being and becoming of our world at all scales. Events provide points of entries for knowledge inquiries and the inquiry processes. Spatial contrasts among before-, during-, and after-events engage us into learning where, when, and how events develop, operate, and shape the landscape, and furthermore anchor our memories and denote our experiences. Events operate on objects, trigger actions, reactions, and interactions, build relationships and induce change and movement (e.g., change locations) to objects, environments, and their relationships. As such, events generate temporal orders that are necessary preconditions to devise causality.

Conceptualization constrains representation, and representation delimits computation and computability. Because most spatial databases objectify events in spatial data models, event analysis is limited to analysis of point patterns (e.g., spatial clustering, kernel density, or hotspot analysis), spatial autocorrelation of polygons with event density, and spatial prediction modeling of occurrences (e.g., MaxEnt, supervised machine learning). These event computing methods help understand what spatial characteristics of sites, environments, and situations are likely to afford event occurrences and predict future happening. Without explicitly representing events' dynamic structures in spatial data models, event computing can only simulate events' temporal parts for exploratory studies. While we can tune input parameters to evaluate effects in the output pattern through simulations, we often fall short on the validity and generalizability of the findings.

Simulations help generate hypotheses, hypotheses need to be tested to validate theories and contribute to generalizable knowledge, and hypothesis testing needs data that are represented according to events. Therefore, we need spatial data models that explicitly represent events, events' partonomies (e.g., spatiotemporal parts and their relationships), and events' dynamic structures (e.g., transitions and trajectories). Such spatial data models foreground events as the organizing principle for geospatial information, so that data are recorded along with event hierarchies, event parts and event's dynamic structures. Hence, event computing is possible to examine event hierarchies, event parts, and event structures. Besides testing hypotheses on event trajectories or event transitions, such event-based spatial data models can support quasi-experimental design for causal geographic factors to event dynamics. Trajectory databases are successful examples with explicit events, event parts, and event structures and have provoked many innovative computing methods to discover new ideas and concepts on movements. Extending points and lines on trajectories to higher dimensional events and event parts is not trivial. Geospatial researchers have proposed many event-based spatial data models since early 1990s, but none of them has been implemented and tested with diverse applications. As these domain-specific efforts of data modeling fall short, a call for an open-science approach to event-based spatial data modeling and event computing is in order.

Acknowledgments

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