An Operator Framework for Real-Time Analytics of Streamed Fields

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Abstract

Continuous geospatial phenomena such as air quality, temperature, soil moisture, or noise evolve smoothly over space while potentially changing rapidly over time. They are increasingly observed through dense, real-time measurement streams from geosensor networks, mobile platforms, and live sensor infrastructures. While data stream engines provide low-latency processing over unbounded streams, they lack higher-level abstractions for spatially continuous phenomena. As a result, real-time field analysis is often implemented via ad-hoc pipelines that combine GIS tools, stream processing, and application-specific logic. In this paper we propose an analytical operator framework for streamed scalar fields. We derive a minimal, composable operator set building on principles of compact operator sets and dimensional reasoning over space, time, and theme. We demonstrate how analytics for streamed continuous phenomena are expressed through primitive operator compositions. The resulting framework provides a systematic basis for describing and implementing extensible stream-based, real-time field analytics.

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1 Introduction

Geospatial phenomena evolve continuously across space and time [18, 37]. Air quality, temperature, soil moisture, and noise levels vary smoothly across spatial domains while undergoing rapid temporal change [19, 34]. These phenomena are increasingly observed through dense streams from wireless geosensor networks, mobile sensing platforms, and live data infrastructures [29, 28, 1]. As sensing technologies proliferate, spatial and temporal coverage increases, yielding large volumes of continuously arriving measurements [23, 14].

Despite improved observational capacity, two core challenges remain. First, continuous phenomena require high-level data representations beyond raw atomic measurements [25, 8]. Second, real-time settings demand analytical frameworks that support automated decision making and operational response [33]. Analysis must proceed incrementally as phenomena unfold [23]. These requirements differ from traditional retrospective Geographic Information Science (GIScience) analysis and from conventional data stream analytics [4, 44]. In particular, analytical processes must operate progressively under strict latency requirements, continuously updating results as new measurements arrive while respecting the spatial continuity and thematic structure characteristic of phenomena [6].

Environmental monitoring illustrates this challenge. In precision agriculture, soil moisture and nutrient levels are measured in real-time as machinery traverses cropland, requiring immediate synthesis to guide irrigation and fertilization [45]. City-wide sensor networks stream air quality measurements that must be continuously aggregated and transformed to detect localized hazards [31, 32]. For example, city-wide air-quality streams may be

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filtered or joined to districts as sensor events. In such settings, analysis proceeds forward in time and must reflect the current state of the phenomenon without complete historical access [4, 23, 44, 2].

Existing analytical frameworks for spatiotemporal phenomena [15, 1] inadequately support real-time field-based analysis. GIS provides a set of extensive operators for spatial fields but they assume static or periodically updated datasets and full access to historical data [15, 37, 26, 8]. Data stream engines (DSEs) support high-throughput, low-latency processing over unbounded streams yet generally operate on flat relational abstractions lacking higher-level representations for spatially continuous fields [4, 6, 44]. Prior geostreaming research has largely focused on moving objects as in PLACE [27], StreamInsight [21], and Galić et al. [16], while work on continuous phenomena has been more limited [42, 25, 2]. Consequently, real-time analysis over continuous geospatial fields is commonly implemented through ad-hoc combinations of GIS tools, stream processing systems, and application-specific logic [24, 1, 23]. These solutions are technically demanding and difficult to generalize [1].

Existing approaches for detailed spatiotemporal continuous field analysis are based on time series analysis; this assumes a fixed time sequence of measurements, which can be revisited arbitrarily, enabling global statistics and retrospective segmentation [15, 37]. In contrast, real-time stream processing operates under an advancing notion of time in which future observations are unavailable and past observations may not be retained [5, 10]. Analysis must therefore be incremental and yield results without access to a complete historical copy of the input stream [23, 44]. At present, there is no broadly accepted compact operator framework that unifies continuous spatial fields, spatiotemporal reasoning, and stream-based constraints into a single analytical vocabulary.

Contributions. This paper introduces a novel operator set for the analysis of streamed-based, spatiotemporal scalar fields. Its design builds on dimensional reasoning over space, time, and theme and integrates the computational operating principles of stream processing. The framework provides a compact, minimal, and expressive set of operators enabling a systematic basis for describing and implementing extensible real-time analytics over spatiotemporal continuous phenomena sampled by spatially and temporally dense sensing environments.

This article is organized as follows: we discuss the background of continuous spatiotemporal phenomena analysis in Section 2. Section 3 introduces our operator framework design, the Streamed Measurement Field (SMF) and the proposed analysis operator set. Section 4 formalizes the operators. Section 5 includes validation and discusses some limitations. Section 6 compares our operator framework with related approaches and we conclude in Section 7.

2 Background

2.1 Analysis of Continuous Spatiotemporal Phenomena

This paper focuses on the analysis of continuous, spatiotemporal phenomena. Fields have long been considered conceptual models of continuous phenomena; they represent functions from spatiotemporal locations to qualities rather than depicting implementation formats [17, 22]. The concept of fields has mostly been used to describe continuous phenomena. Coverages are conceptually similar to fields but have primarily been used to describe data structures for continuous phenomena, providing a more generic data type than rasters or tessellations [13, 19]. In this article, however, we also see fields as data types [8, 24, 35]. Furthermore, we focus specifically on scalar fields, which are functions assigning a single value to each location in space and time, representing the intensity of a phenomenon without directional components. In practice, such fields are observed through discrete measurements at sensor locations at points in time, sampling phenomena such as temperature, air quality, or soil moisture [37, 19]. Here, continuous refers to the conceptual view of a phenomenon as varying continuously over space and time, while dense refers to frequent and proximate samples that support near-real-time field reasoning [42, 20]. Further, we distinguish between observed and derived fields. An observed field consists of discrete, spatiotemporal measurement samples, and a derived field results from interpolation or estimation approximating values over unsampled locations to generate e.g. rasters. Thus, scalar fields and their variation across space and time are the analytical object of interest in this paper.

Historically, analytical capabilities over continuous phenomena were constrained by sparse observations, often in space and time. Early analyses operated on fields observed at discrete time steps, emphasizing spatial interpolation, smoothing, and spatial pattern characterization at individual instants. Change was typically computed by comparing successive static states, following a "Time-Slice Snapshot" model of temporal reasoning [37, 15]. As sensing technologies improved, denser temporal sampling enabled more advanced temporal analysis. Much of this work shifted toward representations centered on moving objects and their trajectories [1]. Although such models support reasoning about duration and ordering, they emphasize persistent identities and discrete trajectories rather than continuous variation over space; the analytical focus remains object-centric.

In recent years, technological advances have produced denser observations across space and time, yielding spatiotemporal scalar fields [29]. Now, analysis includes joint reasoning over space and time: examining evolving spatial patterns, neighborhood change, and region-dependent trends. Rather than isolated snapshots or object-centric histories, analysis operates over continuously varying fields, supporting more faithful representations of dynamic conditions [1]. With geosensor networks and IoT-equipped sensing, sensor streams mark a further advancement. Observations arrive continuously, at high volume and in real-time, enabling analysis as phenomena unfold rather than retrospectively [23, 30]. Dense, real-time observations invite questions about short-term change, local dynamics, and evolving spatial structure that were previously impractical. These observations enable real-time decision making, as found in urban air quality monitoring. However, they require rethinking field-based analysis under monotonic time progression.

2.2 Stream-based Data Acquisition for Spatiotemporal Phenomena

Stream-based analytics takes place as phenomena are observed in real-time [2, 42]. Observations arrive incrementally with minimal delay as sequences of measurements and analyses are immediately and continuously re-evaluated as new data become available. Results are produced relative to t_{now}, rather than over a fixed temporal interval of the past as assumed in traditional spatiotemporal analysis. A defining characteristic of real-time stream-based analytics is explicit management of analytical state [5]. Measurement streams are unbounded, meaning we cannot predict how much data will arrive in the future. At any moment, only a finite subset of data has arrived. DSEs support forward-looking analyses and retain very little historical information [6, 5, 10]. Temporal context is specified through windows defined relative to t_{now} [5]. More general stream algebras define additional window types [36]. In this article, we focus on time-based windows because they match the advancing-time semantics of sensor streams and remain compatible with common data stream engines.

2.3 Analysis via Data Dimensions

A foundational principle in GIS is that analytical intent can be described through dimensions of space, time, and theme [39]. Rather than enumerating specific analysis tasks directly, this perspective characterizes analysis by which dimensions are fixed, controlled, or measured [39]. For example, fixing time while varying location and measuring a quantity such as temperature yields a spatial field representing continuous temperature over a region at a specific moment. Such a representation enables reasoning about spatial variation under a fixed temporal context.

When applied to scalar fields, dimensional reasoning concisely expresses analytical intent without prescribing algorithms and is therefore declarative. A temperature field may be restricted to a spatial subregion or summarized over a recent interval. Measuring spatial variation at a fixed time, summarizing values over time at fixed locations, or examining evolving spatial gradients are all instances of different dimensional configurations of the same underlying spatiotemporal field [39, 15]. This abstraction foregrounds the type of reasoning being performed rather than its implementation. When analyzing a single phenomenon, theme is fixed, but metric observations can be varied or measured.

Similar dimension-oriented thinking also underlies applied systems such as On-Line Analytical Processing (OLAP) [12]. OLAP organizes analysis into multidimensional data tuples (e.g., sales records). Although OLAP does not natively support continuous spatial data, its success illustrates the expressive power of dimensional organization for summarizing and exploring datasets consisting of multidimensional tuples [12].

This view remains meaningful in stream-based settings. The dimensions of space, time, and theme do not disappear when data arrive as unbounded streams [23]. The challenge lies in determining which forms of dimensional reasoning remain well-defined under monotonically advancing time [5, 12]. Grounding analysis in data dimensions rather than specific operations provides a flexible foundation for reasoning about continuous phenomena across observational regimes.

2.4 Analysis Operator Frameworks for Spatiotemporal Fields

Across analytical traditions, a central design principle is that complex behavior can be expressed through the composition of a compact set of primitive operations [11, 41]. Rather than treating each task as a special case, analysis is organized through operator sets that function as a general analytical vocabulary. This principle has proven effective across domains and motivates its extension to continuous spatiotemporal phenomena.

For instance, the relational algebra [11] demonstrated that a limited collection of set-based operators is sufficient to express diverse analytical queries through composition and boolean logic. The emphasis on composability and expressive sufficiency shaped analytical systems such as SQL and other relational algebra or relational calculus languages [9, 4], providing a foundation for high-level data languages.

For continuous spatial fields, Map Algebra provides a comparable vocabulary through local, focal, and zonal operations, enabling the derivation of new fields, neighborhood analysis, and regional aggregation [41]. Extensions such as Cubic Map Algebra generalized these ideas to incorporate time, enabling operations over three-dimensional space-time grids. However, such frameworks largely assume fully materialized rasters or regularly sampled grids and remain primarily spatial in orientation. While influential in GIS practice, they do not constitute a widely adopted, unified operator framework for continuous spatiotemporal fields and they do not support stream processing.

Subsequent work has explored spatiotemporal algebras and operator sets that integrate spatial and temporal reasoning [15, 25]. These approaches facilitate subsetting and statistical reduction over multidimensional grids and emphasize temporal slicing, aggregation, and change analysis. Time series analysis shares this operator logic in that it supports filtering, segmentation, and statistical summarization over ordered observations. However, both time series and many spatiotemporal algebraic frameworks presuppose complete historical access to the temporal extent.

2.5 Limitations of Existing Approaches

Stream-based analytics differs in its computational model. Time series analysis typically assumes a fixed sequence that can be revisited arbitrarily, enabling global statistics and retrospective segmentation [15]. In contrast stream processing operates under an advancing notion of time in which future observations are unavailable and past observations may not be retained [5]. Analysis must therefore be incremental and yield results without access to a complete copy of the input stream [23]. Current geostreaming focuses on moving objects, spatial tuples, and vector geometries [27, 16, 44].

At present, there is no broadly accepted compact operator framework that unifies continuous spatiotemporal fields, spatiotemporal reasoning, and stream-based constraints into a single analytical vocabulary. Existing operator sets depend on representational assumptions and are largely retrospective [15]. The integration of spatial continuity with forward-only temporal semantics remains an open challenge. The combination of spatial and temporal operators under streaming constraints is therefore the central issue.

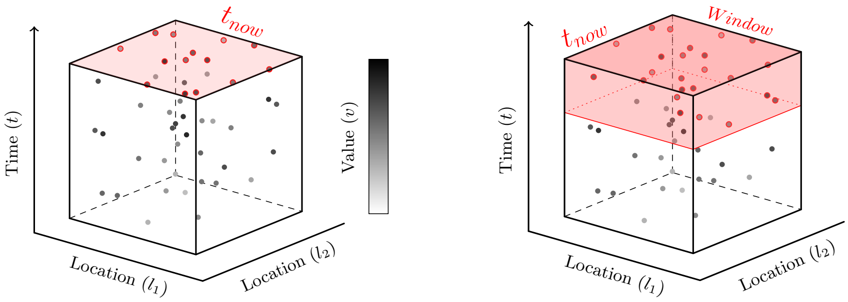
3 An Analytical Operator Framework for Streamed Spatiotemporal Scalar Fields

This section introduces our proposed analytical operator framework for streamed spatiotemporal scalar fields.

3.1 Rationale

In this paper, we call representations of continuous ST phenomena that are sampled by measurement streams a streamed scalar field (S-SF). Our design was driven by the following considerations:

- First, we focused on identifying the *analytical tasks* for streamed scalar fields. An analytical task describes a class of reasoning performed over continuous spatiotemporal phenomenon. Adopting a task-oriented view provides a stable abstraction for assessing analytical expressiveness and allows us to be compatible with other forms of analyzing spatiotemporal fields such as fields based on historic, time-series data.
- The second design principle identifies a *minimal set of primitive operators* [11, 41] to support the analytical tasks of Step 1 rather than building an exhaustive collection of specialized operations. We expect this operator set to be sufficient for expressing complex pattern analytics for continuous phenomena through composition while adhering to stream-based, real-time semantics.
- The third principle targets the *data dimensions* of S-SF (spatial, temporal, and thematic aspects). Our intent is to provide operator primitives that can be equally applied along the different data dimensions of fields.



(a) SMF at t_{now}. **(b)** Window over Streamed Measurement Field.

Figure 1 Streamed Measurement Field Representation.

3.2 The Streamed Measurement Field Data Model

When analyzing continuous phenomena that are captured by streams of measurements, incoming observations are treated as samples of an underlying phenomenon rather than as independent events, which allows analysis to preserve spatial continuity while remaining compatible with real-time stream processing. To represent such streamed fields, we adopt the Streamed Measurement Field Model (SMF) [35]. The SMF data model builds on atomic observations [19] and systematically defines increasingly structured data types: measurements, measurement streams, measurement fields, and streamed measurement fields. We present a selected subset of data types as basis for the operator framework.

▶ **Definition 1** (Measurement). *A measurement $m = ((l,t), Z, z(l,t))$ represents the value of a property Z at a spacetime point $x = (l,t) \in D = L \times T$. The function $z(l,t)$ maps the spacetime point (l,t) to a value of Z. The metric observation $z(l,t)$ is some value $v \in \mathbb{R}$.*

For simplicity, the formal model uses real-valued spatial, temporal, and measurement domains. Implementations necessarily approximate these domains through finite-precision computational representations [38]. We use measurement subscripts to denote component projection, so l_m, t_m, and Z_m denote the location, time, and property of measurement m. Numeric subscripts denote ordered instants, as in $t_0, t_1, \ldots$, while F_t denotes the field induced at time t. A scalar field is classically defined as a function $f : L \times T \to \mathbb{R}$, mapping each spacetime coordinate to a value [19]. A measurement field instantiates this concept over a finite measurement set.

▶ **Definition 2** (Measurement Field). *A measurement field is defined by a set of measurements M, a property Z, and a spacetime domain D.*

$$F = (M_F, Z_F, D_F) \quad \text{where} \quad \forall m \in M_F \mid Z_m = Z_F \wedge l_m \in L_F \wedge t_m \in T_F.$$

Sensor-generated measurements arrive as a time-ordered stream $S \to \langle m_{t_0}, m_{t_1}, \ldots, m_{t_{\text{now}}} \rangle$ [30, 4]. The SMF constrains the stream to a single property Z and spatial domain L. This represents evolving observations of a given phenomenon over time.

▶ **Definition 3** (Streamed Measurement Field). *A streamed measurement field is defined by a measurement stream S, property Z, and location domain L which together indirectly induce a snapshot measurement field F at each instant t_{now}.*

$$SMF = (S, Z, L) \to \langle F_{t_0}, F_{t_1}, \ldots, F_{t_{now}} \rangle$$

where each snapshot measurement field is

$$F_{t_{now}} = \{m \in S \mid Z_m = Z_F \wedge l_m \in L_F \wedge t_m = t_{now}\}.$$

Stream processing requires a bounded state. This is achieved through windowing which defines finite temporal evaluation contexts relative to the present t_{now} [6, 4]. A temporal window selects measurements whose timestamps fall within a specified interval, yielding a finite measurement field F suitable for analysis.

▶ **Definition 4** (Window). *Let $W(i,k)$ denote a window specification with interval length $i > 0$ and slide $k > 0$. The window operator is defined as*

$$\mathsf{Window}_{(i,k)} : SMF \to \langle F_{w,0}, F_{w,1}, F_{w,2}, \ldots \rangle,$$

where each window is indexed by an integer $j \in \mathbb{N}$, and the induced measurement field is

$$F_{w,j} = \{\, m \in S \mid t_m \in I_j \,\} \quad \textit{where} \quad I_j = [t_0 + jk, t_0 + jk + i).$$

Temporal window configurations include tumbling (non-overlapping), sliding (overlapping), and hopping (gapped), and provide a mechanism for temporal reasoning.

3.3 Defining a Core Analysis Task Set

3.3.1 Rationale

The construction of a core analysis task set begins by synthesizing insights from several established analytical traditions that address different aspects of spatiotemporal reasoning [39, 37, 11, 4, 23]. These traditions include field-based analysis in GIS, dimensional perspectives on geographic information, spatiotemporal data models, relational algebra, and stream processing semantics [39, 19, 15, 6]. Established mechanisms appear under different names such as map, combine, and reduce, but they reflect similar forms of analytical intent rooted in the fundamental relationships between what, where, and when [37, 8, 19]. The synthesis makes explicit that the underlying assumptions of these frameworks are not uniform [37, 4, 15]. Retrospective GIS and spatiotemporal models typically assume access to unrestricted history, with time series as prevalent model [37, 15]. Stream processing models instead assume unbounded data and forward-only evaluation [4, 23].

1. One common behavior is the *restriction* of analytical scope. Analysis is often limited to a subset of space, a bounded temporal interval, or a subset of values satisfying a specific condition [39, 11]. This behavior focuses attention on a relevant portion of the phenomenon, without altering the underlying structure of the observations [26, 23].
2. A second recurring behavior is the organization of data into *finite units* of analysis. Continuous phenomena are frequently partitioned into spatial regions, temporal intervals, or value-based categories to make analysis tractable [19, 37].
3. A third behavior is the *summarization* of values within units of analysis. Aggregation operations compute statistics, indicators, or descriptive measures that characterize the phenomenon within each unit [1, 12]. This allows reasoning about local variation while reducing data volume through operations like zonal statistics or global means [41, 26].
4. A fourth recurring behavior is the *transformation* of measurements or fields to derive new representations. Transformations may map values to different units, normalize measurements, or apply functional mappings [8, 41]. Spatially and temporally, transformation allows representation under different projections or encodings.
5. A fifth behavior is the *correlation* or joining of multiple phenomena to examine their interactions. This behavior enables joint reasoning over distinct fields [4, 46].

6. A sixth recurring behavior is the recognition of *patterns*, events, or complex trajectories from the underlying field. This involves extracting discrete episodes with definite beginnings and ends.
7. A seventh recurring behavior is *numeric* derivation which employs basic mathematical primitives such as sum, difference, product, and ratio to compute a new value per unit of observation. These numeric operators are essential for transforming representation of a phenomena or establishing a mathematical relationship between two or more phenomena [41, 8, 19].
8. A final behavior is *neighborhood reasoning*, where the value at a given location is computed based on the context of its spatial or temporal surroundings [41, 26]. These focal operations characterize neighborhood structure, calculate gradients, or estimate distance decay effects within the field [41, 19].

Behaviors that require unrestricted access to the temporal extent of the data are excluded [15, 23]. Analyses that depend on future observations, global temporal segmentation, or the repeated traversal of historical data cannot be evaluated incrementally in stream processing [5, 23, 6, 23]. Furthermore, blocking operators such as sorting or global aggregation are inadmissible because they are unable to produce any output until an infinite stream has reached its end [6, 4, 7].

3.3.2 The Core Task Set

Applying unifying analytics of S-SF along data dimensions with streams yields a set of analytical operator classes that recur across spatial, temporal, relational, and streaming traditions and remain well-defined under forward-only evaluation and bounded state [4, 23, 46]. Each operator class represents a distinct mode of analytical intent that cannot be removed without reducing expressive capacity under stream semantics. We distinguish two families of operator classes (see Table 1):

Representation-Level Operators

Representation-Level Operator classes modify how a phenomenon is expressed. The ***Interpolate*** operator class estimates values at unsampled locations or times to produce a more continuous representation of the underlying scalar field. While interpolation may enable subsequent analysis, it primarily refines representation rather than collapsing dimensions or extracting summary descriptors. The Interpolate operator class has a function specification such as Kriging or Inverse Distance Weighting. The ***Transform*** class maps measurements to alternative spatial, temporal, or thematic encodings while preserving stream structure. Examples include coordinate projection, unit conversion, normalization, and temporal re-encoding.

Analysis-Level Operators

Analysis-Level Operator classes provide the primary means of deriving new insights from the SMF. Together, these seven task classes provide a minimal and composable vocabulary for reasoning over continuous spatiotemporal scalar fields in real-time environments [15, 8].

- **Decomposition** organizes measurements into finite units of analysis to ensure tractable computation over unbounded streams. Spatially, this corresponds to tessellations or regions; temporally, to windows; and metrically to binning or classification.

- **Restriction** limits analytical scope by selecting subsets of measurements according to spatial extent, temporal context, or value predicates. This preserves the underlying structure of measurements while focusing attention on relevant portions of a phenomenon.
- **Summarization** condenses measurements within units to derive statistics, indicators, or condensed representations. Expressed as zonal operations in map algebra or windowed reductions in stream engines, aggregation supports reasoning about trends and short-term variation [41, 4].
- **Numeric** tasks use primitive arithmetic operators on the values of measurements. These operators can be used to make adjustments, compare phenomena, or produce more complex analysis [41, 26].
- **Combination** supports joint reasoning across distinct streamed measurement fields of the same type. This includes spatial overlays and time-aware joins operating over synchronized windows to maintain semantic validity.

Table 1 Operator classes organized by analytical dimension and semantic level.

Operator	**Space** (L)	**Time** (T)	**Value/Theme** (V)
Representation-Level Operators			
Transform	Projection / Translation	Time encoding	Unit conversion
Interpolate	Fill missing locations	Fill missing instants	Fill missing values
Analysis-Level Operators			
Decompose	Spatial units	Window relative to T_{now}	Value classes
Restrict	Subset by spatial region	Measurements at T_{now}	Filter by value predicate
Numeric	Spatially identity	Temporal identity	Mathematical primitives
Summarize	Convex hull	Utilize windows	Metric statistics
Combine	Spatial membership	Synchronized instants	Metric membership

4 Operators

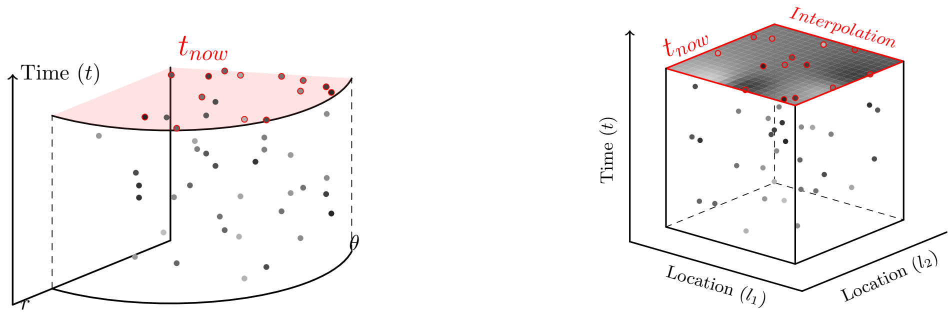
In this section we define the operator classes and their signatures, and examine whether and how they specialize by dimension. Figure 1a illustrates the base SMF upon which the operators act. Overall, we distinguish analytical operators, which extract new insight, and representation-level operators, which modify how the phenomenon is encoded or presented.

4.1 Representation-Level Operators

Representation-level operators often work directly on the measurement streams that constitute a SMF, for instance transform. Interpolation is also included since it produces continuous representations based on the raw measurements.

4.1.1 Transformation

Transformation (Figure 2a) is a measurement-level operator mapping one SMF to another while preserving its dimensional structure. It modifies the representation of space, time, or value without altering stream semantics. Let $\Delta : (T \times L \times V) \to (T' \times L' \times V')$ be a measurement-wise transformation. The operator has type: $\mathsf{Transform}_\Delta : SMF \to SMF'$.



(a) Spatial Transformation. **(b)** Interpolation of SMF.

Figure 2 Examples of Representation-Level Operators.

4.1.1.1 Transformation by Dimension

Transformation modifies representation along a chosen dimension while preserving stream structure. Spatial transformation re-expresses locations in an alternative coordinate system (e.g., map projection). Temporal transformation changes how timestamps are encoded or displayed (e.g., calendar time to UNIX time) without altering stream progression relative to t_{now}. Thematic transformation re-expresses measurement values through unit conversion, normalization, or reclassification (e.g., Fahrenheit to Celsius). In all cases, the underlying spatiotemporal structure of the SMF is preserved; only the representation of individual SMF measurements are modified.

4.1.1.2 Example of Transformation (Unit Conversion)

For temperature, define $\Delta_V(v) = \frac{5}{9}(v-32)$. Applying $\mathsf{Transform}_{\Delta_V}$ converts all measurements from Fahrenheit to Celsius without altering spatial or temporal dimensions.

4.1.2 Interpolation

Interpolation (Figure 2b) is included because real-time field analysis requires estimation at unsampled locations or times. Steenbergen et al. [40] frame interpolation as deriving fields from measures, and Whittier et al. [42] show how such fields can be computed on-the-fly from real-time sensor observations. We therefore treat interpolation as a representation-level operator class that estimates values at target spacetime coordinates to produce a discretized representation of an underlying continuous scalar field.

Let F_w be a finite measurement field induced by a bounded window, and let $Q \subseteq L \times T$ be a set of target spacetime coordinates. An interpolation method κ, such as Inverse Distance Weighting (IDW) or Kriging, has type $I_\kappa : F_w \times Q \to F'_w$.

The output F'_w contains derived measurements at the target coordinates in Q, while preserving the property and domain of the input field. Spatial interpolation estimates values at unsampled locations, temporal interpolation estimates values at intermediate time instants, and spatiotemporal interpolation estimates values over target coordinates in $L \times T$. We do not define value-space interpolation as a separate scalar-field operator because scalar values are measures rather than controls.

4.1.2.1 Example of Spatial Interpolation (IDW)

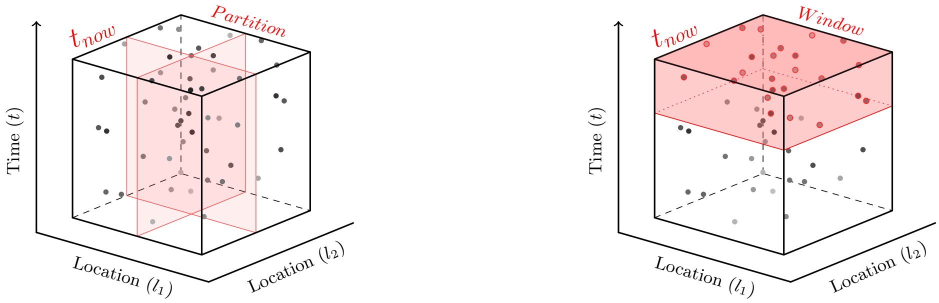
Let $v(l_i, t)$ be observed measurements. For an unsampled location l^*:

$$\hat{v}(l^*, t) = \frac{\sum_i w_i v(l_i, t)}{\sum_i w_i}, \quad w_i = \frac{1}{d(l^*, l_i)^p}.$$

Applying $\mathsf{Interpolate}_{\mathrm{IDW}}$ estimates values at unsampled spatial locations while preserving temporal and thematic dimensions.

4.2 Analysis-Level Operators

4.2.1 Decomposition



(a) Spatial Partitioning of SMF. **(b)** (Temporal) Window on SMF.

Figure 3 Decomposition Operators on SMF.

Decomposition organizes an SMF into evaluation units along a chosen data dimension. Let $D \in \{L, V, T\}$ denote a dimension (space, theme, or time), and let X_D be a decomposition specification over that dimension. Then: $\mathsf{Decompose}_D : SMF \times X_D \to \{F\}$, where $\{F\}$ is a collection of derived fields whose structure depends on D. Decomposition along spatial or metric dimensions produces streamed sub-SMFs. Decomposition along the temporal dimension produces finite Measurement Fields.

4.2.1.1 Spatial and Thematic Decomposition

When $D \in \{L, V\}$, decomposition divides the SMF into sub-SMFs according to a spatial tessellation (Figure 3a) or metric classification. Each sub-SMF remains an unbounded SMF evolving relative to t_{now}.

4.2.1.2 Temporal Decomposition (Windowing)

When $D = T$, decomposition is realized through windowing (Figure 3b). A window specification W defines bounded temporal intervals relative to t_{now}.

$$\mathsf{Decompose}_T \equiv \mathsf{Window} : SMF \times W \to \{F\}$$

The resulting F is a set of finite Measurement Fields. Each contains measurements whose timestamps fall within the window interval. If the decomposition specification induces pairwise disjoint and complete coverage of the parent SMF, the result satisfies classical partition properties. Windowing does not necessarily satisfy partition properties as hopping windows may leave gaps, and sliding windows may overlap.

4.2.1.3 Example of Decomposition

Consider an SMF representing air quality across the state of Maine. A spatial partition by county yields a collection of sub-SMFs, each representing air quality measurements restricted to a single county. Alternatively, applying a tumbling window with a duration of one day yields a finite Measurement Field containing measurements from the most recent complete 24-hour interval.

4.2.2 Restriction

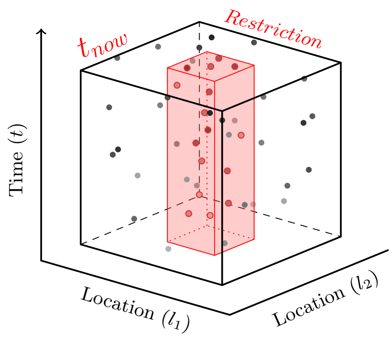


Figure 4 Spatial Restriction of SMF.

Restriction (Figure 4) limits the scope of an SMF by retaining only those measurements that satisfy a predicate. Restriction operates point-wise on measurements and preserves stream structure. Let σ be a predicate over individual measurements, parameterized by a dimension $D \in \{L, V, T\}$. Then:

$\mathsf{Restrict}_\sigma : SMF \times \sigma \rightarrow SMF$

Restriction can express point-wise temporal predicates (e.g., $v \geq 0$). However, interval-based temporal conditions defined relative to t_{now} (e.g., “last 5 minutes”) require access to a bounded history and are therefore expressed via the *Window* operator introduced in the Decomposition section.

4.2.2.1 Example of Restriction

Consider an SMF representing temperature across the state of Maine. Let L_{York} denote the boundary of York County. Define the spatial predicate $\sigma_{York}(t, l, v) \equiv (l \in L_{York})$. Applying $\mathsf{Restrict}_{\sigma_{York}}$ yields an SMF containing only temperature measurements located within York County.

4.2.3 Combination

Combination operators (Figure 5) complement Decomposition and Restriction. While Decomposition separates an SMF along a chosen dimension and Restriction selects measurements satisfying predicates, Combination reconstitutes or relates compatible SMFs using binary set-theoretic operations. Together, these operators form a system for dividing, filtering, and recombining SMFs. Combination operates point-wise over time and produces a new SMF′ composed only of measurements already present in the operands. The general signature is:

$\mathsf{Combine}_\circ : SMF \times SMF \rightarrow SMF,$

where $\circ \in \{\cup, \cap, \setminus, \triangle\}$ denotes *union, intersection, difference*, or *symmetric difference*. Let SMF_A and SMF_B induce measurement sets M_A and M_B at time t_{now}. Each combination operator defines the resulting measurement set as $M' = M_A \circ M_B$.

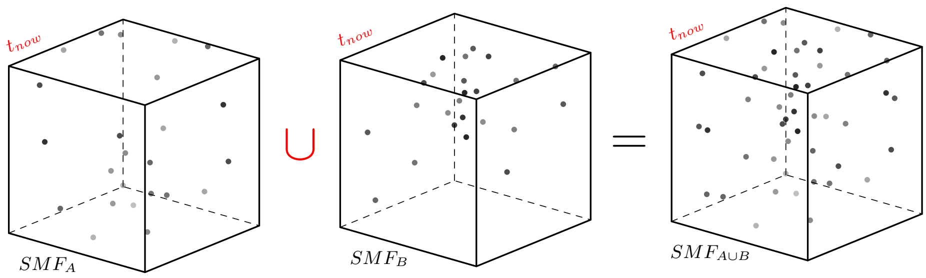


Figure 5 Union of two compatible SMFs.

These operators preserve stream structure and do not generate new measurements. Instead, they reorganize or select from existing measurements at each time index. Combination requires dimensional compatibility such that the two SMFs must share identical thematic definitions, compatible spatial reference systems, and synchronized temporal indices. If encodings differ (e.g., Celsius vs. Fahrenheit), a Transformation must be applied prior to combination. Combination is defined only for compatible theme and domain. If two SMFs contain competing values for the same property at the same location and time, the result is undefined until the conflict is reconciled through transformation, interpolation, summarization, or an application-specific rule.

4.2.3.1 Example of SMF Union

Let SMF_A represent air quality measurements in Orono, Maine, and SMF_B represent air quality measurements in Old Town, Maine. The union $SMF_A \cup SMF_B$ yields a new SMF representing air quality across both locations, preserving the temporal stream structure.

4.2.4 Numeric

Numeric operators derive new SMFs by applying primitive mathematical operations to values from an input SMF and a second operand. The second operand may be (i) another SMF, (ii) a static measurement field F (for example a historical snapshot), or (iii) a scalar constant. Numeric preserves stream progression and yields an SMF' whose measurements share the spatial and temporal identity of the left operand. Let $\circ \in \{+, -, \times, /\}$ denote a primitive numeric operator. We define the numeric operator class as:

$$\mathsf{Numeric}_\circ : SMF \times B \to SMF, \quad B \in \{SMF, F, \mathbb{R}\}.$$

At each time instant t_{now}, the left operand induces a measurement field $F_A(t_{now})$ and the right operand B induces a compatible value source. The base-case semantics assume one-to-one alignment by space-time identity. Thus, Numeric is defined for operands whose controls are aligned over $L \times T$. When supports differ, alignment must be established first through windowing, transformation, or interpolation. Formally, let $m_A = ((l,t), Z, v_A)$ be a measurement in the induced field of the left operand at t_{now}. If the right operand provides a corresponding value v_B for the same spacetime identity (l,t), or if the right operand is a scalar constant, $c \in \mathbb{R}$, then the resulting measurement is:

$$m' = \big((l,t), Z, v_A \circ v_B\big) \quad \text{or} \quad m' = \big((l,t), Z, v_A \circ c\big).$$

If no corresponding value exists in the right operand under identity alignment, the result at that spacetime identity is undefined and may be treated as missing. Missing data may be estimated using previously described interpolation. Note that in addition to local atomic operators, the Map Algebra uses focal, zonal, and global operators. In our framework, these may be approximated with decomposition and summarization such that the units of analysis within the operands are now regions rather than strictly atomic.

4.2.4.1 Example of Numeric between co-located SMFs

Let SMF_T be a temperature stream and SMF_H be a humidity stream produced by co-located sensors that report at identical spacetime coordinates. Define a numerical function ψ_{HI} that maps a temperature value and a humidity value to a heat-index value. The derived streamed field is:

$$SMF_{HI} = \mathsf{Numeric}_{\psi_{HI}}(SMF_{Temp}, SMF_{Hum}).$$

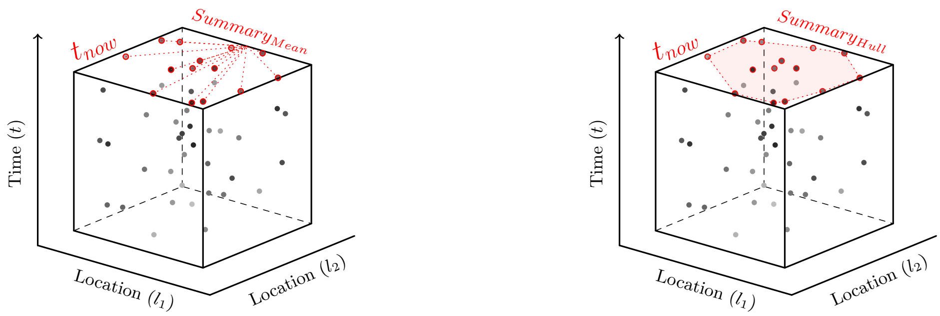
For each aligned pair of co-located and synchronized measurements

$$m_T = ((l,t), Z_{Temp}, v_{Temp}) \quad \text{and} \quad m_H = ((l,t), Z_{Hum}, v_{Hum}),$$

the resulting heat-index measurement is:

$$m_{HI} = \big((l,t), Z_{HI}, \psi_{HI}(v_{Temp}, v_{Hum})\big).$$

4.2.5 Summarization



(a) Metric Summary via Mean.

(b) Spatial Summary via Hull.

Figure 6 Summarization Operators.

Summarization collapses one or more dimensions of an SMF into a derived result that no longer retains the SMF structure. Let F_w be a finite measurement field and let ϕ specify the summary function and the dimensions to be collapsed. The operator has type

$$\mathsf{Summarize}_\phi : F_w \to R_\phi,$$

where R_ϕ is the result type determined by ϕ. For example, R_ϕ may be a scalar statistic, a time-indexed statistic, a region-indexed statistic, a geometry, or a structural descriptor. Summarization operates over the induced measurement field $F_{t_{now}}$, producing an aggregate, condensed, or geometric characterization of the measurements.

Value summarization collapses the metric dimension while retaining spatial or temporal context, yielding statistics such as mean(v), max(v), min(v), sum(v), or var(v) (Figure 6a). Location summarization collapses the spatial dimension, producing a set of locations satisfying a condition or a derived geometry such as a bounding box, convex hull, or alpha shape (Figure 6b).

Summarization may also collapse multiple dimensions jointly. Multidimensional summaries characterize relationships among values and their spatial or temporal configuration. Examples include spatial autocorrelation statistics such as Moran's I or Geary's C, which summarize similarity as a function of spatial proximity, and regression or spatiotemporal trend estimators that jointly summarize L, T, and V. In these cases, the result is a structural descriptor rather than a reduced subset of measurements.

4.2.5.1 Example of Summarization

Summarizing an SMF representing rainfall where $v > 50\,\text{mm}$ may yield a bounding region describing the spatial extent of heavy precipitation. This is distinct from restricting an SMF using an equivalent predicate which would preserve the structure and additional information within the SMF. Here we are collapsing the SMF to return locations.

4.3 Query Composition

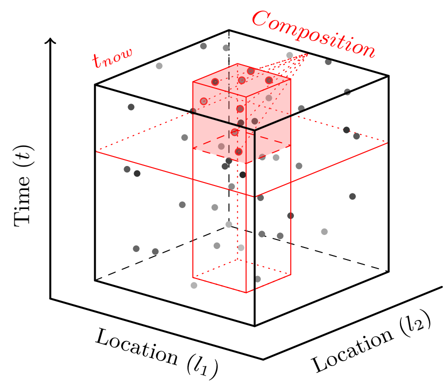


Figure 7 Workflow composition of Restriction, Windowing, and Summarization.

Query composition defines analytical workflows through the chaining of the operators. No new primitives are introduced; expressive power arises from combining the existing operator classes into executable pipelines under real-time constraints. Figure 7 illustrates a typical workflow:

$$\mathsf{Summarize}\big(\mathsf{Window}(\mathsf{Restrict}(SMF))\big).$$

In this example, the input SMF flows through three stages. First, *Restriction* reduces the spatial scope of the stream. Second, *Window* establishes a bounded temporal evaluation context. Finally, *Summarization* derives an aggregate descriptor from the finite measurement field produced by the window. The resulting output is the mean value of measurements within the selected region over the most recent complete window.

Composition therefore describes a directed evaluation workflow in which data are progressively transformed from streamed structure to bounded context to derived result. Operator ordering is governed by signature compatibility. In this workflow,

$$\mathsf{Restrict}_\sigma : SMF \to SMF, \quad \mathsf{Window}_{i,k} : SMF \to \{F_w\}, \quad \mathsf{Summarize}_\phi : F_w \to R_\phi.$$

Here, $\{F_w\}$ denotes the collection of finite measurement fields induced by the window specification, and each $F_w \in \{F_w\}$ may be passed to $\mathsf{Summarize}_\phi$.

Because $\mathsf{Summarize}_\phi$ collapses dimensional structure and produces a derived result rather than an SMF, it terminates the workflow. Execution order is thus determined by type compatibility and evaluation context.

5 Discussion

In this section, we validate our proposed operator set by comparing it against the requirements analysis in Section 3.3.1. Further, we also discuss some of its limitations.

5.1 Validation

We validate our analysis operator framework using two criteria: (i) *analytical expressiveness*, meaning systematic coverage of the recurring analytical behaviors for streamed spatiotemporal scalar fields identified in Section 3.3.1; and (ii) *minimality*, meaning that no operator class can be removed without losing essential analytical capability under forward-only evaluation and bounded state.

5.1.1 Analytical Expressiveness

Analytical expressiveness is established by explicitly matching each analytical behavior from Section 3.3.1 to either (a) a direct operator class defined in Section 4, or (b) a workflow expressed as a composition of the defined operator classes. The workflow patterns reuse the signatures and composition principles already introduced in Section 4 and Figure 7.

Behavior 1. The restriction of analytical scope is directly supported via the ***Restriction*** operator class. Spatial, temporal, and metric restriction are expressed as point-wise predicates over measurements (Section 4). Temporal restriction defined as an interval relative to t_{now} is realized as temporal decomposition through windowing (Behavior 2).

Behavior 2. The construction of finite evaluation units is directly supported through the ***Decomposition*** operator class. Spatial and thematic decomposition induce evaluation units such as regions, tessellations, or value classes, enabling tractable computation over unbounded streams. Temporal decomposition is realized through windowing, which bounds state relative to t_{now}: $\mathsf{Decompose}_T \equiv \mathsf{Window} : SMF \times W \to \{F\}$.

Behavior 3. The summarization of data can be interpreted globally or within units. Globally, this behavior is supported directly via the ***Summarization*** operator class. When summarization is to occur within sub-units of analysis, this behavior is supported through the composition of ***Summarization*** with ***Restriction*** or ***Decomposition***. For example, if we want to determine the mean temperature in Orono, Maine over the last hour every thirty minutes, we can compose a workflow utilizing behaviors 1, 2, and 3 as follows:

$$Temperature = \mathsf{Summarize}_{Mean}\Big(\mathsf{Decompose}_{T_{(60,30)}}\big(\mathsf{Restrict}_{L_{Orono}}(SMF)\big)\Big),$$

A single pipeline demonstrating the same task behaves as follows:

$$SMF \to \mathsf{Restrict}_{L_{Orono}} \to \mathsf{Decompose}_{T_{(60,30)}} \to \mathsf{Summarize}_{\mathrm{Mean}} \to Temperature$$

Behavior 4. Transformation of representation is directly supported via the ***Transformation*** operator class. This re-encodes spatial, temporal, or metric representations while preserving stream semantics. Transformation supports both standalone tasks (for representation compatibility) and pre-processing steps that enable downstream combination and comparison.

Behavior 5. Correlation between phenomena is expressed as a composition of ***Numeric*** and ***Summarization*** operators. Numeric operators construct derived and product fields, which are then aggregated within a bounded evaluation context. For two aligned streamed fields SMF_A and SMF_B, covariance may be expressed as:

$$\begin{tikzcd}
SMF_A \arrow[r] \arrow[dr] & \mathsf{Summarize}_{\mathrm{Mean}} \arrow[r] & SMF_{\bar{A}} \arrow[dl] \\
& \mathsf{Numeric}_{\mathrm{Minus}} \arrow[r] & SMF_{A'} \arrow[dr] \\
& & & \mathsf{Numeric}_{\mathrm{Covariance}} \arrow[r] & R \\
& \mathsf{Numeric}_{\mathrm{Minus}} \arrow[r] & SMF_{B'} \arrow[ur] \\
SMF_B \arrow[r] \arrow[ur] & \mathsf{Summarize}_{\mathrm{Mean}} \arrow[r] & SMF_{\bar{B}} \arrow[ul]
\end{tikzcd}$$

Numeric provides the step that constructs interaction fields, while summarization performs bounded statistical aggregation. No additional primitive is required.

Behavior 6. Pattern and event recognition are expressed by a composition of ***Numeric*** and ***Summarization*** over bounded contexts. A threshold-based detector may be expressed as: $R = \mathsf{Summarize}_{\mathrm{DETECT}}\Big(\mathsf{Window}_W\big(\mathsf{Numeric}_\psi(SMF)\big)\Big)$, where ψ constructs binary or deviation fields prior to aggregation. Stream-feasibility is preserved through windowing.

Behavior 7. Numeric derivation of new fields is directly supported through ***Numeric***. This enables construction of derived fields such as difference fields, ratios, anomaly streams, interaction terms, and composite indicators.

Behavior 8. Neighborhood reasoning is expressed through a composition of spatial ***Decomposition*** followed by ***Numeric*** or ***Summarization***. Numeric may construct gradients or difference fields prior to summarization, enabling focal-style reasoning without introducing a dedicated neighborhood primitive.

5.1.2 Minimality of the Operator Set

Minimality is established at the level of operator classes under streamed constraints. An operator class is minimal if removing it eliminates expressiveness that cannot be reconstructed from the remaining classes without violating (i) bounded state, (ii) forward-only evaluation, or (iii) type preservation over the SMF. First we distinguish related operator classes.

Both *Restriction* and *Decomposition* operators limit analytical scope, but they do so with different type effects. *Restriction* preserves stream structure ($SMF \to SMF$) while applying predicates over time, location, or value. It reduces the count of $m \in SMF$ but still yields a SMF. *Decomposition*, by contrast, constructs a collection of sub-SMFs or sets of finite Measurement Fields from unbounded streams ($SMF \rightarrow \{SMF\}$ or $\{F\}$). Although a decomposition may be implemented as a family of restrictions, it is not reducible to *Restriction* at the operator-class level because it returns $\{SMF\}$ or $\{F\}$ for subsequent analysis. Temporal decomposition, or windowing, is the mechanism that enforces bounded state relative to t_{now}, making rolling indicators well-defined.

Both *Numeric* and *Summarization* operators work over values, but they differ in type effect. *Numeric* operators generate new measurement values while preserving streamed structure ($SMF \rightarrow SMF$). Differences, ratios, anomaly streams, and interaction terms are value-level constructions that remain streams. *Summarization* collapses one or more dimensions to produce analytical descriptors ($SMF \rightarrow$ finite descriptor). Statistics, indicators, and structural measures require dimension reduction.

The remaining classes ensure structural and representational coherence in multi-input workflows. *Combination* enables structural recombination of compatible streamed fields. *Combination* operators reorganize compatible measurement sets. These are distinct operations at the type level. *Transformation* guarantees representational compatibility across spatial, temporal, or thematic encodings. Without it, semantically equivalent measurements encoded in different coordinate systems or units would be ill-typed under Combination or Numeric operators. *Interpolation* provides alignment under sparse or asynchronous sampling. Without it, multi-input workflows would implicitly assume perfect co-location and synchronization, which exceeds typical streamed measurement conditions. Taken together, these operator families form a minimal operator set: removing any family eliminates a capability that cannot be reconstructed from the others without violating streamed semantics or type discipline.

5.2 Limitations

The framework is deliberately constrained to analyses that remain well-defined under forward-only time and bounded state. Methods requiring unbounded historical access, backward temporal traversal, or end-of-stream knowledge fall outside the scope of stream-based analysis (e.g., full retrospective segmentation or long-horizon discovery over the entire past). Future work may introduce an additional architectural layer that integrates this framework with systems designed for long-term storage and retrospective time-series analysis; however, this paper focuses specifically on real-time stream processing over continuously evolving fields. The framework also distinguishes analysis from presentation and restructuring: operations such as pivoting, reshaping, or report-oriented schema transformations are important for visualization and communication, but they are not treated as core analytical tasks over continuous spatiotemporal phenomena. Object tracking, trajectory mining, geometric event streams, and human-sensed spatiotextual streams are adjacent geostreaming problems, but they fall outside this paper's scalar-field scope.

6 Related Work

In this paper, we have proposed a novel operator set that follows two criteria: it supports analysis of continuous spatiotemporal phenomena and it supports the computational rigor of stream processing.

Steenbergen et al. [40] define transformations among core geographic concept types such as objects, fields, networks, and events. For fields, the focus of this article, which they model conceptually as relations between locations and measured qualities, they introduce representation-level operators such as interpolate for estimating a continuous field from point-wise samples, and invert or revert for switching between functional fields and coverage-based structures like contours. They also formalize field-level derivations, summaries and secondary fields. Spatiotemporal reasoning is not considered.

Decades ago, Map Algebra introduced the influential operator framework of local, focal, and zonal functions for deriving and summarizing fields through composition [41]. Cubic Map Algebra extended these ideas into spacetime [26]. Spatiotemporal algebras generalized field-based reasoning across additional dimensional configurations and transformations [15, 8]. These approaches make important contributions to the analysis of continuous phenomena and support fine-grained spatial and temporal reasoning. However, they generally assume materialized datasets in which time is retrospectively traversable, enabling global analysis over stored data. They therefore do not directly address forward-only evaluation, bounded memory, or window semantics characteristic of stream processing. The SMF occupies a restricted Sinton configuration in which space and time control a measured scalar theme, but adds stream-time semantics to this scalar-field setting. Within each window, the SMF supports the same kind of spatiotemporal field reasoning addressed by these prior algebras, while extending it to continuously arriving measurements under bounded-state streaming constraints.

By contrast, DSEs support low-latency processing of massive amounts of measurements and have introduced windowing, incremental aggregation and basic operators [5, 6]. Spatially enabled DSEs add spatial filtering over streams of spatial objects [44]. This work supports moving objects, spatial predicates, and vector geometries over streams [27, 21, 16, 44, 10]. Yet these systems operate over collections of low-level geometries and do not support higher-level abstractions such as fields or analytical operators for them.

Closest to our scope are approaches that treat sensor streams as observations of continuous phenomena, including window queries over continuous phenomena [42], phenomena-aware stream processing [3] and streamed field data types [24]. [43, 25, 3] focus on high-throughput query processing rather than a compact field-level operator vocabulary and proposed real-time algorithms for specific spatiotemporal field operations, such as interpolation or update propagation over high-volume streams [1, 23, 21, 25]. [24] introduced a higher-level abstraction for streamed fields that rely on the relational data model; however, it does not include analysis operators.

7 Conclusions and Future Work

This paper introduced a novel operator set for the analysis of stream-based spatiotemporal fields. While continuous geospatial phenomena are increasingly observed through dense, real-time measurement streams from geosensor networks and IoT platforms, data stream engines provide low-latency processing over unbounded streams, but they lack higher-level abstractions for spatially continuous phenomena. Our proposed analytics operator framework for streamed scalar fields builds on compact operator sets and dimensional reasoning over space, time, and theme. The resulting framework provides a systematic basis for describing and implementing extensible stream-based, real-time field analytics. Future work includes establishing the algebraic properties of these primitive operators for analyzing real-time continuous phenomena and implementing this design with a live geosensor network.

References

1 Md Mahbub Alam, Luis Torgo, and Albert Bifet. A survey on spatio-temporal data analytics systems. *ACM Comput. Surv.*, 54(10s), November 2022. doi:10.1145/3507904.

2 M. H. Ali, Mohamed F. Mokbel, and Walid G. Aref. Phenomenon-aware stream query processing. In *2007 International Conference on Mobile Data Management*, pages 8–15, 2007. doi:10.1109/MDM.2007.11.

3 Mohamed H. Ali. *Phenomenon-aware Data Stream Management Systems*. Phd dissertation, Purdue University, 2007. Accessed: 2026-05-27. URL: https://faculty.washington.edu/mhali/Publications/documents/ali_dissertation.pdf.

4 Arvind Arasu, Shivnath Babu, and Jennifer Widom. The cql continuous query language: semantic foundations and query execution. *The VLDB Journal*, 15(2):121–142, June 2006. doi:10.1007/s00778-004-0147-z.

5 Arvind Arasu and Jennifer Widom. A denotational semantics for continuous queries over streams and relations. *SIGMOD Rec.*, 33(3):6–11, September 2004. doi:10.1145/1031570.1031572.

6 Brian Babcock, Shivnath Babu, Mayur Datar, Rajeev Motwani, and Jennifer Widom. Models and issues in data stream systems. In *Proceedings of the Twenty-First ACM SIGMOD-SIGACT-SIGART Symposium on Principles of Database Systems*, PODS '02, pages 1–16, New York, NY, USA, 2002. Association for Computing Machinery. doi:10.1145/543613.543615.

7 Shivnath Babu and Jennifer Widom. Continuous queries over data streams. *SIGMOD Rec.*, 30(3):109–120, September 2001. doi:10.1145/603867.603884.

8 Gilberto Camara, Max J. Egenhofer, Karine Ferreira, Pedro Andrade, Gilberto Queiroz, Alber Sanchez, Jim Jones, and Lubia Vinhas. Fields as a generic data type for big spatial data. In Matt Duckham, Edzer Pebesma, Kathleen Stewart, and Andrew U. Frank, editors, *Geographic Information Science*, pages 159–172, Cham, 2014. Springer International Publishing. doi:10.1007/978-3-319-11593-1_11.

9 Donald D. Chamberlin and Raymond F. Boyce. Sequel: A structured english query language. In *Proceedings of the 1974 ACM SIGFIDET (Now SIGMOD) Workshop on Data Description, Access and Control*, SIGFIDET '74, pages 249–264, New York, NY, USA, 1974. Association for Computing Machinery. doi:10.1145/800296.811515.

10 Sirish Chandrasekaran, Owen Cooper, Amol Deshpande, Michael J. Franklin, Joseph M. Hellerstein, Wei Hong, Sailesh Krishnamurthy, Samuel R. Madden, Fred Reiss, and Mehul A. Shah. Telegraphcq: continuous dataflow processing. In *Proceedings of the 2003 ACM SIGMOD International Conference on Management of Data*, SIGMOD '03, page 668, New York, NY, USA, 2003. Association for Computing Machinery. doi:10.1145/872757.872857.

11 E. F. Codd. A relational model of data for large shared data banks. *Commun. ACM*, 13(6):377–387, June 1970. doi:10.1145/362384.362685.

12 George Colliat. Olap, relational, and multidimensional database systems. *SIGMOD Rec.*, 25(3):64–69, September 1996. doi:10.1145/234889.234901.

13 Open Geospatial Consortium. OGC API – Styles – Part 1: Core. OGC Draft Standard 19-087, Open Geospatial Consortium, 2019. Accessed 2026-05-27. URL: https://docs.ogc.org/DRAFTS/19-087.html.

14 Elias Dritsas and Maria Trigka. Remote sensing and geospatial analysis in the big data era: A survey. *Remote Sensing*, 17(3), 2025. doi:10.3390/rs17030550.

15 Karine Reis Ferreira, Gilberto Camara, and Antônio Miguel Vieira Monteiro. An algebra for spatiotemporal data: From observations to events. *Transactions in GIS*, 18(2):253–269, 2014. doi:10.1111/tgis.12030.

16 Z. Galić, M. Baranović, K. Križanović, and E. Mešković. Geospatial data streams: Formal framework and implementation. *Data and Knowledge Engineering*, 91:1–16, 2014. doi:10.1016/j.datak.2014.02.002.

17 Antony Galton. A formal theory of objects and fields. In *Proceedings of the International Conference on Spatial Information Theory: Foundations of Geographic Information Science*, COSIT 2001, pages 458–473, Berlin, Heidelberg, 2001. Springer-Verlag. doi:10.5555/646128.681085.

18 Antony Galton. Fields and objects in space, time, and space-time. *Spatial Cognition & Computation*, 4(1):39–68, 2004. doi:10.1207/s15427633scc0401_4.

19 Michael F. Goodchild, May Yuan, and Thomas J. Cova. Towards a general theory of geographic representation in gis. *Int. J. Geogr. Inf. Sci.*, 21(3):239–260, January 2007. doi:10.1080/13658810600965271.

20 Leila Hashemi Beni, Mir Abolfazl Mostafavi, Jacynthe Pouliot, and Marina Gavrilova. Toward 3d spatial dynamic field simulation within gis using kinetic voronoi diagram and delaunay tetrahedralization. *Int. J. Geogr. Inf. Sci.*, 25(1):25–50, February 2011. doi:10.1080/13658811003601430.

21 Seyed Jalal Kazemitabar, Ugur Demiryurek, Mohamed Ali, Afsin Akdogan, and Cyrus Shahabi. Geospatial stream query processing using microsoft sql server streaminsight. *Proc. VLDB Endow.*, 3(1–2):1537–1540, September 2010. doi:10.14778/1920841.1921032.

22 Karen K Kemp and Andrej Vckovsky. Towards an ontology of fields. In *International Conference on GeoComputation*, 1998. URL: https://www.geocomputation.org/1998/index.html.

23 Wenwen Li, Yan Liu, and Sizhe Wang. Real-time gis programming and geocomputation. *Geographic Information Science & Technology Body of Knowledge*, 2022, January 2022. doi:10.31223/X5CF22.

24 Qinghan Liang, Silvia Nittel, and Torsten Hahmann. From data streams to fields: Extending stream data models with field data types. In Jennifer A. Miller, David O'Sullivan, and Nancy Wiegand, editors, *Geographic Information Science*, pages 178–194, Cham, 2016. Springer International Publishing. doi:10.1007/978-3-319-45738-3_12.

25 Qinghan Liang, Silvia Nittel, John C. Whittier, and Sytze de Bruin. Real-time inverse distance weighting interpolation for streaming sensor data. *Transactions in GIS*, 22(5):1179–1204, 2018. doi:10.1111/tgis.12458.

26 Jeremy Mennis, Roland Viger, and C. Tomlin. Cubic map algebra functions for spatio-temporal analysis. *Cartography and Geographic Information Science*, 32:17–32, March 2013. doi:10.1559/1523040053270765.

27 Mohamed Mokbel, Xiaopeng Xiong, Moustafa Hammad, and Walid Aref. Continuous query processing of spatio-temporal data streams in place. *GeoInformatica*, 9:343–365, January 2005. doi:10.1007/s10707-005-4576-7.

28 Rohan Murty, Geoffrey Mainland, Ian Rose, Atanu Roy Chowdhury, Abhimanyu Gosain, Josh Bers, and Matt Welsh. Citysense: An urban-scale wireless sensor network and testbed. In *2008 IEEE Conference on Technologies for Homeland Security*, pages 583–588, June 2008. doi:10.1109/THS.2008.4534518.

29 Silvia Nittel. A survey of geosensor networks: Advances in dynamic environmental monitoring. *Sensors*, 9:5664–5678, July 2009. doi:10.3390/s90705664.

30 Silvia Nittel. Real-time sensor data streams. *SIGSPATIAL Special*, 7(2):22–28, September 2015. doi:10.1145/2826686.2826691.

31 Roger Cesarié Ntankouo Njila, Mir Abolfazl Mostafavi, and Jean Brodeur. A decentralized semantic reasoning approach for the detection and representation of continuous spatial dynamic phenomena in wireless sensor networks. *ISPRS International Journal of Geo-Information*, 10(3), 2021. doi:10.3390/ijgi10030182.

32 Ainhoa Osa Sanchez and Begoña Zapirain. Real-time air quality monitoring: A smart iot system using low-cost sensors and 3d printing. *IEEE Journal of Radio Frequency Identification*, PP:1–1, January 2025. doi:10.1109/JRFID.2025.3541816.

33 Yohanes Yohanie Fridelin Panduman, Nobuo Funabiki, Evianita Dewi Fajrianti, Shihao Fang, and Sritrusta Sukaridhoto. A survey of ai techniques in iot applications with use case investigations in the smart environmental monitoring and analytics in real-time iot platform. *Information*, 15(3), 2024. doi:10.3390/info15030153.

34 Jinho Park, Taeyoung Yoo, Seongjae Lee, and Taehyoun Kim. Urban noise analysis and emergency detection system using lightweight end-to-end convolutional neural network. *INTERNATIONAL JOURNAL OF COMPUTERS COMMUNICATIONS & CONTROL*, 18, August 2023. doi:10.15837/ijccc.2023.5.5814.

35 JJ Paul and Silvia Nittel. The streamed measurement field model: Supporting real-time geospatial analysis of continuous phenomena using streams. *Under Review*, 2026.

36 Loïc Petit, Cyril Labbé, and Claudia Lucia Roncancio. An algebric window model for data stream management. In *Proceedings of the Ninth ACM International Workshop on Data Engineering for Wireless and Mobile Access*, MobiDE '10, pages 17–24, New York, NY, USA, 2010. Association for Computing Machinery. doi:10.1145/1850822.1850826.

37 Donna J. Peuquet. It's about time: A conceptual framework for the representation of temporal dynamics in geographic information systems. *Annals of the Association of American Geographers*, 84(3):441–461, 1994. doi:10.1111/j.1467-8306.1994.tb01869.x.

38 T. Poston. *Fuzzy geometry*. Phd dissertation, University of Warwick, June 1971. URL: http://webcat.warwick.ac.uk/record=b1733602~S1.

39 David S. Sinton. The inherent structure of information as a constraint to analysis: Mapped thematic data as a case study. *Harvard Papers on Geographic Information Systems*, 6:1–17, 1978.

40 Niels Steenbergen, Eric Top, Enkhbold Nyamsuren, and Simon Scheider. Procedural metadata for geographic information using an algebra of core concept transformations. *Journal of Spatial Information Science*, pages 51–92, December 2023. doi:10.5311/JOSIS.2023.27.268.

41 C. Dana Tomlin. Map algebra: one perspective. *Landscape and Urban Planning*, 30(1):3–12, 1994. Special Issue Landscape Planning: Expanding the Tool Kit. doi:10.1016/0169-2046(94)90063-9.

42 J. C. Whittier, Silvia Nittel, Mark A. Plummer, and Qinghan Liang. Towards window stream queries over continuous phenomena. In *Proceedings of the 4th ACM SIGSPATIAL International Workshop on GeoStreaming*, IWGS '13, pages 2–11, New York, NY, USA, 2013. Association for Computing Machinery. doi:10.1145/2534303.2534305.

43 J.C. Whittier. *Towards an Efficient, Scalable Stream Query Operator Framework for Representing and Analyzing Continuous Spatio-Temporal Fields*. Dissertation, University of Maine, 2018. URL: https://digitalcommons.library.umaine.edu/etd/2927.

44 Jia Yu, Jinxuan Wu, and Mohamed Sarwat. Geospark: a cluster computing framework for processing large-scale spatial data. In *Proceedings of the 23rd SIGSPATIAL International Conference on Advances in Geographic Information Systems*, SIGSPATIAL '15, New York, NY, USA, 2015. Association for Computing Machinery. doi:10.1145/2820783.2820860.

45 Yuanzhen Zhang, Guofang Wang, Lingzhi Li, and Mingjing Huang. A monitoring method for agricultural soil moisture using wireless sensors and the biswas model. *Agriculture (Switzerland)*, 15, February 2025. doi:10.3390/agriculture15030344.

46 Ariane Ziehn, Jan Szlang, Steffen Zeuch, and Volker Markl. Unraveling the impact of window semantics: Optimizing join order for efficient stream processing. In *Proceedings of the VLDB Endowment*, volume 18, pages 2468–2481. VLDB Endowment, 2025. doi:10.14778/3742728.3742741.