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Research Article

Towards a General Field model and its order in GIS

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Geospatial data modelling is dominated by the distinction between continuous-field and discrete-object conceptualizations. However, the boundary between them is not always clear, and the field view is more fundamental in some respects than the object view. By viewing a set of objects as an object field and unifying it with conventional field models, a new concept, the General Field (G-Field) model, is proposed. In this paper, the properties of G-Field models, including domain, range, and categorization, are discussed. As a summary, a descriptive framework for G-Field models is proposed. Then, some common geospatial operations in geographic information systems are reconsidered from the G-Field perspective. The geospatial operations are classified into order-increasing operations and non-order-increasing operations, depending on changes induced in the G-Field's order. Generally, the order can be viewed as an indicator of the level of information extraction of geospatial data. It is thus possible to integrate the concept of order with a geo-workflow management system to support geographic semantics.

Keywords: General Field model; Order of General Field; Order-increasing operation; Non-order-increasing operation; Geographic information system

1. Introduction

Continuous-field and discrete-object conceptualizations constitute the foundation of geospatial data modelling at the conceptual level of abstraction (Couclelis 1992, Goodchild 1992, Burrough and McDonnell 1998, Worboys and Duckham 2004). The field view regards the real world continuously, providing answers to queries of the form 'What is there?', while the object view abstracts the real world discretely and can readily identify the location of a given object (Vckovski 1998). Despite these differences, Cova and Goodchild (2002) demonstrated that field and object concepts can coexist, while Câmara *et al.* (2000) presented a unified object-based framework for object and field models in terms of their operations. From an ontological point of view, Peuquet *et al.* (1998) proposed four conceptual models of geographic space: plenum, categorical coverage, hard partition, and object (or entity). The same

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phenomenon can be modelled using any of these four approaches, and the boundaries among them are thus not clear. Generally, the first one is field-like, while the last one is more object-like. Kjenstad (2006) presented the Parameterized Geographic Object Model (PGOModel) using UML (Unified Modelling Language) to integrate object-based and field-based models in a Geographic Information System (GIS). Although the PGOModel focuses on abstraction at the conceptual level, it provides a promising solution leading to a unified GIS beyond field and object models, as well as raster and vector data. Finally, Goodchild *et al.* (2007) showed that both field and object conceptualizations can be derived from a single fundamental construct, termed the geo-atom.

We believe that the field view is more fundamental than the object view for two reasons. First, since physical reality (tier-zero ontology) can be seen as a four-dimensional field (Frank 2001), and is captured as such in imaging systems, the field view of the real world (where its attributes vary continuously over space) represents a stage prior to the identification of discrete features that has been termed *pre-ontological* (this term implies a rather narrow definition of ontology; pre-feature might be preferable) (Harding 2002). Different aspects of geographic space are measured, a series of fields are established, and then corresponding geographic objects are conceptualized based on those fields (e.g. buildings). For example, built-up areas are identified from a land-use/land-cover field. Identification of objects in the real world gives them ontologies in the sense of Harding (2002). Fonseca *et al.* (2000) summarized issues such as bona fide and fiat objects, boundaries, and mereotopology in top-level ontologies. According to Frank (2001), objects are located at the third tier. It should be noted that the level of granularity of spatial observation or measurement plays an important role during this conceptualization process. For example, one cannot pick out a forest by measuring at the millimetre scale.

Second, a field model can in theory be transformed into an object model by inverting the field function (Shekihar and Chawla 2003). However, calculating the inverse of field functions is extremely difficult. It is thus more practical to deal with fields directly. Therefore, objects could be extracted from a field based on corresponding identification processes, which may be cognitive (Smith and Mark 2003) or mathematical (Shekihar and Chawla 2003). In other words, object models usually have a higher level of abstraction. Hence, for the sake of integrating these two perspectives, a reasonable approach is to combine them at the lower abstraction level, that is, by managing the objects using a special field.

This idea is not wholly new. Galton (2001) proposed formal descriptions for feature and field, and their transformations, and defined the concept of a feature field. As argued by Cova and Goodchild (2002), an object field is a continuous field in which locations are mapped to spatial objects. These two concepts are very similar. However, compared with Galton's definition, the latter is more general.

The purpose of this paper is to extend and clarify these arguments by introducing the concept of a General Field (G-Field). We will show how the conventional field and object-field can both be seen as specialized G-Fields. We will discuss the properties of G-Fields, and focus on an important property that we term the order of a G-Field. The remainder of this paper is organized as follows. In section 2, after a brief review of field models, we discuss the characteristics and classifications of General Field models from three aspects: domains, ranges, and representation methods. Based on the above three aspects, a three-dimensional descriptive framework for G-Fields is developed. Then, ordinary object models, as well as the object-field models proposed by Cova and Goodchild (2002), are discussed and categorized in the context of G-Field models. Since a geospatial data set is an instance of a General Field, all geospatial operations and analyses (e.g. buffer, overlay) are transformations on one or more specific G-Field data sets. Section 3 focuses on these points and defines the order of G-Field data. Geospatial operations are categorized into two classes according to their influence on the change of order. Finally, an example is provided to illustrate the concept of a G-Field and its order. Section 4 presents our conclusions.

2. General Fields

2.1 *Conceptual models and logical models*

In geography or GIScience, geographic space is large-scale space, that is, space that is beyond the human body and that may be represented by many different geometries at many different scales (Egenhofer and Mark 1995). Without considering the temporal component, a geographic space is a subset, which is usually topologically closed, of three-dimensional Euclidean space, that is, three parameters are required to define a position inside it. If temporal measurements are involved, we need one additional dimension. However, geographic space is often abstracted to be two-dimensional for the sake of representation and management in many applications. For example, a country can be viewed as a two-dimensional space. On the other hand, since the limits of a geographic space are defined in practice by a feature (e.g. a bounding box or the limits of a study area), we can employ the topological dimension of this feature, which is mathematically abstracted to a connected topological manifold, as the dimension of the geographic space. According to geometric topology, if a manifold is locally homeomorphic to Euclidean n-space, then n is the number of its dimension. Consequently, a linear feature, for example a river, forms a one-dimensional space.

We can measure a number of properties at every position inside a geographic space, and the mapping between positions and properties can be modelled using a field. There are many fields (e.g. land use and soil) associated with a given geographic space (e.g. a state), but not all may be available or relevant in a given context. A geographic space is therefore a plenum whose geographic features and spatial heterogeneity (Anselin 1989, Goodchild 2004) make geographic research valuable. Obviously, field models provide a straightforward and suitable approach to representing phenomena in a geographic space.

Theoretically, a field can be viewed as a mapping between a locational reference frame and an attribute domain (Worboys and Duckham 2004): $f: x \rightarrow z$, or as a function $z=f(x)$. In a field model, every location in a spatial framework is associated with a set of attributes measured on a variety of scales. Fields are spatially continuous by definition, but such continuity might be induced by the measurement scale (Cova and Goodchild 2002); for example, density estimation transforms discrete individuals into a continuous field using a scale-specific kernel function.

Goodchild argues that all geographic information can be decomposed into point sets or geo-atoms, each geo-atom consisting of a point x in space time and a property-value pair $<Z, z(x)>$, where $z(x)$ is the value of property Z at x (Goodchild *et al.* 1999, 2007, Goodchild 2001). They show how both object and field models can be represented using different aggregation approaches. For an object, the semantics of the constituent geo-atoms in it should meet certain requirements that are formally defined according to the ontologies of the geographic objects (GrenonSmith 2004). However, a field consisting of geo-atoms is not affected by such semantic constraints, that is, it is pre-ontological.

The G-Field model provides a theoretical foundation for unified representations of geospatial data at the conceptual level. However, since the complexity of the real world is infinite while the capacity of a computer system is finite, some proper generalization and discretization processes are necessary to design logic models. There are primarily two approaches to establish and manage such logic models: sampling and interpolation-based field (S&IBF) models and tessellation-based field (TBF) models. These two models were first proposed by Goodchild (1992). Assuming the space is n-dimensional, an S&IBF model is represented by a set of sampling geometries whose topological dimensions vary from 0 to $n-1$, as well as specific interpolation methods; while a TBF model divides the space into a set of subdivisions with the same topological dimension as the space, and where the boundaries between two neighbouring parts can be presented using $(n-1)$-dimensional geometries. Obviously, at this abstraction level, a field is represented based on a series of discrete objects. Hence, there have also been efforts to unify geospatial models in an object-based approach (Nunes 1991, Câmara *et al.* 2000). This approach is not in conflict with the proposed G-Field model, since the latter is defined at the conceptual level, while object-based unified models are at the logic level. In other words, the latter is closer to concrete implementation. By extending the abstraction process of Longley *et al.* (2005), a new diagram considering both field and object models is shown in figure 1. The schema is consistent with the concept of a G-Field, as well as the arguments presented by Câmara *et al.* (2000). It is reinforced by the ease with which modern object-relational database management systems (ORDBMS; e.g. Oracle® Database 10g) can manage geospatial data based on objects.

2.2 *Definition of a General Field*

The relevant ontology of field models should consider the following four aspects (Kemp and Vckovski 1998):

1. properties of the domain;
2. properties of the range;
3. properties of the association rule; and
4. properties of the field as a whole.

We start with its domain and range in order to have an insight into the concept of a General Field. The domain of a field, dom(f), is determined by the geographic space of interest. The dimension of the space varies from one to four (three spatial dimensions x_1, x_2, x_3 plus one temporal dimension t). According to the spatial dimensions, the domains of mapping f are categorized in table 1.

The range of a mapping f varies according to what the field is intended to represent. For example, the range of a DEM (digital elevation model) field covering the entire land surface of Earth is $\{h | h \in R \wedge -408 \leq h \leq 8848\}$. Here, the units are metres, and –408 and 8 848 are the lowest (Dead Sea) and the highest (Mount Everest) elevations on land. We denote the type of field variables as ran(f), and the range of a DEM as R.

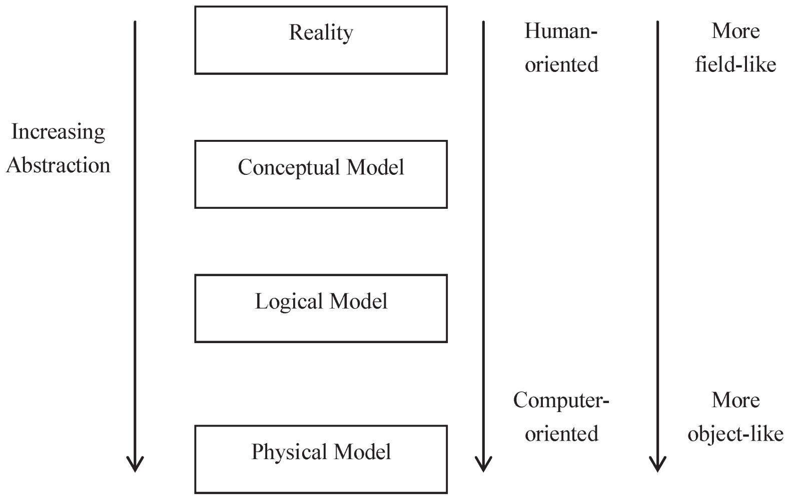

Figure 1. Extended abstraction schema considering field and object models, after Longley *et al.* (2005).

Table 1. Categorizing fields according to the dimension of dom(*f*).

Dimension	Space	Field
1: $<x_1>$	Road	Traffic flow
2: $<x_1, x_2>$	State	DEM, land use, etc.
2: $<x_1, t>$	River + day	Changing water flow
3: $<x_1, x_2, x_3>$	Lake	Temperature of the water
3: $<x_1, x_2, t>$	Country + year	Changing precipitation
4: $<x_1, x_2, x_3, t>$	Lake + month	Changing water temperature

The most common field types are scalar, vector, and tensor (Cova and Goodchild 2002). Scalar variables can be further sub-classified into nominal, ordinal, interval, and ratio cases, according to their scales of measurement. As argued by Hunter and Goodchild (1995), a vector field can be represented by two (or more) scalar fields, while a tensor field can be represented using a matrix at every location. Suppose a field is modelled using a mapping *f.* In the scalar cases, ran(*f*) is of simple type, while ran(*f*) is a collection of simple types for a vector or tensor field. In the latter cases, ran(*f*) can also be viewed as a complex class. We can further extend the set of field types (or ran(*f*)) such that it covers common geographic objects, such as rivers, cities, etc. In computer programming, type is a template to define variables. In general, the entities that can become associated with a type include: data type (type of a value, e.g. *Integer*), class (type of an entity, e.g. *City*; we use the word entity rather than object to avoid confusion with the object models in GIS), kind (type of a type), etc. In order to represent geospatial data, we primarily consider simple data types and class types. However, the differences between simple types and classes are not clear, and we may therefore be able to treat them as equivalent. Actually, some of the latest OO programming languages, such as C#, do support such a mechanism, for example, boxing and unboxing in C# (Liberty 2005), that views a simple type (e.g. *Integer*) or a number (e.g. 5) as either a class or an entity.

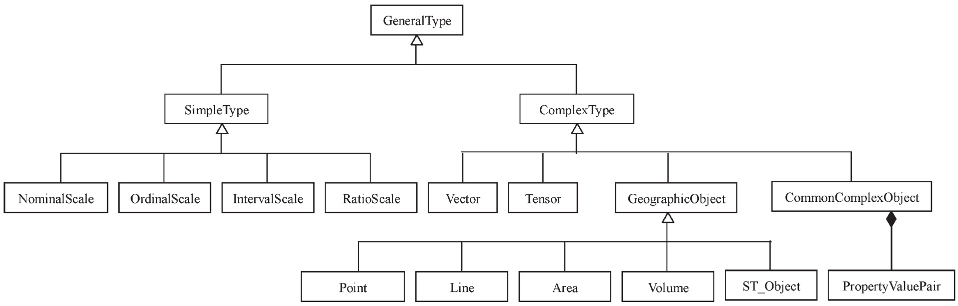

Figure 2. Type system for General Fields.

Using a hierarchical generalization structure, a type system could be established (figure 2). Simple data types and complex class types are distinguished in this diagram within the common root type *GeneralType*. The former can be further specialized to four sub-types associated with the four different attribute scales. The latter consists of the types vector, tensor, common complex entity, and geographic entity, whose instances include cities, rivers, etc. Following Goodchild *et al*. (2007), we define *CommonComplexObject* as an aggregation of *PropertyValuePair* entities. In the context of GIS, the subtypes of *GeographicObject* include point, line, area, volume, and spatio-temporal object types according to their topological dimensions. Consequently, we reach the following definition of a General Field:

Definition 1:

A General Field (G-Field) is a single-valued mapping $f: x \mapsto z$, where dom(f) is an n-dimensional geographic space (usually $1 \leqslant n \leqslant 4$), and ran($f$) can be a data type or definable class type.

According to Definition 1, the type of a G-Field may be complex, such as matrix or line (the latter instance is an object field and will be discussed in detail in the following section), or simple (such as an integer or text string). Following this direction, a field with vector variables (e.g. wind field) and an object-based layer (e.g. drainage map) could both be viewed as specialized cases of a G-Field. By assigning appropriate types, the G-Field model covers both the conventional field model and the O-Field model proposed by Cova and Goodchild (2002; table 2).

Discrete objects can be accommodated in this scheme in two ways. First, any discrete object can be converted to a binary field using the variable $\{z(x)=1$ or an attribute of the object if x is in the object, else $0\}$. Second, a set of non-overlapping discrete objects can be regarded as a special case of an object field in which each point x maps to the identity or attributes of any object in which it lies, else 0. This second approach is adopted here and will be developed in more detail below.

Using OO concepts, we can identify three instantiation approaches leading to a concrete G-Field based on the proposed type system.

Table 2. Some examples of G-Field data.

	Field type	Examples
Conventional field data	*SimpleType*	DEM, RS imagery, ….
Conventional object data	*GeographicType*	Rivers, Cities, ….
Object field data	*GeographicType*	Viewshed, ….

1. Constraint: By attaching constraints to an existing type, we can form a specialized subtype corresponding to a field. For example, the type global DEM field is a subtype of *RatioScale* with constraint $-408 \le h \le 8848$, where h denotes values in the field in metres.
2. Inheritance: This is the most common approach to obtain a subtype derived from an existing type. For a map showing lines of surficial drainage as discrete objects, the type is derived from *Line* with associated properties or from *Nominal* as discussed earlier. In GIS, the G-Field types are often derived from the leaf nodes of the inheritance tree (figure 2). However, some arbitrarily defined types, such as *Notification*, are permitted, as long as we can find a mapping from geographic space to these types. They can be defined as direct subtypes of *GeneralType*, if they cannot be defined based on *CommonComplexObject*. At the implementation level, the instances of such types can be encoded, and concrete properties are managed in a data table. The field is consequently transformed to an ordinary nominal one.
3. Aggregation: In some applications, we should aggregate the instances of existing types or derived types to obtain a new entity type, in the form of a collection of *GeographicObject* entities. This makes the scheme compatible with the specification of the Open Geospatial Consortium (Herring 2006). The point-set object field mentioned by Cova and Goodchild (2002) is a typical example of this case.

2.3 *Sampling and interpolation-based fields and tessellation-based fields*

2.3.1 Sampling and interpolation-based fields. Since a field in the real world may be infinitely complex, an acceptable approach to manage it in GIS is to select a finite set of sampling geometries in the field. Then, we can compute the value at each position in the field using the measured values of the sampling geometries and appropriate interpolation methods. In S&IBF, the topological dimensions of the sampling geometries are various, but they are always lower than that of dom(f). For example, a two-dimensional field can be represented based on zero-dimensional points (figure 3(a)) or one-dimensional contour lines (figure 3(b)) or transects, and a three-dimensional field can be represented using two-dimensional sampling surfaces (figure 3(c)) or profiles.

For an S&IBF, three issues should be considered. They are: (1) sampling method; (2) fundamental principle of interpolation; and (3) available interpolations for a given field. There are several sampling strategies available for an S&IBF, including random sampling, systematic sampling, and stratified sampling (Longley *et al.*

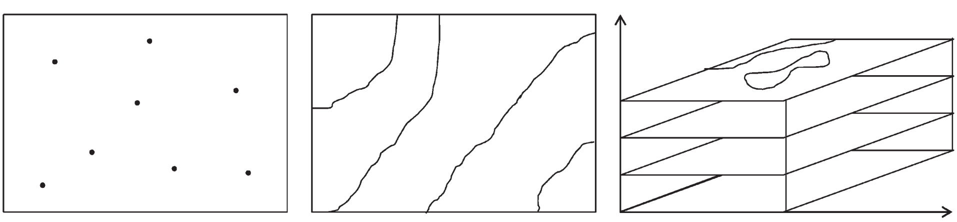
(a) (b) (c)

Figure 3. Three examples of S&IBF: (a) point samples in two-dimensional space; (b) line samples in two-dimensional space; and (c) surface samples in three-dimensional space.

2005). In practice, achieving an ideal sample design may be difficult due to natural or artificial restrictions. The theoretical foundation of S&IBF is Tobler's First Law (TFL) of geography, that is, 'everything is related to everything else, but nearby things are more related than distant things' (Tobler 1970). Without TFL, any spatial interpolation would be unreliable (Goodchild 2004). It is because of TFL that many spatial interpolation algorithms consider distance as an important factor. Besides distance, another factor involved in spatial interpolation is the attribute scale of field variables. For example, it is more difficult to measure the similarity between two values in a quantitative manner for nominal or ordinal cases than for interval or ratio cases. The inverse distance weighted (IDW) interpolation (or similar methods, e.g. Kriging) is thus not appropriate in the nominal and ordinal cases; while a Voronoi-diagram-based value assignment method is acceptable for these two types of fields.

2.3.2 Tessellation-based fields. In a TBF, the space is divided into finite tesserae or pieces, and the boundaries between every two tesserae are deterministic. We can thus manage the field data by recording the boundaries, although it is not necessary in some cases. According to the shape of the tesserae, the tessellation may be categorized into: (1) regular tessellation; (2) irregular but geometrically shaped tessellation; and (3) arbitrarily shaped tessellation. Clearly, for the first two cases, boundaries are derivable, and we need not record the boundaries explicitly. Figure 4 demonstrates these three types of TBF in two-dimensional space, but they can be extended to higher-dimensional spaces. For example, the basic unit of three-dimensional regular tessellation is a voxel, while three-dimensional Voronoi diagrams can also be generated (Ledoux and Gold 2004).

Regarding the values of tesserae, the terms spatially extensive and spatially intensive (Goodchild *et al.* 2005, Longley *et al.* 2005) can be introduced for further categorization. If the values of a field are averaged within tesserae, the results are said to be spatially intensive, while if the values are integrated, as for example when population density within a tessera is integrated to obtain the area's total population, the result is said to be spatially extensive. Spatially extensive and spatially intensive variables behave differently when areas are split or merged. For example, in the case of merging two areas, spatially extensive variables sum, while spatially intensive variables average. Following this direction, a remote sensing image is spatially intensive, since the values of two pixels should be averaged when they are merged.

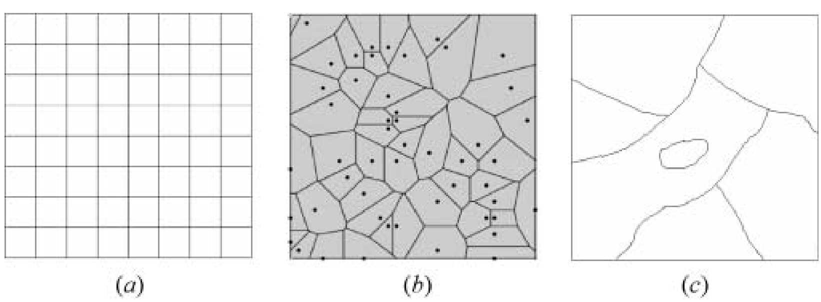

Figure 4. Three types of tessellations: (*a*) regular tessellation: raster data; (*b*) irregular but geometrical-shaped tessellation: Voronoi diagram; and (*c*) arbitrary-shaped tessellation.

Table 3. Mapping relationships between the six representations of Goodchild *et al.* (2005) versus S&IBF and TBF.

S&IBF	regularly spaced sample points, irregularly spaced sample points, isolines
TBF	rectangular grid cells (raster), irregularly shaped polygons, triangulated irregular network

2.3.3 Comparisons. S&IBF and TBF provide a suitable approach for managing geospatial data in GIS. The six concrete methods proposed by Goodchild *et al.* (2005) can be classified into these two categories (table 3).

Let us take a gridded digital elevation model (DEM) and a raster of remotely sensed (RS) imagery as examples to illustrate the differences between TBF and S&IBF. Their logical data models are very similar, since both can be recorded using a matrix. However, the grid DEM is an S&IBF, where an element in the matrix stands for a zero-dimensional sampling point. To compute the value of a specific point in the field, an appropriate interpolation method, for example bilinear interpolation, should be adopted. Meanwhile, the RS image is a tessellation-based field, since an element in the matrix stands for a two-dimensional square. It is necessary to determine which square the point is located in for the sake of obtaining the value at this point. As a general rule, if we want to compute the field value at a point x, for an S&IBF, at least one geometry that is close to x should be found; however, only one geometry that contains x is sufficient for a TBF. Note, however, that obtaining estimated values from remotely sensed imagery is more complex if a simple model of uniform response within pixels is replaced by a more realistic model of the sensor's IFOV (instantaneous field of view).

2.4 *Object Fields*

From a discrete-object perspective, space is perceived as a region populated with discrete entities, each with identity, spatial embedding, and attributes (Cova and Goodchild 2002). As mentioned earlier, an O-Field is a mapping from geographic space to geographic object types. The mapping can be formally defined as: $f : x \mapsto g$, where g is an instance of *GeographicObject* class. Moreover, the mapping from a position to a null object is permitted, in other words, gaps may exist in an object field. The first two types of fields in the following categories have this characteristic.

For an O-Field, we may study the properties based on the topological dimension of its type. For example, *Point* type is zero-dimensional, while *ST_Object* (spatio-temporal object) type is four-dimensional (Worboys 1992, Yuan 1999). In the context of O-Fields, we use dim(ran(f)) to denote the topological dimension of an instance of *GeographicObject*. It should be noted that the dimension concept here is different from the definition presented by Vckovski (1998), where dimensions are used to describe vector (or tensor) fields. On the other hand, the domain of a mapping, that is, a geographic space, also has the dimension attribute. Generally, a lower-dimensional space could not be mapped to higher-dimensional geographic objects. However, there are some exceptions. For example, along a one-dimensional river, each point may be associated with a two-dimensional catchment basin. In such cases, it is usually managed in the higher-dimensional space, since higher-dimensional objects cannot be populated in a lower-dimensional space.

Without considering the common aspatial attributes of geographic objects, five types of object fields can be identified according to the relations between the dimensions of dom(f) and ran(f):

1. dim(ran(f))<dim(dom(f)): An example of this type of O-Field is a point city map or a line river map in two-dimensional space (figure 5(a)). The dimension characteristic makes it like an S&IBF; thus, objects in such a field can be considered as sampling geometries with associated attributes. However, this type does not support common spatial interpolation, that is, the values in the gap area cannot be calculated using interpolation. However, for this type of O-Field, in general, prediction is possible for a previously unknown object by interpolating two or more sampling geometries. For example, the track of a moving object can be interpolated based on known sampling geometries (Hornsby and Egenhofer 2002, Yu *et al.* 2003). This is different from common spatial interpolation based on values, and we name it *object interpolation*.
2. dim(ran(f))=dim(dom(f)), $\bigcup_{i=1}^{n} O_i \subset \mathrm{dom}(f)$, and $\forall O_i, O_j \in \mathrm{ran}(f), O_i \cap O_j = \varnothing$: In this type of O-Field (figure 5(b)), the union of all objects cannot cover the domain of mapping f. For example, lakes of a region form an object field of this type. Since empty areas are allowed, this type belongs to TBF.
3. dim(ran(f))=dim(dom(f)), $\bigcup_{i=1}^{n} O_i = \mathrm{dom}(f)$, and $\forall O_i, O_j \in \mathrm{ran}(f), O_i \cap O_j = \varnothing$: This is a very general type of TBF, and an example is administrative data, such as a county map of a state (figure 5(c)). For most purposes, however, it will be better to regard such maps as instances of nominal fields in which location x maps to values denoting identities or attributes of each administrative area.
4. dim(ran(f))=dim(dom(f)) and $\exists O_i, O_j \in \mathrm{ran}(f), O_i \cap O_j \neq \varnothing$: Obviously, a viewshed O-Field in two-dimensional space accords with these conditions (figure 5(d)).
5. dim(ran(f))>dim(dom(f)): In military applications, the effective range of a radar installation at a given location can be simulated in three-dimensional

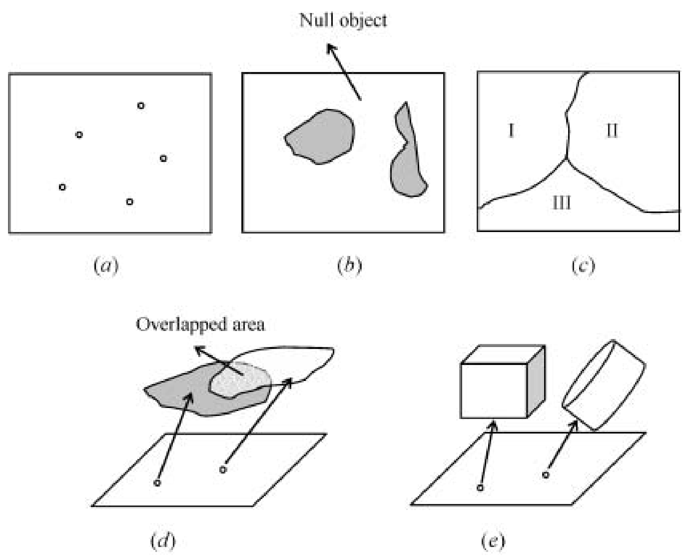

Figure 5. Five types of object fields in two-dimensional space.

space based on a DEM. The range is approximately a hemisphere mapped from two-dimensional space, and such objects are usually managed in higher-dimensional space (figure 5(*e*)).

These five types of O-Fields are illustrated in figure 5. The common O-Fields (or data sets represented in traditional discrete-object models), such as a drainage layer, always belong to the first three types. The last two types of O-Fields can only be derived from other fields. However, as noted earlier and by Cova and Goodchild (2002), the first three types can also be derived from O-Fields. Using the order concept defined in the next section, the orders of the first three types of fields may be 1 or a larger number, while the orders of the other two are always greater than 1. Another difference between common O-Fields and derived O-Fields is that the former can be stored and managed directly in a GIS, while the latter are always generated in a real-time manner. For a derived O-Field, we can obtain an object corresponding to a given position in dom(*f*); however, since the number of positions is infinite, it would be impossible to store all derived objects. Moreover, interpolation operations are not appropriate for O-Fields. Thus, given two positions p_1 and p_2 and their associated objects O_1 and O_2, the object associated with a point between p_1 and p_2 cannot be simply inferred based on p_1, p_2, O_1, and O_2. Additionally, in a derived O-Field, it is not normally possible to identify a homogeneous region where all points are associated with the same object. Thus, for the convenience of implementation, in contrast to S&IBF and TBF, a third type of G-Field termed a Real-Time Generated Field (RTGF) is defined for these cases. The generation rule and the original field are two key elements of an RTGF. Clearly, RTGF is suitable not only for derived O-Fields, but also for common fields. For example, a slope field can be obtained based on a DEM at any moment. Furthermore, if a field is represented using mathematical functions (Haklay 2004), it also belongs to the class RTGF.

In the above discussions, the objects in an O-Field are always determinate. However, there is ubiquitous vagueness in the real geographic world, as geographic features with truly crisp boundaries are rare (Couclelis 1996). If a field includes a set of vague objects, then it is possible that two objects might overlap. Employing fuzzy set theory, a location in the field belongs to different objects with respective membership degrees. Thus, an element in the range of such a field is a set of ordered pairs: $\{<O_1,\mu_1>,<O_2,\mu_2>,\ldots,<O_n,\mu_n>|O_i\in\boldsymbol{O},0\le\mu_i\le1\}$, where $\boldsymbol{O}$ is a set consisting of n objects, and μ denotes the associated membership degrees. If $\boldsymbol{O}$ is known, then the range can be simplified as: $\{<\mu_1,\mu_2,\ldots,\mu_n>|0\le\mu_i\le1\}$ for the convenience of management. Thus, it is transformed into a vector field that can be represented by n ordinary scalar fields. This representation implies that it is more reasonable to deal with vague objects using conventional field models. An early discussion on this issue was provided by Goodchild (1989).

2.5 *Descriptive framework for G-Fields*

The three attributes of G-Field: domain, range, and management, are nearly independent or orthogonal. Thus, a descriptive framework for G-Fields is established by viewing these three aspects as three axes. The framework is three-dimensional (figure 6), and any geospatial data set can be located at an appropriate position in the space. For example, a grid DEM field can be represented by (ratio, $<x_1, x_2>$, S&IBF).

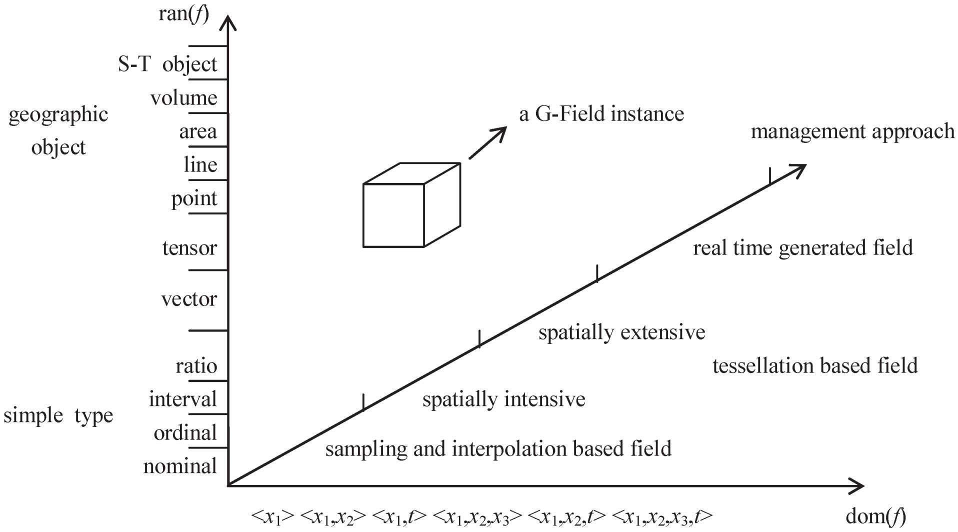

Figure 6. Descriptive framework for G-Fields.

3. Order of a G-Field

Now that we can use the G-Field to unify common geospatial data models, and most geospatial data can be seen as the specialized instances of G-Fields, geospatial analyses can be decomposed into a series of sequential operations on G-Field data. Most such analyses have one input field and one output field. For instance, in a terrain-based drainage extraction, the input is a grid DEM, while the output is an object field that contains the extracted rivers. Since functional programming languages are suitable for formally defining an algebra (Hughes 1989), there have been several efforts to represent spatial operations using such a language. Haklay (2004) has employed Haskell for this purpose, and Winter and Nittel (2003) have used Lambda Calculus. Employing Haskell, such an operation with one input and one output in two-dimensional geographic space can be expressed as:

```
orifield :: Double->Double->t1
newfield :: Double->Double->t2
g :: Double->Double->(Double->Double->t1)->t2
orifield =\x y->(f x y)
newfield =\x y->(g x y (\u v->(orifield u v)))
```

In the above statements, two functions, `orifield` and `newfield`, denote the original and result field, respectively. (Note: the program is incomplete. We should define `f`, `g`, `t1`, and `t2` in order to make a complete one.) `t1` and `t2` are types of these two fields and can be customized types in the type system (figure 2), while `x` and `y` define a position in two-dimensional space. The original field `orifield` is represented by the function `f`, which is a mapping from geographic space to `t1`. `g` is a function that implements the corresponding spatial operation. The types of the three parameters of g are `Double`, `Double`, and `orifield`, respectively, while the type of the returned values is `t2`. The above example operation (drainage extraction), which is implemented by a function `op`, can thus be expressed as:

```
op::Double->Double->(Double->Double->Double)->Line
```

The above Haskell codes indicate the possibility of a unified representation of geospatial operations based on G-Field models at the conceptual level. After an operation, we may obtain data with a higher abstraction level, that is, more useful information or even knowledge may be extracted. To represent the abstraction level of geospatial data, an indicator, the order of field data, is defined in the following sections.

3.1 *Definitions*

In the context of geospatial analysis, each field data set has a property named order, which describes its relevant evolution process. The order of a General Field is a non-negative integer number. In terms of order, we have the following definitions:

Definition 2:

A field is zero-order if it represents the real world in a continuous-field conceptualization.

The real world is the primary source of all kinds of geospatial data in GIS, and the latter can be viewed as employing different levels of abstraction of the real world. Geographic space is filled with various geographic phenomena from which meaningful objects are later identified. Thus, zero order denotes the primitive General Field for GIS data.

Definition 3:

A field is first-order if the values and positions of the sample objects (they are often sampling points) in an S&IBF or geometrical-shaped TBF are measured directly, or the values and boundaries in an arbitrarily shaped TBF are measured directly.

A zero-order field cannot be managed in information systems due to its infinite complexity. Abstracted from the real world directly, a first-order field is discretized to be stored digitally. For S&IBF and TBF, different storage and management methods could be adopted. For example, a TIN model is constructed using global positioning systems (GPS) and altimeters, and is a typical first-order S&IBF, while a census-district map is an example of first-order TBF. However, it is impossible for an RTGF to be first-order, since it is always derived from a lower-order field.

Definition 4:

A geospatial analysis operation is an order-increasing operation (OIO) if it is mathematically irreversible; otherwise, it is a Non-OIO (NOIO).

Assuming data set B is generated from data A after an operation O, O is mathematically irreversible if there is no deterministic approach to obtain A based on B and associated parameters; otherwise, it is reversible. For example, adding a constant number to all attribute values of a TIN is reversible by simply subtracting the number. Here, we avoid addressing precision issues for floating-point representations. For example, in digital computation, x might not be precisely equal to $\left(\sqrt{x}\right)^2$, but we still believe that the square-root operation is reversible. Usually, if an operation is irreversible, something essentially new will be created from the original data after the execution of the operation, increasing the abstraction and order of the geospatial data.

Definition 5:

Assume a field B is derived from A after an OIO. If A is a k-order field, then the order of B is $k+1$. Moreover, if B is generated from a series of fields A_1, A_2, …., A_n, and the orders of A_1, A_2, …., A_n are O_1, O_2, …., O_n, respectively, then the order of B is $\max(O_i)+1$, where $1 \leqslant i \leqslant n$.

According to Definitions 4 and 5, order can only increase or remain unchanged during a geospatial analysis processes; it cannot decrease. If a data set A is generated from another one B by an NOIO, that is, the orders of A and B are equal, then A and B should be considered as different views of the same data. This means they are essentially equivalent. Hence, the order is an indicator of the abstraction level of a General Field, increasing along with the analysis process. In other words, a higher order usually means more useful information is concentrated and extracted, although there are some trivial examples of irreversible operations that could hardly be said to be adding value, for example arbitrary deletion. Regarding the copyright protection of geospatial databases, many laws in the USA and Europe specify that originality in the selection or arrangement of the content is a precondition for protection (Longley *et al.* 2005). Obviously, if one performs a set of OIOs on a data set, one may partially own the derivative result.

3.2 *Order-increasing operations*

Map algebra defines four classes of operations on raster data: local, focal, zonal, and global (Tomlin 1990). These categories can be extended to describe operations on G-Field data. As a general rule, focal, zonal, and global operations are always order-increasing operations, while local operations can be either OIOs or NOIOs. Following this direction and taking into account other operations that are not covered by these four categories, a series of order-increasing operations for General Fields can be specified as follows:

1. Reclassification: Reclassification is a common local operation. In general, qualitative information can be extracted from quantified source data using reclassification. For example, a field representing the distance from a given feature can be reclassified to a more qualitative field including the following distinctions: 'very close', 'close', 'far', etc. Obviously, this is an irreversible operation. Let us return to the four attribute scales. Since the sequence of their abstraction level is ratio $<$ interval $<$ ordinal $<$ nominal, a reclassification operation can only leave the abstraction level unchanged or increase it.
2. Focal operations: Focal operations such as slope calculation, template-based filtering, or the evolution steps in cellular automata are very common in GIS and image-processing systems. An important characteristic of OIO is that we can obtain identical data sets from different original data sets. This characteristic can be viewed as an analogue of inverse functions, that is, a function must be a bijection to have a valid inverse. Most local operations have this characteristic and are thus considered to be OIOs.
3. Zonal operations: A common zonal operation on a raster results in the replacement of every cell's value by the count or area of continuous cells with the same value. This is the raster equivalent of the calculation of a polygon's area and is clearly irreversible.

4. Global operations: Global operation can be seen as a special cases of zonal operations in which the entire raster is processed, to return a single value such as the mean, median, mode, or standard deviation. The result no longer has a spatial distribution, and thus the operation is clearly irreversible.
5. Subset or slice operation: Subset or slice operations extract a specific part of the original data. Generally, subset operations do not change the spatial dimension of the source data, while slice operations decrease it.
6. Object identification: As mentioned earlier, the conventional continuous-field model is more fundamental than the discrete-object model. From a field, in the form for example of a gridded DEM, it is possible to identify objects of interest such as mountains and valleys based on specific rules, thereby transforming from a field to an object conceptualization. According to Harding (2002), ontology is created in this process. The boundaries of identified objects are sometimes vague, and fuzzy objects provide an alternative representation (Schneider 1999). Such transformations are clearly irreversible.
7. Generalization: Generalization can be applied to both raster data and vector data. Detail is removed from a data set in the process of generalization, often to make processing or visualization easier. Generalization is irreversible.
8. Overlay: Only one original data set is involved in each of the above operations. However, a new data set may be generated from two or more data sets using overlay operations, which are many-to-one operations. Classification using multiple remotely sensed images is a typical local overlay operation. Overlay operations are usually irreversible in raster, since rules are used to create new values for each cell, but the polygon overlay operation in vector, in which each new polygon is given the attributes of both input polygons, is reversible. Some overlay operations in raster, such as combining two 8-bit images to create a 16-bit image using a bit operation, may also be reversible.

3.3 *Non-order-increasing operations*

Besides OIOs, many NOIOs are implemented in GIS and remote-sensing data-processing systems. Their objectives are not extracting useful information but creating a new view of the data. They make the representation or the analysis more efficient, so they still play an important role in GIS. Some common NOIOs are described as below:

1. Geometrical transformation: Geometrical transformations include zoom operations, rotate operations, affine transformations, as well as project transformation. They bring convenience for viewing a map without creating any new information, and are generally reversible.
2. Exact interpolation: With a given exact interpolation method, the original data and derived data can be created from one another easily, provided a sufficient number of points are interpolated. 'Exact' here means that the values at the sampling geometries are unchanged during the interpolation. For example, TIN, grid, contour line, and discrete points are different views of DEM data in the implementation of many GIS software packages. Figure 7 illustrates this point in the case of linear interpolation.
3. Fourier transformation (or principal-component analyses (PCAs)): In many image-processing systems, Fourier transformation and PCAs are often used.

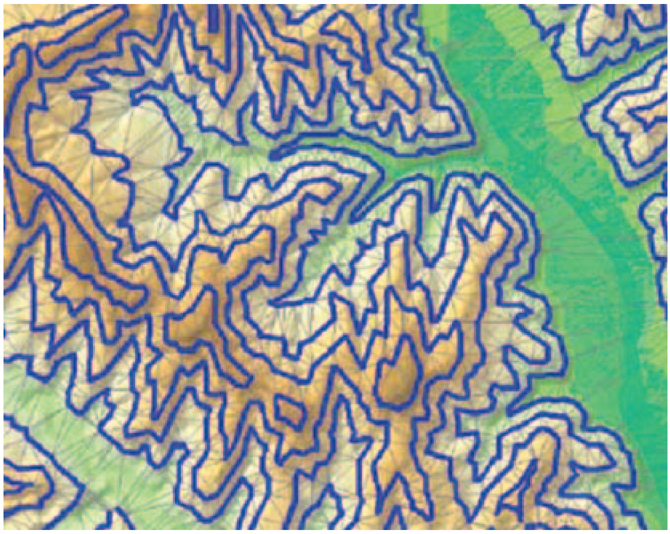

Figure 7. TIN, grid, contour line, and discrete points as different views of DEM data. They can often be derived from each other using exact interpolation.

The former transforms an image from the spatial domain to the frequency domain, while the latter is an axis-rotating transformation to find the principal components from a group of variables. They are reversible though subject to previous comments about numerical precision.

3.4 *Example demonstrating G-Field order*

The order of a G-Field may be changed during a sequence of geographic operations. Consider an example in the realm of tectonic analysis. It is well known that the drainage in an area is affected by tectonics. The distribution characters of rivers or streams, such as shape, direction, and density, are thus sensitive indicators that may reflect deep and hidden tectonic activities (Hovius 1996, Jackson *et al.* 1998). In the 1980s, some scholars developed a method to reveal concealed tectonics using drainage density (Han *et al.* 1983, 2003). The principle of the drainage density method is described as follows: in a region with tectonic sinkage, the ground is low-lying, the rivers or streams are usually sinuous, and the drainage density is high; while in a region with tectonic upheaval, drainage is much straighter, and drainage density is lower.

The source data used to compute drainage density are primarily remotely sensed images, which are first-order fields. After classifying the images, a land-use map and drainage map are obtained. To calculate the spatial distribution of drainage density, a GIS operation is employed. Finally, different tectonic regions are recognized from the field of drainage density. During the process summarized in table 4, more useful information is extracted as G-Fields are created with a progressively higher order.

3.5 *Integrating G-Field order with geo-workflow*

Besides representing the information extraction process, the order of a General Field provides support for tracing the lineage of geospatial data. It is thus possible to

Table 4. Fields and their orders in the drainage density analysis.

Data set name	Operation	Type	Order
RS image	Directly measure the real world	Regular tessellation-based field with interval scale	1
Land-use map	Classification	Regular tessellation-based field with nominal scale	2
Drainage map	Object identification	Line object field	3
Drainage density map	Zonal operation	Regular tessellation-based field with ratio scale	4
Geological tectonic map	Object identification	Area object field	5

integrate G-Field order with geo-workflow, which is a partially ordered set of geospatial operations. By incorporating workflow technology with a GIS, a geo-workflow system can be established to manage complex geospatial processes. Some geospatial-process support systems have been built, such as GeoLineus (Lanter 1991), Geo-Opera (Alonso and Hagen 1997), and SPMS (Spatial Process Modelling System; Marr *et al.* 1998).

By integrating order into geo-workflow, the derivation processes can be identified in each workflow instance. A geo-workflow can be formally defined as a directed acyclic graph (DAG) $G=(\boldsymbol{V}, \boldsymbol{A})$, where $\boldsymbol{V}$ denotes the sets of data involved, while $\boldsymbol{A}$ denotes the set of geospatial operations. Figure 8 depicts a hypothetical geo-workflow, where the numbers in circles are the orders of geospatial data sets. The dashed circle marked by V_0 indicates the real world. For a data set $V_i \in \boldsymbol{V}$ $(i>0)$, let $O(V_i)$ denote its order. Obviously, $O(V_i)$ equals the length of the longest path from V_0 to V_i. If $O(V_i)<O(V_j)$, then V_i is an ancestor of V_j. Furthermore, if we can find a path from V_i to V_j, then V_i is a direct ancestor; otherwise, V_i is an indirect ancestor. If $O(V_i)=O(V_j)$, then they are siblings. For instance, in figure 8, B is the direct ancestor of G, C is the indirect ancestor of G, and E and F are siblings. If we sort the data sets according to their order, the result, $ABCDFEGH$ in figure 8, is one of the valid topological sorts on the graph G. This characteristic provides a convenient implementation of a geo-workflow management system where geographic semantics are involved.

We would like to elaborate this point by considering spatial data quality. It is well known that some quality issues, such as error, are closely associated with spatial data (Goodchild 2001). Generally, errors are introduced during measuring, and propagated in spatial analyses. OIO and NOIO may both produce errors. However, the errors are created due to computation precision for an NOIO, while the errors

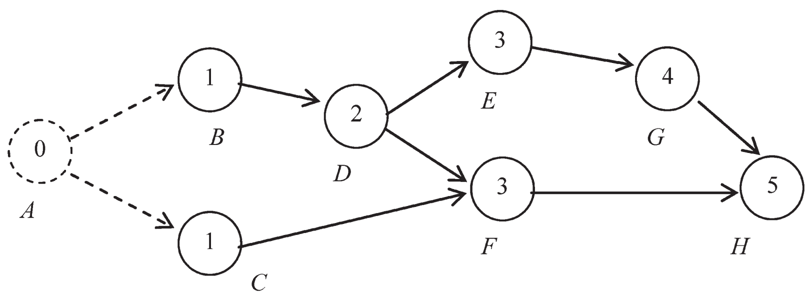

Figure 8. Hypothetical geo-workflow with order considered.

are propagated due to the algorithm of an OIO (e.g. the buffer operations studied by Shi *et al*. 2003). For the purpose of data quality control in a geo-workflow, we can update higher-ordered data sets when errors are found in a lower-ordered data set.

4. Conclusions

This paper focuses on two issues. First, the concept of a General Field (G-Field) has been proposed as a way of integrating continuous-field and discrete-object conceptualizations, by regarding objects as a special type that can be mapped in a field model as a special case of O-Fields. The domain of a General Field may vary from one to four in spatial dimensions, and its range may be a scalar, vector, tensor, geographic object, or even a customized type. To be conveniently managed in information systems, G-Fields can be further implemented using one of three approaches: sampling and interpolation-based field, tessellation-based field, and real-time generated field. The geospatial data in GIS, such as a TIN, a raster image, or even a map in vector format, can be classified into these categories.

Second, geographic analysis can be viewed as a sequence of operations on General Fields. These operations play different roles in the process of information extraction. Some are used to extract significant information; while others only create a new view of the source data set. Following this point, they are classified as either OIOs or NOIOs, where order is an indicator of the degree of abstraction of a General Field. Generally, a higher order means more useful information, or even knowledge. An important distinction between OIOs and NOIOs is that the former are mathematically irreversible, while the latter are reversible. We also discussed and compared the influence of some common GIS operations on a G-Field's order.

In summary, the G-Field and its order provide a consistent way for us to deal with geospatial data and geospatial operations. Since a geospatial data set can be viewed as an instance of a G-Field, we could gain insight into the geospatial operations according to their contributions to information extraction, without considering concrete models at the implementation level, such as raster, vector, etc. Meanwhile, the order of a G-Field brings two advantages: (1) it embodies the abstraction level of a data set; and (2) it can be adopted to trace data lineage and integrated with geo-workflow.

Two issues need to be resolved in future work: (1) we need to devise a more complete system for categorizing OIOs and NOIOs, and (2) it would be useful to find a more quantitative approach to model the information change between different orders of geospatial data sets. In addition, the authors plan to develop a full-scale implementation of the approach, in order to demonstrate the substantial simplifications and efficiencies that it can provide in organizing workflow, describing data sets, and defining user interfaces.

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