[DM-02-023] Field-Based Representation of Space and Time

Abstract

Representations of space and time are central to GIScience. Field-based representations conceptualize space and time as continuous surfaces where each location is associated with measurable attribute values. Traditional models, such as raster grids and Triangulated Irregular Networks (TINs), discretize continuous fields for computational efficiency. However, these models often rely on rigid pixel assumptions and linear interpolations that fail to capture subtle curvatures and variations in real-world phenomena. To address these shortcomings, surface adjustment methods refine spatial measurements by constructing local terrain models that better represent spatial variations. Beyond static spatial fields, higher-dimensional models integrate space, time, and scale into a unified framework. Time-geography introduces the space-time cube, where space and time are integrated into a 3D field. Additionally, the Triangle Model (TM) and Pyramid Model (PM) incorporate scale into temporal and spatial analysis, respectively. These models allow for more nuanced analysis, such as tracking objects, assessing interaction probabilities, and exploring cross-scale relationships in space and time. Taken together, these models form a multi-scale spatio-temporal framework with four key dimensions: spatial location (s), spatial scale (s′), temporal location (t) and temporal scale (t′), providing a systematic approach to analyze dynamic geographic phenomena across multiple dimensions.

Keywords: continuous data, fields, multi-scale analysis, Pyramid model, spatiotemporal event, Triangle model

Author & citation

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Explanation

1. Introduction

Concepts of space and time vary across disciplines such as physics, mathematics, and philosophy. In GIScience and geography, ongoing debates focus on absolute vs. relative and field-based vs. object-based representations. Traditional representations of space are rooted in maps that attempt to mimic real-world phenomena in absolute Newtonian space or Euclidean geometry. In GIS, various data models are used to represent continuous fields. However, these models rely on discrete spatial structures that struggle to capture the curvature and subtle variations of real-world phenomena. Moreover, these models often represent space as static snapshots at a specific time and scale, limiting their ability to depict the continuity of geographic phenomena across space, time, and scales. This entry reviews the fundamental distinction between object-based and field-based representations, explores their theoretical foundations, and discusses emerging data models and analytical methods designed to overcome the limitations of existing field-based representations.

2. Entity- vs. Field-Based Representation

A fundamental controversy in GIScience is whether space is viewed as entities or fields (Couclelis 1999). In the former view, space is perceived as an empty container filled with discrete, identifiable entities with distinct boundaries and attributes. This representation aligns with how humans often perceive the world, understanding geographic phenomena as discrete entities. A key assumption in entity-based representation is the ability to draw crisp boundaries separating entities from their surroundings. While this task may appear straightforward, it becomes complex in real-world scenarios. For example, maps typically use a shoreline to separate the sea and land. However, shorelines are dynamic, influenced by tides and other environmental factors. Some researchers turn to rough set (Pawlak 1982) and fuzzy set (Zadeh 1965; Qi 2024) to model entities with non-crisp boundaries, while others argue that this is a scale issue. In contrast, the field-based view perceives space as continuous and fully occupied, with each location associated with a measurable attribute value. Spatial clusters of similar attribute values are interpreted as meaningful patterns or “things”. Field-based representations are suitable for modeling phenomena that vary continuously across space, such as elevation, temperature, and precipitation. In addition to the physical phenomena, fields can also represent social phenomena such as accessibility, population density, and travel velocity fields (Angel and Hyman 1976). Cova and Goodchild (2002) discussed methods of linking field-based and entity/object-based representations.

The entity vs. field distinction also exists in temporal representations: whether time should be viewed as discrete events (e.g., time intervals) or continuously varying attributes along a timeline (e.g., time series) (Figure 1) (Song 2019). Allen’s time algebra defines thirteen atomic relations between time intervals (Allen 1983), which was the foundation for spatial reasoning frameworks such as Region Connection Calculus (Cohn et al. 1997). Time series analysis and temporal interpolation are primarily based on temporal interpolation.

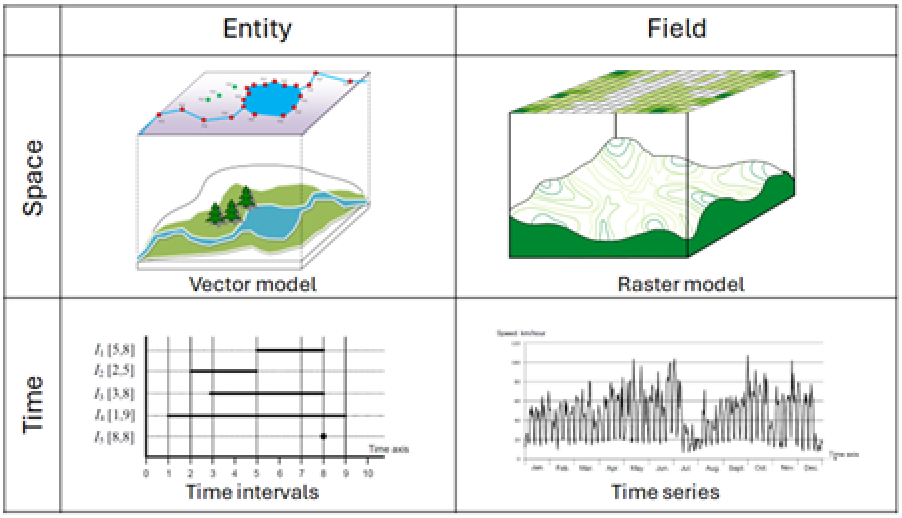


Figure 1. Entity and field-based representatoins of space and time. Source: author.

3. Data Models for Fields

Newton's absolute space serves as the mathematical foundation for field-based representations (Couclelis 1999). In Newtonian space, all phenomena can be described as attributes (or sets of attributes) that vary within a coordinate system:

Equation 1

$$(A_1, A_2, \ldots, A_n) = f(x, y)$$

where x and y are coordinates in a Cartesian reference system and $(A_1, A_2, \ldots, A_n)$ are attributes at the coordinates.

For sampling and storage purposes, continuous fields must be represented in discretized data models. The raster model divides space into a grid of uniform cells, where each cell represents a sample of the field. The raster model assumes that attribute values remain constant within a cell but change abruptly across cell boundaries. As a result, the raster model introduces rigid, stairstep patterns that fail to areflect the natural curvature of real-world phenomena. Alternatively, fields can be represented using vector-based models. The Triangulated Irregular Network (TIN) models space as non-uniform triangles, allowing more flexibility in representing different spatial patterns. Contour lines, a classic cartographic technique, are often used to model topographic surfaces. Both TIN and contour lines assume that attribute values change linearly between triangle vertices or between contours. Despite their differences, the raster model, TIN, and contour lines are all based on discrete sampling of continuous field data. For realistic reconstruction of continuous fields, spatial interpolation techniques are often used to fill the gaps between discrete sampling points or lines with accurate attribute estimates.

4. Surface Adjustment Methods

As the most commonly used model for continuous fields, rasters assumes a “rigid pixel paradigm” that overlooks the sub-pixel variations (Ghandehari 2019). For example, the digital elevation model (DEM) cannot accurately capture the slope and curvature of a terrain surface within each pixel (see Figure 2). This issue also exists in the Triangulated Irregular Network (TIN), which assumes linear elevation changes across each triangular facet. Research indicates that the rigid pixel paradigm can cause a 2–5% error in distance measurements over terrain surfaces (Qiang, Buttenfield, and Joseph 2021). To address these limitations, various surface-adjustment methods have been developed to enhance the accuracy of distance and area measurements (Ghandehari, Buttenfield, and Farmer 2019; Qiang et al. 2021). Figure 3 illustrates several surface adjustment methods for distance measurement in the raster model and TIN. These methods relax the rigid pixel assumption by constructing models that better represent local spatial variations. Subsequently, distance and area can be calculated from the re-sampled elevation. For example, the weighted average method estimates elevation by calculating reverse-distance-weighted average of the elevation at surrounding sampling points. The Bi-Linar, Bi-Cubic and Bi-Quadratic methods use different polynomial equations to estimate elevation from nearby sampling points. These surface-adjustment methods improve the accuracy of distance, area and volume measurement (Ghandehari 2019 and Qiang et al. 2021), which are fundamental for spatial analysis such as proximity analysis and areal interpolation. These studies also suggest that no single surface-adjustment model can universally fit all types of terrain. The choice of an appropriate adjustment method depends on several factors, including terrain roughness, analytical scale, DEM resolution, and computational resources.

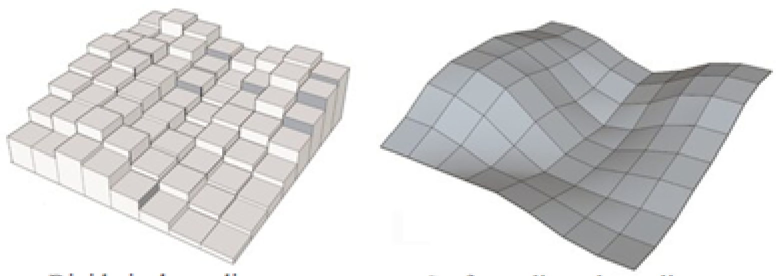


Figure 2. The rigid pixel paradigm of the raster model (left) and surface-adjusted paradigm (right). Source: Ghandehari et al. 2019.

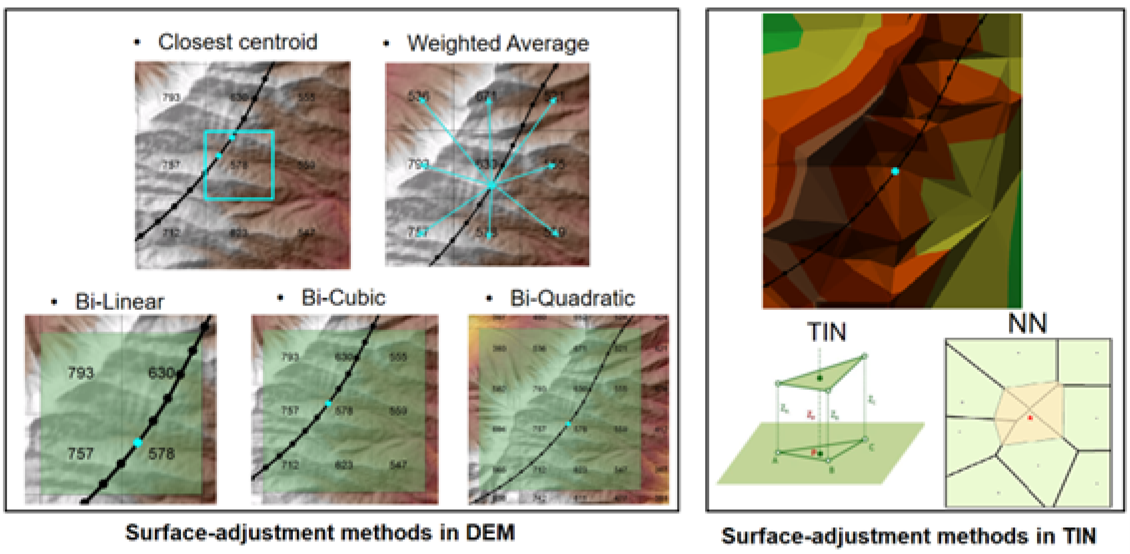


Figure 3. Surface adjusted methods for distance measurements. Source: Qiang et al., 2021.

5. Integrated Fields of Space and Time

Time is widely recognized as an essential component of geographic phenomena (Peuquet 1994). Traditionally, a map or GIS dataset represents only a snapshot of the real world with a timestamp indicating when the data was collected, or the map was created. Dynamics are then represented by a time series of such snapshots. However, this snapshot approach breaks continuity in time and fails to capture events or transitions occurring between time stamps. To overcome this limitation, time geography proposes a conceptual framework that simultaneously represents space and time in a 3D space-time cube, where the x and y axes represent geographic locations, and the z axis represents time. A comparable concept in remote sensing is the image cube, which consists of stacked images taken at different times. These integrated space-time fields offer significant advantages over the snapshot approach, allowing analysis of continuous movement trajectories of objects, potential interactions in space and time, and image spectral patterns across space and time. However, it is important to acknowledge that the space-time cube is an artificial construct, as time is not inherently visible as a vertical 3rd dimension above geographic space. Integrating space and time into such a 3D representation can impose a cognitive load, particularly for novice users. Additionally, many spatial analysis techniques, such as distance measurement and proximity analysis, are not compatible with this artificial 3D structure because the x, y, and z axes operate on different measurement units and scales. Other criticisms include the inability of the space-time cube to handle the complex nature of time, such as branching time, where events diverge into multiple outcomes, and cyclic time, which represents recurring patterns and periodic phenomena. Despite these limitations, the space-time cube remains a valuable tool for visualizing and analyzing spatiotemporal dynamics.

6. Multi-Scale Spatio-Temporal Models

Spatio-temporal data are typically represented at a single scale, which risks overlooking patterns and relationships at other scales. The importance of scale in spatio-temporal data analysis has been epitomized by the well-known Modifiable Areal Unit Problem (MAUP) and its temporal equivalent. Prevalent multi-scale data models primarily focus on optimizing data storage and querying. For example, quadtree and R-Tree store spatial objects at multiple scales in hierarchical structures to facilitate spatial data indexing and query (Samet 1990). Image pyramids were created to accelerate multi-scale rendering of raster data (Yang et al. 2005). Recently, several innovative data models and frameworks have been developed to incorporate scale as an explicit dimension for multi-scale analysis (Qiang and Van de Weghe 2019). As an example, the Triangle Model (TM) projects linear time intervals into a 2D space, using the mid-point and length of the interval as x and y coordinates. In essence, the TM creates a 2D field (□(□, □′)) that integrates temporal location (□) and temporal scale (□′) so that temporal patterns at different scales (i.e., in different interval lengths) can be observed in a unified space (Figure 4, upper panel). Unlike the linear chart (on the left) which displays time series data at a single scale, the TM (right) incorporates temporal scale in the vertical axis, enabling simultaneous visualization of both short-term and long-term variations. Colors indicate statistics of the time series calculated in different intervals. By transforming linear time into a two-dimensional coordinate space, the TM enables the application of spatial analysis techniques, such as overlay and map algebra, to explore patterns and relationships within time series data. Based on similar principles, the Pyramid Model (PM) extends this approach into a 3D space (□(x, y, s)) to incorporate spatial scale (Figure 4, lower panel). In the PM, the x and y axes represent spatial locations, and the z axis represents the size of the spatial unit, for example, the size of raster cell or focal window. This 3D field (□(x, y, s)) enables the exploration of spatial patterns and relationships across multiple spatial scales. Leveraging advanced 3D visualization techniques, the PM can reveal hierarchical and nested structures in spatial patterns (such as point pattern, fractals and spatial autocorrelation). For example, using isosurface and volume slicing, the PM can display landscape fragmentations, point clusters, and hot/cold spots detected at different spatial scales. These analyses enhance the detection and interpretation of fine- and coarse-scale processes and their interrelationships (Qiang, Buttenfield, and Xu 2022).

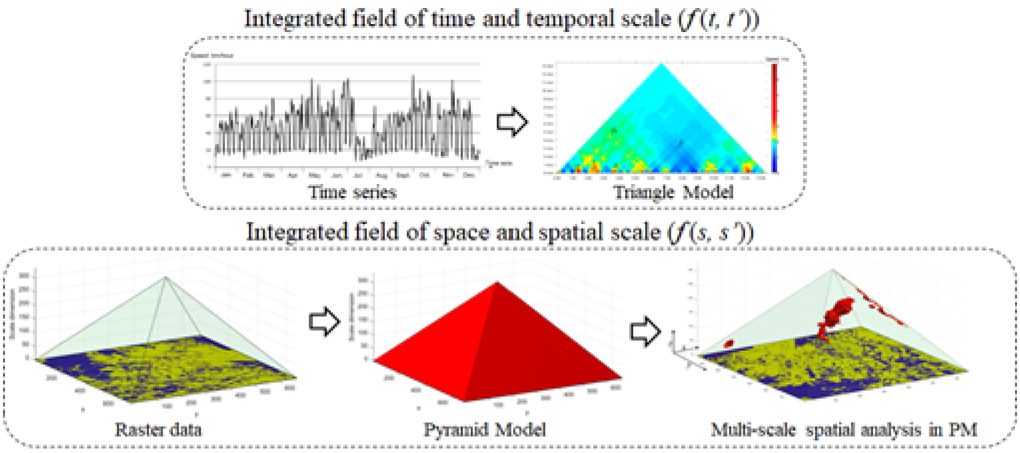


Figure 4. Integration of space & spatial scales (Triangle Model), and time & temporal scales (Pyramid Model). Source: author.

The TM, PM, and space-time cube share a common conceptual basis: the integration of space, time, and scale into a unified analytical space to examine attribute variation from multiple perspectives. The GIS&T Body of Knowledge entry on Relationships between Space and Time (Yuan 2020) discusses the fundamental aspects of space-time relations, while Capturing Spatiotemporal Dynamics in Computational Modeling (Shaw and Ye 2019) reviews various spatio-temporal models and analyses. These integrated space-time models are typically confined to 2D and 3D fields, mainly due to the technical challenges of visualizing high-dimensional fields. Theoretically, a comprehensive spatio-temporal framework should consider at least four dimensions: spatial location (s), spatial scale (s’), temporal location (t), and temporal scale (t’). For example, the spatio-temporal information “the average precipitation in the City of Tampa on 30th October, 2020 is 0.5 inches” can be deconstructed as follows:

Analysis Dimension	Example
Spatial location (s)	City of Tampa
Spatial scale (s')	City
Temporal locatoin (t)	30th October, 2020
Temporal scale (t')	Day

Using this framework, spatio-temporal analyses can be conceptualized as functions with one or more dimensions as variables (Qiang and Van de Weghe 2019; Van de Weghe et al. 2014). These can be

- □(s): Spatial analysis examining data variations at different spatial locations (Figure 5, P1.1).
- □(s, t): Spatio-temporal analysis, such as visualizing moving trajectories in a space-time cube (Figure 5, P2.1).
- □(□): Temporal analyses investigating change over time (Figure 5, P2.2).
- □(s, s’): Multi-scale spatial analysis, as represented in the PM (Figure 5, P3.1)
- □(t, s’): Temporal analysis across spatial scales, for example, comparing housing price trends between counties and states (Figure 5, P3.2)
- □(□’): Cross-scale spatial analysis, such as comparing precipitation in Tampa to state or national averages (Figure 5, P3.3).
- □(s, t’): Spatial analysis across temporal scales, such as comparing spatial patterns of crimes in daily, monthly and yearly intervals (Figure 5, P4.1).
- □(t, t’): Multi-scale temporal analysis, as seen in the TM (Figure 5, P4.2)
- □(s’, t’): Multi-scale temporal analysis, as seen in the TM (Figure 5, P4.3)
- □(t’): Cross-scale temporal analysis, such as comparing the temperature on a day with the monthly and annual mean (Figure 5, P4.4).

The integration of any of the four dimensions leads to a total of 15 types of analyses, calculated using combinations of one or more dimensions: $\binom{4}{1}+\binom{4}{2}+\binom{4}{3}+\binom{4}{4}$. However, the existing data models and analytical tools are limited to one or two dimensions. For example, spatial analysis (as the examples in Figure 5, P1.1) and temporal analysis are considered as 1D analyses, as they only concern the attribute variation in the spatial and temporal dimensions respectively. This high-dimensional framework offers a systematic approach to understanding the complex interactions among space, time and scale, facilitating the development of more nuanced and comprehensive spatio-temporal analyses.

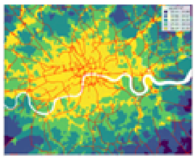
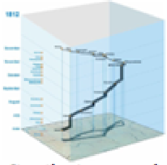
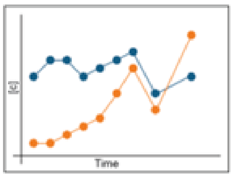
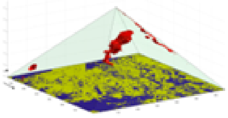
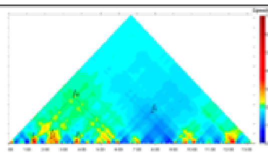
	Spatial location (*s*)	Temporal location (*t*)	Spatial scale (*s'*)	Temporal scale (*t'*)
Spatial location (*s*)	 **P1.1**: Spatial analysis (*f*(*s*))			
Temporal location (*t*)	 **P2.1**: Spatio-temporal analysis (*f*(*s*,*t*)). *Example: ST cube*	 **P2.2** Temporal analysis (*f*(*t*))		
Spatial scale (*s'*)	 **P3.1**: Multi-scale spatial analysis (*f*(*s, s'*)). *Example: Pyramid Model*	**P3.2**: Temporal analysis across spatial scales *f*(*t, s'*) *Example: comparing housing price trends between county and state*	**P3.3**: Cross-spatial-scale analysis (*f*(*s'*)). *Example: aggregating daily temperature into monthly or annual means.*	
Temporal scale (*t'*)	**P4.1**: Spatial analysis across temporal scales *f*(*s, t'*) Example: *comparing spatial patterns of crimes on a specific day with the annual average.*	 **P4.2** Multi-scale temporal analysis (*f*(*t, t'*)). *Example: Triangle Model*	**P4.3**: Analysis across spatial and temporal scales(*f*(*s'*,*t'*)). *Example: simultaneous comparison of housing price across spatial scales (zipcode, county…) and temporal scales (monthly, annual)*	**P4.4**: Cross-temporal-scale analysis (*f*(*t'*)) *Example: comparing the temperature on a day with the monthly and annual mean.*

Figure 5. Analyses integrating two dimensions in the multi-scale spatiotemporal framework. Source: author.

References

Allen, J. F. (1983). Maintaining Knowledge About Temporal Intervals. Communications of the ACM 26(11):832–43.

Angel, S. and Hyman, G. M. (1976). Urban Fields: A Geometry of Movement for Regional Science. London: Pion.

Cohn, A.G., Bennett, B., Gooday, J.M., & Gotts, N.M. (1997). Qualitative Spatial Representation and Reasoning with the Region Connection Calculus. GeoInformatica 1(275–316).

Couclelis, H. (1999). Space, Time, Geography. Geographical Information Systems 1:29-38.

Cova, T. J., & Goodchild, M. F. (2002). Extending geographical representation to include fields of spatial objects. International Journal of Geographical Information Science, 16(6), 509–532.

Ghandehari, M. (2019). Cross-Scale Analysis of Surface-Adjusted Measurements in Digital Elevation Models. Doctoral dissertation, University of Colorado - Boulder.

Ghandehari, M., Buttenfield, B. P., & Farmer, C. J. Q. (2019). Comparing the accuracy of estimated terrain elevations across spatial resolution. International Journal of Remote Sensing, 40(13), 5025–5049.

Pawlak, Z., Grzymala-Busse, J., Slowinski, R., and Ziarko, W. (1995). Rough Sets. Communications of the ACM 38, 11 (Nov. 1995), 88–95.

Peuquet, D. J. (1994). 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.

Qi, F. (2024). Fuzzy Models. The Geographic Information Science & Technology Body of Knowledge (2024 Edition), John P. Wilson (Ed.)

Qiang, Y., & Van de Weghe, N. (2019). Re-Arranging Space, Time and Scales in GIS: Alternative Models for Multi-Scale Spatio-Temporal Modeling and Analyses. ISPRS International Journal of Geo-Information, 8(2), 72.

Qiang, Y., Buttenfield, B., & Xu, J. (2022). Analyzing multi-scale spatial point patterns in a pyramid modeling framework. Cartography and Geographic Information Science, 49(4), 370–383

Qiang, Y., Buttenfield, B.P. and Joseph, M.B. (2021), How to Measure Distance on a Digital Terrain Surface and Why it Matters in Geographical Analysis. Geogr Anal, 53: 588-622.

Samet, H. (1990). Applications of Spatial Data Structures: Computer Graphics, Image Processing, and GIS. Addison-Wesley Longman Publishing Co., Inc.

Song, Y. (2019). Time. The Geographic Information Science & Technology Body of Knowledge (4th Quarter 2019 Edition), John P. Wilson (ed.).

Van de Weghe, N., de Roo, B., Qiang, Y., Versichele, M., Neutens, T., & de Maeyer, P. (2014). The continuous spatio-temporal model (CSTM) as an exhaustive framework for multi-scale spatio-temporal analysis. International Journal of Geographical Information Science, 28(5), 1047–1060.

Yang, C., Wong, D. W., Yang, R., Kafatos, M., & Li, Q. (2005). Performance-improving techniques in web-based GIS. International Journal of Geographical Information Science, 19(3), 319-342.

Yuan, M. (2020). Relationships between Space and Time. The Geographic Information Science & Technology Body of Knowledge (3rd Quarter 2020 Edition), John P. Wilson (ed.)

Zadeh, L. A. (1965). Fuzzy Sets. Information and Control 8(3):338–53.