

Tri-Space Modeling and Visualization: Concept, Implementation, and a Case Study in Wildfire Recovery

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Abstract:

Multivariate and multitemporal data are bountiful in contemporary society. Examples include hyperspectral land cover monitoring, longitudinal medical studies, climate modeling, and multi-year crime statistics. Geographic information scientists have put forth a number of principal approaches to formally represent such data with a view towards pattern discovery and decision support. These have included the “triad” (Peuquet 1994), “pyramid” (Mennis et al. 2000), and “three-domain” (Yuan 1999) frameworks. Meanwhile, the “tri-space” approach (Skupin 2010, Kolovos et al. 2010, Wang et al. 2013) represents an effort at systematic reconfiguration of multivariate observations for discrete entities at multiple time slices. In the tri-space, an individual observation exists at the intersection of three arrays, typically corresponding to these three elements: locus, time, attribute. Unlike in other frameworks, a locus does not necessarily correspond to a geographic location or object, but merely denotes an entity that has a distinct and persistent identity in some physical or abstract space. The tri-space then proceeds to define objects whose identity is delineated by a particular combination of one or two of these arrays, with the remaining arrays defining an object’s location in a particular high-dimensional space. In this manner, six different perspectives can be constructed, to which common multivariate analysis and visualization techniques can then be applied.

The high-dimensional nature of the different tri-space perspectives calls for dimensionality reduction and cartography to be deployed in a novel manner. In contrast with black-box operations typical for machine learning and AI, this opens a path toward new forms of explainable AI (XAI), thanks to concepts and principles borrowed from cartography and geographic information science. As an example, consider the use of remote sensing to monitor landscapes recovering from wildfires. Unlike traditional monitoring in geographic space, the different perspectives afforded by the tri-space framework range from the fine granularity of individual cells moving across multispectral space (Figure 1) to aggregate views, such as when whole satellite images are condensed into a single position, which over time forms a trajectory across a space of extremely high dimensionality (Figure 2). Among the key advantages of this approach is that it allows the analysis of complex geographic phenomena to “break out of the prison of geographic space” such that even geographically distant events and processes can be observed in a unified manner. Finally, thanks to contemporary back- and front-end technologies, exploring these tri-space perspectives can now occur within browser-based web apps.

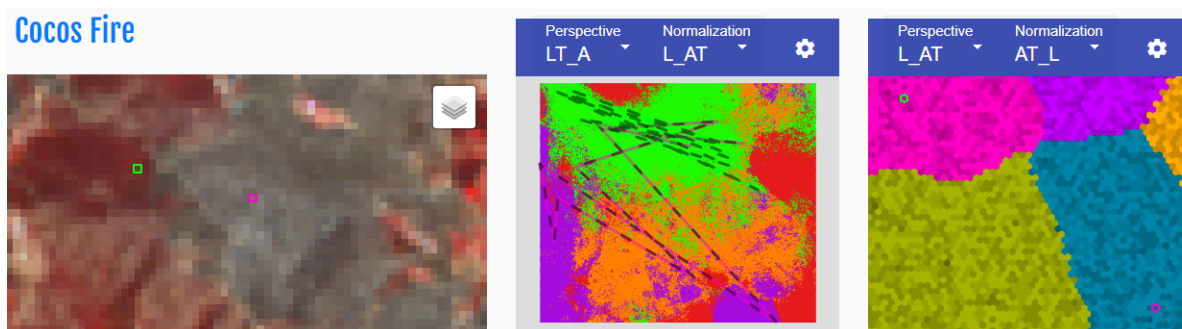


Figure 1. Screenshot of a web application for exploration of wildfire recovery patterns. Juxtaposed are views of a burnt cell (green) and an unburnt cell (purple) in geographic space and in two tri-space perspectives. The center panel shows the unburnt cell continuing its regular oscillation between dry and wet seasons, while the trajectory of the burnt cell dramatically changes after the wildfire.

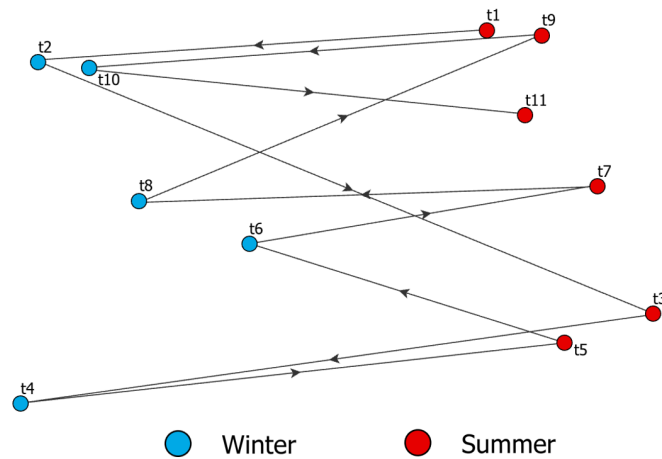


Figure 2. Tracking the effects of a wildfire (occurring between t2 and t3) and landscape recovery in a Mediterranean climate. with a highly aggregate view of whole satellite images, captured semiannually, represented in a 133,000-dimensional feature space, and projected into the two-dimensional display space.

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