

AN EXTREME-VALUE TEST FOR STRUCTURAL BREAKS IN SPATIAL TRENDS

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Abstract: Non-stationary spatial phenomena are common in various fields such as climate and medical image processing. While many methods examine non-stationary spatial covariance structures, more methods are needed for detecting sudden trend breaks in spatial data. Based on the maximal value of the neighboring discrepancy measurement in the sample space, this paper presents an extreme-value test statistic to detect trend breaks. A simulation-based algorithm is developed to detect breaks in spatial trends at various locations, from which the shape of changing boundaries can be revealed. A simulation study reveals that the test is very effective in detecting structural breaks, especially when they appear at the boundary of the sampling region. Analyses of Australian rainfall and lung tumor data demonstrate the accuracy and wide applicability of the proposed method.

Key words and phrases: Change boundary, extreme value theory, inference, long-run variance.

1. Introduction

Non-stationary spatial phenomena are commonly detected in biological, environmental and geographical fields. Non-stationarity can occur in both spatial trends and covariance structures. While many studies have examined non-stationary covariance structures, non-stationarity in the spatial trends needs more attention. One of the most popular methods for the inference of spatial trends is kriging, as discussed by Cressie (1993). However, when little is known about the covariance structure of the data, kriging may not be effective. Furthermore, many kriging methods cannot accurately detect a sudden change in trends, such as those reported by Jun and Stein (2008) for air pollution, Sherwood (2007) for climate change modeling, Neill (2012) for infectious disease patterns, and Otto and Schmid (2016) for computer tomography scans of tumors. It is essential to detect not only structural breaks, but also specific spatial patterns in the underlying spatial trend to avoid misspecifications of spatial models.

Specifically, assume that the data are described by the following spatial model:

$$Y(\mathbf{s}) = \mu(\mathbf{s}) + \epsilon(\mathbf{s}),$$

where \mathbf{s} denotes a location in the sample space. That is, the data Y at point \mathbf{s}

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