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Heuristic Approach to Multidimensional Temporal Assignment of Spatial Grid Points for Effective Vegetation Monitoring and Land Use in East Africa

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Abstract: In this research, vegetation trends are studied to give valuable information toward effective land use in the East African region, based on the Normalized Difference Vegetation Index (NDVI). Previously, testing procedures controlling the rate of false discoveries were used to detect areas with significant changes based on square regions of land. This paper improves the assignment of grid points (pixels) to regions by formulating the spatial problem as a multidimensional temporal assignment problem. Lagrangian relaxation is applied to the problem allowing reformulation as a dynamic programming problem. A recursive heuristic approach with a penalty/reward function for pixel reassignment is proposed. This combined methodology not only controls an overall measure of combined directional false discoveries and nondirectional false discoveries, but make them as powerful as possible by adequately capturing spatial dependency present in the data. A larger number of regions are detected, while maintaining control of the mdFDR under certain assumptions.
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1 Introduction

Analysis of vegetation life cycles is fundamental in monitoring and planning agricultural endeavors and optimizing land use. In particular, gaining knowledge of current vegetation trends and using them to make accurate predictions is essential to minimize times of food scarcity and manage the consumption of natural resources in underdeveloped countries. Needing to understand the Earth's ecology and land cover is increasingly important as the impacts of climate change start to affect animal, plant, and human life. Vegetation trends are also closely related to sustainability issues, such as management of conservation areas and wildlife habitats, precipitation and drought monitoring, improving land usage for livestock, and finding optimum agriculture seeding and harvest dates for crops.

For this reason, there are many agencies and organizations that focus on the study of land use and land cover trends, linking them to climate change and the socioeconomic consequences of these changes. The United States Global Change Research Program (Land Use and Land Cover Change Interagency Working Group), the United Nations Framework Convention on Climate Change (Land Use, Land Use Change, and Forestry), and NASA's Land Cover Land Use Change Program are just three examples of well-known interdisciplinary/ interagency programs that conduct and sponsor research related to the question of global land change as noted in OCHA (2011).

Assessment of changes in a region's vegetation structure is challenging, especially in topographically diverse areas, like East Africa. Forecasting future vegetation and agricultural planning become particularly difficult when

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unknown trends are occurring. However, the regions with vegetation changes are often the areas of most interest in land use management. Ideally, an automated screening process can identify areas with significant vegetation changes and facilitate objective decision making about land-use management such as in Cressie & Wikle (2011).

As a first step in creating an automatic screening processes, data collection on vegetation and land cover is needed. This is typically done through satellite remote sensing. The remote sensing imagery is used to convert the observed elements (i.e., the image color, texture, tone, and pattern) into numeric quantities at each pixel in the image. The image pixels correspond to a square grid of land, the size of which depends on the satellite's resolution. One such numeric indicator is the normalized difference vegetation index (NDVI). In this article, the NDVI series came from satellite remote sensing data collected between 1982 and 2006 over 8,000-meter grid points. It has been shown to be highly correlated with vegetation parameters such as green-leaf biomass and green-leaf area, and hence is of considerable value for vegetation monitoring as in Curran (1980) and Jackson, Et al. (1983).

The NDVI standard scale ranges from −1 to 1, indicating how much live green vegetation is contained in the targeted pixel. An NDVI value close to 1 indicates more abundant vegetation. For example, low values of NDVI (say, 0.1 and below) correspond to scarce vegetation consisting mostly of rock, sand and dirt. A range of moderate values (0.2 to 0.3) indicates small vegetation such as shrub or grassland; larger NDVI values can be found in rainforests (0.6 to 0.8). Often, negative NDVI values are consolidated to be zero since negative values indicate non-vegetation and are of little use for vegetation monitoring. Vegetation activity is a continuous space-time process and NDVI data provide a space-time lattice system, in the sense that observations are available over equally spaced regular grids. Often, the spatial resolution ranges from 1000 to 8000 meters, while the temporal one ranges from 7 days to 1 month.

Statistical and computational methods are needed to analyze remotely sensed data, like NDVI values, to determine trends in land condition and to predict areas at risk from degradation. Methodologies that detect land cover changes need to be sensitive as well as accurate, since it can be costly and risky to relocate human populations, agriculture or livestock to new regions of detected change. In such spatio-temporal data, time series models are tempting for representing such processes. Other existing change detection methodologies include the geographically weighted regression of Foody (2003), the principal component analysis of Hayes & Sader (2001), and the smoothing polynomial regression of Chen & Tamura (2004). However, these methods are unable to provide an upper bound on false detections. Since there is large risk associated with falsely declaring an area to have significant vegetation changes, land use managers seek new methods that have a meaningful control over such errors.

In this article, we build on the previous work of Vrieling, et al. (2008) and Clements, et al., (2014). Vrieling, et al. (2008) first investigated this vegetation screening problem in the hypothesis testing framework of but did not attempt to address the inherent multiplicity issue by controlling an overall false detection rate while making their final conclusions. Clements, et. al. (2014) made improvements by incorporating the spatial dependencies, somewhat arbitrarily, before applying multiple testing procedures. The arbitrary spatial dependency was accounted for by dividing the region into square blocks, based on an overall measure of spatial correlation using a semivariogram plot. After creating such sub-regions, two-sided monotonic trend tests from Brillinger (1989) were used to identify significant increasing or decreasing monotonic vegetation changes based on these arbitrarily chosen square regions of land. They demonstrated that this screening procedure controlled the mixed directional false discovery rate (mdFDR), which is defined as the expected proportion of Types I errors (False Positives) and Type III errors (Directional errors) among all rejected null hypotheses, introduced by Benjamini & Yekutieli (2005).

In this article, we utilize the same historic NDVI time series for East Africa from 1982 to 2006. Since real-time monitoring for change is not part of the scope, we focused improving the methodologies previously used to identify significant changes in land cover in the region. We do this by first framing the research question as an NP-hard temporal multi-objective assignment problem. Using heuristics to solve this problem, we first find improved sub-regions than the previous arbitrarily chosen square grids. Using this approach allows us to adequately capture the specific data structure and answer questions in the present context. Secondly, we reapply the multiple testing procedures in Clements, et al., (2014) and demonstrate that the testing procedure become more powerful while still maintaining control an error rate, the mdFDR. In summary, our methods aim to incorporate spatial local dependencies using a multi-dimensional assignment problem formulation to improve sub-region formation, which in turn improves the multiple testing results.

We organize the paper as follows. In the next section, we give a review of the literature followed by a detailed description of the historical data set. We then describe the temporal assignment problem formulation to create more homogeneous sub-regions and explain the heuristic procedure using dynamic programming. Next, we apply the multiple testing procedures to the improved sub-regions. Finally, we reveal the results of the model implementation, followed by a discussion, conclusions, and final remarks.

2 Literature

2.1 Multiple Testing Overview

To control over false vegetation trend detections, multiple testing procedures can be employed. An overview of multiple testing notation and procedures are described next. When testing a single null hypothesis against a two-sided alternative, two types of error can occur when a directional decision is made following rejection of the null hypothesis. These are Type I error and Type III (or directional) errors. The Type I error occurs when the null hypothesis is falsely rejected, while the Type III error occurs when the null hypothesis is correctly rejected but a wrong directional decision is made about the alternative.

Consider testing n hypotheses simultaneously, such as testing for trend changes in n pixels over the East African region. Table 1 gives the various outcomes of these tests, where $\mathrm{H}_{i0}: \theta_i = \theta_{i0}$ is the null hypothesis and $\mathrm{H}_{i1}: \theta_i \neq \theta_{i0}$ is the two-sided alternative, for $i = 1, 2, \ldots, n$. Of these quantities in Table 1, only n, A, and R (where $R = R_1 + R_2$) are known after applying a particular testing procedure. The number of Type I errors, Type II errors, and Type III errors are $V = V_1 + V_2$, $T = T_1 + T_2$, and $U = S_2 + S_3$ respectively. All three quantities are unknown but

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desirably small. Most multiple testing procedures focus on controlling V in some capacity. In this paper, we utilize a procedure that controls V and U.

		Decision			
		Fail to Reject Null	*Reject Null* $H_0^{(+)}$	*Reject Null* $H_0^{(-)}$	Total
Truth	$\theta = \theta_0$	W (Correct Decisions)	V_1 (Type I errors)	V_2 (Type I errors)	n_0
	$\theta > \theta_0$	T_1 (Type II errors)	S_1 (Correct Decisions)	S_2 (Correct Decisions)	n_+
	$\theta < \theta_0$	T_2 (Type II errors)	S_3 (Correct Decisions)	S_4 (Correct Decisions)	n_-
	Total	A	R_1	R_2	n

Table 1: Multiple Testing outcomes from testing n hypotheses

One of the most commonly used measures of overall Type I error is called the Familywise Error Rate (FWER). The FWER is the probability of making one or more Type I errors. In other words, out of n simultaneously tested hypotheses, where V is the number of Type I errors made out of n decisions (recall: V is an unknown quantity), then FWER =Prob{$V > 0$}. In the case of multiple hypothesis testing, the FWER should be controlled at a desired overall level, called α. The Bonferroni procedure is the most popular method to control the FWER, but there are other techniques, such as those in Holland & Copenhaver (1987), Hochberg & Tamhane (1987), Šidák (1967), Holm (1979), Hochberg (1988), Sarkar (1998), and Sarkar & Chang (1997).

The False Discovery Rate (FDR), proposed by Benjamini and Hochberg (1995), is the second most common measure of Type I errors. The FDR is the expected proportion of Type I errors among all the rejected null hypotheses. If there are no rejected hypotheses, the FDR is defined to be zero. In terms of Table 1, FDR = $\mathrm{E}\left[{}^{\mathrm{V}}/_{\max(\mathrm{R},1)}\right]$. Comparatively, the FDR is less conservative than the FWER, meaning FWER control ensures FDR control. However, a multiple testing procedure with FDR control will not necessarily maintain control of the FWER. The FDR is a widely accepted and utilized notion of Type I errors in large-scale multiple testing investigations. Recent literature has proposed methods to control the FDR, including Benjamini and Hochberg (1995), Benjamini and Yekutieli (2001), Sarkar (2002), Blanchard and Roquain (2009), Storey, Taylor, and Siegmund (2004), and Benjamini, Krieger, and Yekutieli (2006).

Often, it becomes essential for researchers to determine the direction of significance, rather than significance alone, when testing multiple null hypotheses against two-sided alternatives. In other words, for each test, researchers have to decide whether or not the null hypothesis should be rejected and, if rejected, determine the direction of the alternative. Typically, this direction is determined based on the test statistic falling in the right- or left-side of the rejection region. Such decisions can potentially lead to one of two types of error for each test resulting in rejection of the null hypothesis - the Type I error if the null hypothesis is true or the directional error, also known as the Type III error, if the null hypothesis is not true but the direction of the alternative is falsely declared (i.e. a rejection of a false null using a two-sided alternative, but where the sign of the true parameter, say β_i, is opposite of its estimate $\widehat{\beta_i}$).

Two variants to deal with Type I and Type III errors have been introduced in the literature. First is the pure directional FDR (dFDR), which is the expected proportion of directional errors among rejected hypotheses. Second is the mixed directional FDR (mdFDR), which is the expected proportion of Type I and Type III errors among rejected hypotheses. To deal with both errors in an FDR framework, the notion of mixed directional FDR (mdFDR) was been introduced by Benjamini et al. (1993). Since then, other methods to control directional errors have been introduced, including Benjamini and Yekutieli (2005), Benjamini and Hochberg (2000), Shaffer (2002), Williams et al. (1999), Guo et al. (2009), and Sarkar and Zhou (2008).

Controlling both false discoveries (V, from Table 1) and directional false discoveries (U, from Table 1) is important in this application. For instance, when declaring a particular 8,000 m × 8,000 m grid of land as 'significantly' changing in terms of vegetation, a Type I error is made if the area is not truly changing, and a Type III error is made if the area is truly changing but in the opposite direction of what is determined from the data. When such decisions are made simultaneously based on testing multiple hypotheses, one should adjust for multiplicity and control an overall measure of Types I and III errors. Without such multiplicity adjustment, more Types I and III errors can occur than the desired α level. It is particularly important to avoid these errors as much as possible in the present application. Land use managers, government and local farmers are looking to relocate East African populations of people, livestock and crops to areas of promising vegetation changes and avoid regions with decreasing changes. Since these migrations can be risky and costly, a careful consideration of the multiplicity issue seems essential when making declarations of significant vegetation changes.

In this article, p-values generated using the monotonic trend test in Brillinger (1989) are computed for each site (8,000 m × 8,000 m grid of land) and provide evidence of vegetation change occurring over the years—the smaller the p-value, the higher is the evidence of a significant vegetation change. For each site, a decision must be made regarding the significance of vegetation change that might have occurred over the years at that site, and, if vegetation change is found significant, determine the direction in which this change has taken place. This must be done simultaneously for all sites (≈50,000) in the East African region in a multiple testing framework designed to ensure a control over a meaningful combined measure of statistical Types I and III errors.

In this paper, we will first be framing the research question as a heuristic multi-objective temporal assignment problem, in which better sub-regions were created than the arbitrarily chosen square grids in Clements et.al. (2014). By using temporal assignments to create subregions, we will demonstrate that the testing procedure becomes more powerful. Also in this article, we provide theoretical proof that the mdFDR is still controlled under sub-region independence.

2.1 Temporal Assignment Problem Overview

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There is a wealth of research on assignment problems and specialized assignment problems that display complicating constraints. Though the generalized assignment problem is solvable, once the number of dimensions reaches 3, as in the formulation presented in this paper, this is no longer the case.

The multidimensional assignment problem was introduced by Pierskalla (1968) and a bibliography of multidimensional assignment problems was prepared by Gilbert & Hofstra (1988). Miori (2011, 2008, 2014) used assignment problems to model truckload routing problems and the Pollyanna gift exchange problem. Scheduling medical residents with the temporal component was addressed by Franz & Miller (1993). Bandelt, Et al. (1994, 2004) addressed multi-dimensional assignment problems with decomposable costs. The three-dimensional assignment problem was applied to teaching schedules by Frieze & Yadegar (1981) and Balas & Saltman (1991). Multidimensional approximation was applied to capacity expansion problems by Troung & Roundy (2011). Lagrangian Relaxation was applied to a multi-dimensional assignment problem arising from multi-target tracking by Poore & Rijavec (1993). Multi-tracking data was also addressed by Robertson (2001).

Approximations to the multi-dimensional assignment problem were generated by Kuroki & Matsui (2007), Gutin, Et al. (2008), Krokhmal, Et al. (2007), and Karapetyan &Gutin (2011). The multi-objective assignment problem seeking solutions to the assignment problem in the face of additional objectives using efficient sets was posed by White (1984). A weighting function approach has also been applied to multi-objective (multicriteria) problems with conflicting objectives by Phillips (1987).

Agricultural planning problems have been addressed by Samuelson (1952), Takayama (1964), Norton & Scandizzo (1981), Kutcher & Norton (1982), Önal & McCarl, and Weintraub & Romero (2017). Multicriteria approaches to agriculture decisions have also been applied by Gasson (1973), Harper & Eastman (1980), Wheeler & Russel (1977), Hayashi (2000), and Romero & Rehman (2003).

2.2 Land Use Optimization Overview

The most basic methods in land use optimization involve limited enumeration of alternatives and developing metrics to directly assess these alternatives. Landscape metrics addressing various land use goals were used by Kuchma, Et al. (2013) to evaluate enumerated options for land use. A similar approach was proposed by Wang & Guldmann (2015) to mitigate seismic damages in Taichung, Taiwan.

Heuristic methods and in sustainable land use were applied by Steward, Et al. (2004), Cao, Et al. (2011), Liu, Et al. (2016) and Sahebgharani (2016). Genetic algorithms were presented Cao, Et al. (2012) and the Analytical Hierarachy Process was utilized by Memarian, Et al. (2014). Multi-objective linear programming with sensitivity analysis was found effective by Sadeghi, Et al. (2009) while Soil and Water Assessment Toll (SWAT) was employed by Sunandar, Et al. (2014).

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3 Data Description

East Africa spans a wide variety of climate types and precipitation regimes which are reflected in its vegetation cover. To capture this, satellite imagery was collected over a sub-Saharan region of East Africa that includes five countries in their entirety (Kenya, Uganda, Tanzania, Burundi and Rwanda) and portions of seven countries (Somalia, Ethiopia, South Sudan, Democratic Republic of Congo, Malawi, Mozambique and Zimbabwe). This roughly 'rectangular' region extends from 27.8°E to 42.0°E longitude and 15.0°S to 6.2°N latitude. Also included in the region are several East African Great Lakes such as Lake Victoria, Lake Malawi and Lake Tanganyika. Vegetative analysis in this region is of interest for a variety of reasons, including the importance of the region for global biodiversity and the vulnerability of the region to climate change, deforestation of the Congo, urban development, civil conflict, and agricultural practices.

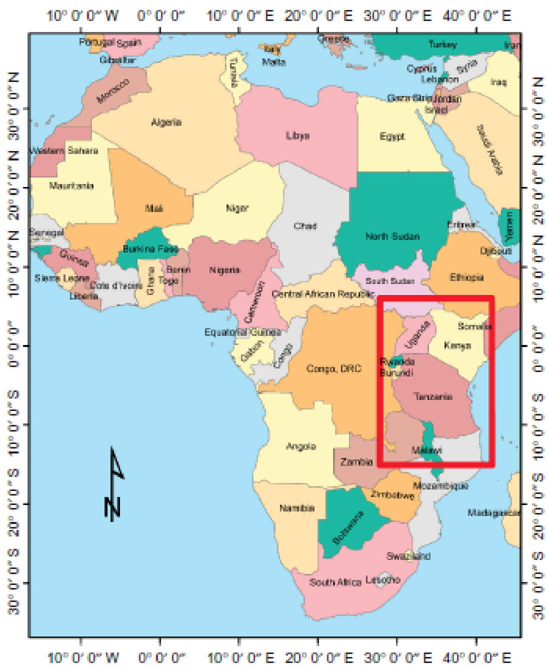

Figure 1 The study area, as indicated by the box.

The remotely sensed images were recorded twice a month from 1982–2006 and then converted to NDVI values. Hence, the spatio-temporal data set consists of approximately 50,000 sites (pixels), each with 600 time series observations (24 observations per year over 25 years). The satellite's resolution corresponds to each pixel spanning an 8,000m × 8,000m grid of land, which we will refer to as a 'location.' This Global Inventory Modeling and Mapping Studies (GIMMS) data set is derived from imagery obtained from the Advanced Very High Resolution

Radiometer (AVHRR) instrument onboard the National Oceanic and Atmospheric Administration (NOAA) satellite series 7, 9, 11, 14, 16 and 17. The NDVI values have been corrected by Tucker, Et al. (2005) for calibration, view geometry, volcanic aerosols, cloud coverage and other effects not related to vegetation change.

All the negative NDVI values were consolidated to zero, as commonly done in vegetation monitoring, and re-scaled the remaining values by 1,000. Negative NDVI values indicate non-vegetation areas, and so they are of no use in our statistical analysis. Prior to the analysis, we examined the data for quality assurance and eliminated a small number of pixels that were found to have several consecutive years with identical data values, which may be due to data entry errors or machine malfunction.

When this data was first examined in Vrieling, de Beurs and Brown (2008), the percentage of pixels with the trend test p-value less than $\alpha = 0.10$ was reported separately for positive and negative slopes. The reported results indicate that much of the region has 'significant' vegetation change. For example, the cumulative NDVI indicator detected 44.2% of sites with p-values less than 0.10. However, this result fails to address the important statistical issue of multiplicity when making these claims about significant vegetation changes and their directions simultaneously for all the regions based on hypothesis testing. Later, Clements, et. al. (2014) addressed the multiplicity issue by proposing a 3-stage multiple testing procedure to control the mixed-directional False Discovery Rate (mdFDR), but did so on subregions of East Africa that were not optimally formed.

The associated csv file for this analysis is the information generated from Clements, et al, (2014) which was the initial starting point for this analysis. It contains the following fields:

- site: Consecutive ID number, acting as a unique identified
- xcoord: pixel longitude
- ycoord: pixel latitude
- ndvi.avg: Overall pixel average NDVI from 1982 to 2006 (observations taken twice monthly)
- pval: Resulting p value from the Brillinger Trend Test (Brillinger, 1989)
- slp: Resulting slope from the Brillinger Tren Test (Brillinger, 1989)
- block: Block number – initial assignment was arbitrary

Using the algorithm below, followed by the multiple testing procedure, users may generate the revised and improved block assignments.

4 Assignment Problem Formulation

We propose an assignment formulation to this problem, using these analysis results, with the goal of an improved solution. The object of the geographic assignment problem is to map each pixel within the satellite images to an appropriate block based upon a target value for each block. The block target values represent equal size ranges within the overall range of the objective function values. The objective function for the pixel assignment is the sum

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of absolute difference between the pixel NDVI and the block target NDVI. The number of blocks is set objectively and may be reset for each assignment problem solution generated.

Note that pixels may be formed entirely of water; these pixels have been assigned arbitrarily high NDVI values to effectively eliminate them from consideration in the block assignments. A 'water block' with an arbitrarily high target value ensures that all of these pixels may be assigned to blocks.

The objective of the pixel assignment problem is to minimize the NDVI difference function. Let m = the number of pixels, let n = the number of blocks, and let T = the number of time periods. The decision variable x_{ij}^k is a binary variable that represents the assignment, or lack of assignment, of pixel i to block j at time k. The constraints formulated ensure that each pixel is assigned to a block, during each period of time. The formulation in Eq. (1) – (3) follows the notation.

$x_{i,j}^k$	Decision variable $\in (0,1)$ $i = 1, \cdots, m; j = 1, \cdots, n;\ k = 1, \cdots, T$
$N_{i\cdot}^k$	Pixel i NDVI score for time k: $i = 1, \cdots, m;\ k = 1, \cdots, T$
$N_{\cdot j}^k$	Block j NDVI target for time k: $j = 1, \cdots, n;\ k = 1, \cdots, T$

Table 2 Assignment Problem Notation.

$$Minimize \sum_k \sum_j \sum_i \left| N_{\cdot j}^k - N_{i\cdot}^k \right| \cdot x_{i,j}^k \tag{1}$$

Subject to:

$$\sum_i \sum_j x_{i,j}^k = 1 \;\; for\ k = 1, \cdots, T \tag{2}$$

$$x_{i,j}^k \in (0,1) \tag{3}$$

The binary decision variables utilize three indices, rendering the problem NP hard. We therefore propose and employ a heuristic approach that relies heavily on dynamic programming.

5 Assignment Problem Solutions

5.1 Lagrangian Relation

Restatement of the pixel assignment problem as a Markov Process will facilitate alternative solution methodologies. We present a Lagrangian relaxation of the formulation and introduce a Lagrangian multiplier (φ_k) for the single constraint to be relaxed in each time period k = 1, ⋯, T. We include a simplifying assumption that the penalty is constant over all time periods and is denoted as φ The revised formulation is presented in Eq. (4) - (5).

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$$Minimize \sum_k \sum_j \sum_i \left|N_{\cdot j}^k - N_{i\cdot}^k\right| \cdot x_{i,j}^k + \sum_k \varphi\left(\sum_j \sum_i x_{i,j}^k - 1\right) \tag{4}$$

Subject to:

$$x_{i,j}^k \in (0,1) \tag{5}$$

A dynamic programming formulation may now be presented using the relaxed formulation.

5.2 Dynamic Programming Formulation

The pixel assignment decisions may be made in stages, and while the outcome of each decision is not fully predictable, it can be observed before the next decision is made. We begin the dynamic programming formulation by organizing the problem into a tree structure (Fig. 2) reflecting pixels and levels (time increments). Each level of the tree corresponds to a time increment, beginning with time 0 which represents the first satellite images retrieved within the data set and ending at the final images at time T-1 and the pixels in each level number from 1 to m. The tree provides a discrete-time dynamic system.

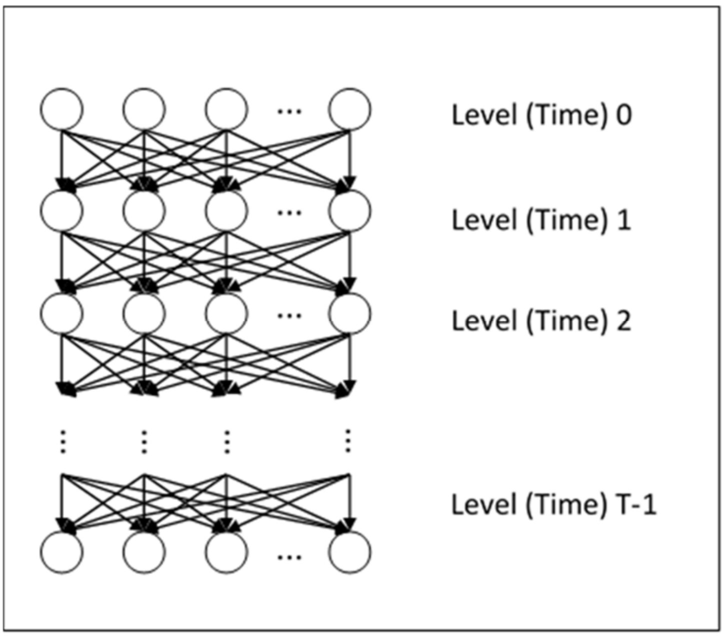

Figure 2 General Tree Structure.

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An additive value function reflects both present cost of each pixel assignment to a block, and potential future cost of all pixel assignments to blocks (expected cost-to-go). Block NDVI targets must be established in order to match pixels to blocks. Initialization of these targets is accomplished by evenly distributing the range of NDVI values across n candidate blocks. Recall that the NDVI values ranges between 0 and 1000, resulting in block targets starting at zero with an increment $1000/\mathrm{n}$ up to 1000.

To calculate expected cost-to-go, we must also identify and calculate transition probabilities. In doing so, we consider only the current level (time period). The Markov Property (6) allows us to omit consideration of the probabilities of the path leading to the current level. The tree may now be viewed as a finite Nonhomogeneous Markov Process with transition probability matrix $\mathrm{P}^{(\mathrm{k})}$ representing transitions at any level.

$$P(X_{k+1} = x_{k+1} | X_0 = x_0, \dots, X_k = X_k) = P(X_{k+1} = x_{k+1} | X_k = x_k) \quad (6)$$

The objective of the dynamic programming formulation is the minimization of the sum of cost at the current stage, and the cost-to-go (the best case to be expected from future stages). The notation required for the formulation follows.

$A(k+1,k)$	Available pixels at level (time) *k+1*, depends on pixel chosen at level *k*
m_{k+1}	Cardinality of $A(k+1,k)$ (the number of pixels available at level *k+1*, depends on pixel selected at level *k*)
$s(k)$	The pixel chosen at level *k*
$\boldsymbol{P}^{(k)}$	Transition probability matrix at level *k*
$\boldsymbol{P}_{i,j}^{(k)}$	Transition probability of moving from pixel *i* to pixel *j* at level *k*
$C_{s(k),j}$	Cost of adding node *j* after the pixel chosen at level *k*
$U(i,k)$	The number of unassigned pixels if we choose pixel *i* at level *k*
$f(i,k)$	Expected cost-to-go if we choose pixel *i* at level *k*
$f(1,0)$	Initialize to 0
φ	Pixel assignment penalty

Pixel assignments to blocks may begin at any pixel in level 0 of the tree and end at any pixel in level T-1. All pixels must be assigned to a single block but individual blocks need not have pixels assigned to them. Let z be the candidate block.

$$f(s(k),k) = \min_{z \in A(k+1,k),\varphi} \left\{ C_{s(k),z}^{k} + \boldsymbol{P}_{i,j}^{(k)} \varphi U(s(k),k) + f(z,k+1) \right\} \quad (7)$$

$$C_{s(k),z}^{k} = \left| N_{\cdot z}^{k} - N_{s(k)\cdot}^{k} \right| \quad (8)$$

Though this approach resolves issues with the original assignment formulation, it necessitates the calculation of transition probability matrices $\left(\mathrm{P}^{(\mathrm{k})}\right)$ at each level. Transition probabilities are dependent on the number of blocks chosen, and the ability to statistically characterize the changes in vegetation in the pixels over time. With as few as

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100 blocks, the probabilities would have a very small order of magnitude and an expectation of high levels of inaccuracy, resulting in a lack of ability to detect meaningful differences. We present a heuristic, rooted in dynamic programming principles to render an efficient and useful solution to the pixel assignment problem.

5.3 Recursive Heuristic Procedure

Due to the original assignment problem being NP hard, and the dynamic programming approach resulting in extreme computational and structural complexity, we introduce a heuristic method that leverages knowledge gained in the assignment and dynamic programming approaches. This heuristic also leverages the previous research completed in controlling the mdFDR.

The heuristic procedure was initialized with the 150 blocks used in Clements et. al (2014) and 56,355 total pixels, and utilized the previously calculated slopes and resulting p-values from monotonic trend tests. Rather than assigning the pixels to blocks over the duration of the 25-year span of the data collection as the assignment formulation would, this approach focused on assignment at the final observations in the 25th year but the use of slope and p-value allowed the approach to reflect the trends that occurred over time. This same approach could be used at any time during the study, reflecting all previous data.

The heuristic performance metric, like the objective function in the pixel assignment problem, required the calculation of block values corresponding to the pixel values. The metric leverages the initial random blocks by including the block average NDVI, the block average slope, the block average p-value, and the slope change indicator variable. Notation is introduced in Table 3, followed by the formulation of the performance metric.

y_{fg}	Block assignment $\in (0,1)$ $f = 1, \cdots, m; g = 1, \cdots, n$
I_{fg}	Slope change Indicator variable
$N_{f\cdot}$	Pixel i NDVI score at final observation: $i = 1, \cdots, m$
NR_g	NDVI range for block g
$S_{f\cdot}$	Pixel i slope over time: $i = 1, \cdots, m$
SR_g	Slope Range for block g
$P_{f\cdot}$	Pixel i p-value over time: $i = 1, \cdots, m$
PR_g	p-value range for block g
w_d	Weight for scoring factor d: $d = 1, \cdots 4$

Table 3 Heuristic Metric Notation.

Let f = pixel number and let g = block number and let

$$y_{fg} = \begin{cases} 1 & \text{if pixel } f \text{ is assigned to block } g \\ 0 & \text{if pixel } f \text{ is not assigned to block } g. \end{cases}$$

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Development of the performance metric required definition of the block average values for NDVI, slope and p-value shown in Eq (9) – (11). In addition, the indicator parameter, signaling slopes of opposite sign is shown in Eq. (12).

$$\bar{N}_{\cdot g} = \sum_{f \ni pixels \in block\ g} \frac{N_{fg}}{n} \quad \forall g = 1, \cdots, n \tag{9}$$

$$\bar{S}_{\cdot g} = \sum_{f \ni pixels \in block\ g} \frac{S_{fg}}{n} \quad \forall g = 1, \cdots, n \tag{10}$$

$$\bar{P}_{\cdot g} = \sum_{f \ni pixels \in block\ g} \frac{P_{fg}}{n} \quad \forall g = 1, \cdots, n \tag{11}$$

$$I_{fg} = \begin{cases} 1 \text{ if } sign\left(S_{f\cdot} * \bar{S}_{\cdot g}\right) \text{ is negative } \forall f \ni \text{pixels } \in \text{block } g \\ 0 \text{ if } sign\left(S_{f\cdot} * \bar{S}_{\cdot g}\right) \text{ is positive } \forall f \ni \text{pixels } \in \text{block } g \end{cases} \tag{12}$$

The minimum value of the performance metric in Eq. (13) determines the highest quality heuristic solution. Pixels whose current assignment leaves them on the border between blocks are evaluated. The metric is calculated for their incumbent (current) assignment and their prospective assignment(s). The pixel is then assigned to the block yielding the lowest value of the metric. As pixels are reassigned, newly exposed border pixels are evaluated in the same fashion. This procedure continues until all border pixels belong to the block with the best fit.

$$w_1 \frac{\left|N_{f\cdot} - \bar{N}_{\cdot g}\right|}{NR_g} + w_2 \frac{\left|S_{f\cdot} - \bar{S}_{\cdot g}\right|}{SR_g} + w_3 \frac{\left|P_{f\cdot} - \bar{P}_{\cdot g}\right|}{PR_g} + w_4 I_{fg}$$

$$\forall \text{ pixel } f = 1, \cdots, m; \text{bordering block } g = 1, \cdots, n \tag{13}$$

The dynamic programming concept of forward and backward passes has been adapted for the heuristic to compensate for directional bias in the results. In this way, all border pixel assignments may be evaluated in all directions. Four starting points and starting directions are identified in Fig. 3. Fig. 4 shows the four passes to be completed for the first starting direction (upper left-hand corner). The first two passes are the forward direction evaluation and the second two passes are the backward direction evaluation. These same four passes are adapted for each starting point/direction, with the first pass always corresponding to the starting position.

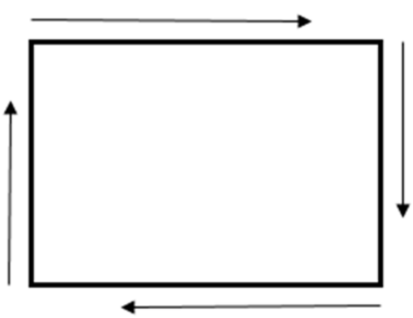

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Figure 3 Starting Directions for Evaluation of Pixel Assignments.

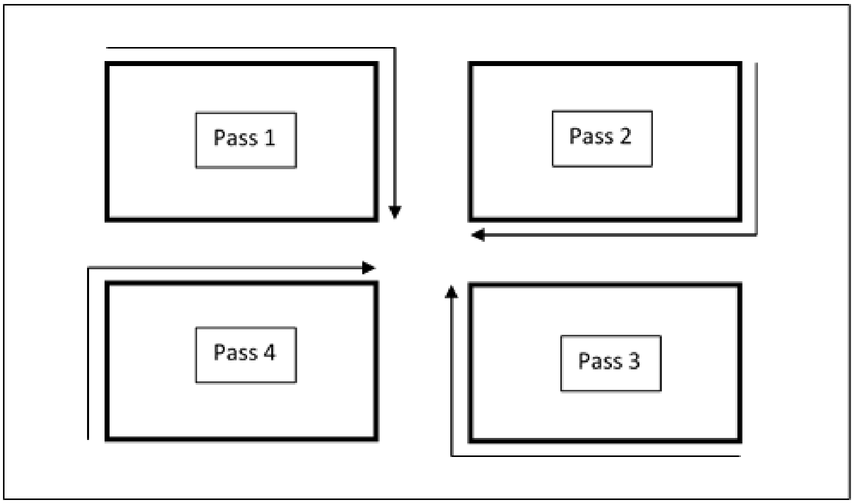

Figure 4 Forward-backward evaluation: Forward passes 1 and 2; Backward passes 3 and 4.

Implementation and validation of the heuristic was accomplished through the development of a program written in the C programming language.

6 Reassignment Model and Implementation

An approach inspired by dynamic programming was utilized to find the best solution to the heuristic problem based on weight factors that varied between 0 to 1, under the condition that $\sum_{i=1}^{4} w_i = 1$. Table 4 shows a subset of the factor weight combinations that were examined. As seen in Table 4, selecting the solution with factor scores of $w_1 = 1$, $w_2 = 0$, $w_3 = 0$, and $w_4 = 0$ generates the smallest value of the performance metric in Eq. (13). Since factor 1 represents the NDVI average value at the final observation, this solution suggests performing pixel reassignment based solely on NDVI information with no weight applied to factors such as slope and p-value. The average score function of initial arbitrary square grid solution (calculated to be 0.1339) was compared to the proposed reassignment solution (calculated to be 0.0998), and yielded an improvement of 25.5%.

[Table 4 near here]

The spatial map in Fig. 5 visualizes the initial arbitrary block assignment using square grids (left) compared to the final solution (right) that gave the minimum value of the performance metric in Eq. (13). The contrast in maps reveals how the solution to the pixel assignment problem created natural looking clusters of differing sizes. For example, along some coastline areas, clusters are long and narrow. This is intuitive because NDVI values tend to be

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similar along the coast where many areas are comprised of sand and rock. In other areas, clusters became circular and cover vast areas of known deserts in the East African regions. Small clusters also exist in the solution and, after investigating, we found that many of these clusters comprise of cities and urban areas that have little vegetation. It is logical that such pixels should be reassigned into the same cluster.

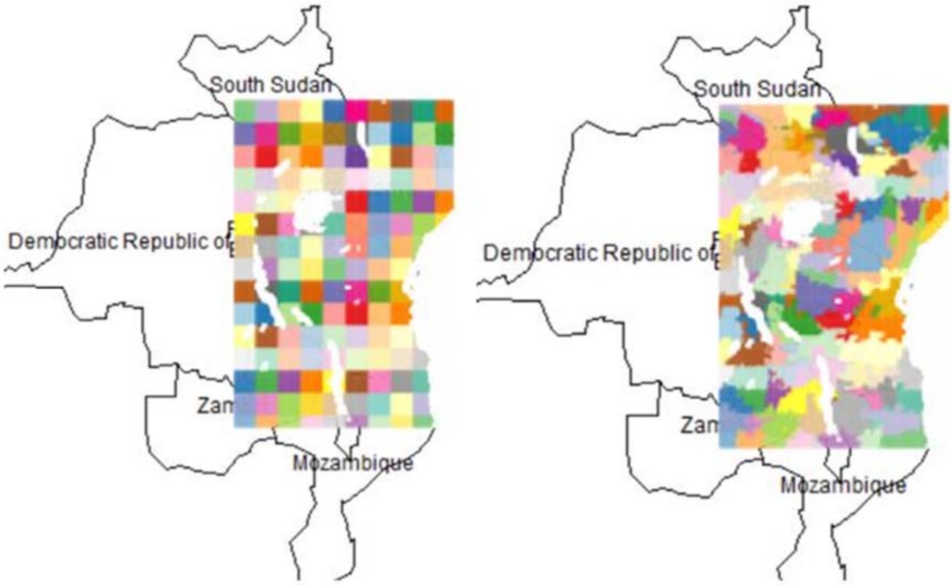

Figure 5 Initial arbitrary block assignment (left) compared to final solution (right).

An unbiased validation of the reassignment solution can be calculated using the average coefficient of variation for the final pixel assignment and compare it to the initial square block assignment. The coefficient of variation (CV) is a unit-less measure of spread that describes the amount of variability relative to the mean. CV is defined as the ratio of standard deviation over the mean. Smaller values of CV indicate higher homogeneity of the clusters. The average of cluster's coefficients of variations for our final pixel assignment solution is 11.762. This is a 27.4% decrease compared to the average coefficient of variation for the original square blocks, which was 16.205. This is a statistically significant difference in CV averages ($p=0.000529$), providing further evidence that the pixel reassignment solution was able to increase the level of homogeneity within clusters. Having homogeneous clusters is important when making large scale decisions about regions in East Africa that have experienced significant vegetation trend changes.

7 Multiple Testing Implementation and Results

Now we can assume that the pixels in the East African region are divided into homogeneous subregions using temporal assignments, as described above. Next, we summarize and apply the multiple testing procedure given in Clements, et. al. (2014).

For notation, let m be the number of such subregions and n_i be the number of pixels/locations in the i^{th} subregion. P-values at each location were calculated using a two-sided monotonic trend test at each location using the Brillinger (1989) test. Specifically, we denote β_{ij} as the monotonic trend parameter as defined in the Brillinger test for the i^{th} subregion and j^{th} location, where $i = 1, 2, \dots, m$, $j = 1, 2, \dots, n_i$. We also let T_{ij} and P_{ij} be, respectively, the test statistic and the corresponding p-value for testing the null hypothesis $H_{ij}: \beta_{ij} = 0$ against its two-sided alternative $H_{i1}: \beta_{ij} \neq 0$.

We apply Clements, et. al. (2014) suggestion of using a Bonferroni correction at each subregion, which combines the p-values by calculating $P_i = n_i \min_{1 \le j \le n_i} (P_{ij})$. With H_{ij} representing the null hypothesis corresponding to P_{ij}, consider $H_i = \bigcap_{j=1}^{n_i} H_{ij}$ as the null hypothesis corresponding to i^{th}subregion. We will test the H_{ij}'s against their respective two-sided alternatives and detect the direction of the alternatives for the rejected hypotheses. Specifically, we apply the procedure using α=0.05 in the following three steps:

Multiple Testing Procedure Applied to Homogeneous Sub-regions:

1) Apply the BH method to test H_i, $i = 1, 2, \dots, m$, based on their respective p-values $P_1, P_2, \dots, P_m$ as follows: consider the increasingly ordered versions of the P_i's, $P_{(1)} \le P_{(2)} \le \dots \le P_{(m)}$. Find $S = \max\{i: P_{(i)} \le {}^{i\alpha}/_{m}\}$. Reject the H_i's for which the p-values are less than or equal to $P_{(S)}$, provided this maximum exists, otherwise, accept all H_i.

2) For every i such that H_i is rejected at step 1, consider testing H_{ij}, $j = 1, 2, \dots, n_i$ based on their respective p-values P_{ij}, $j = 1, 2, \dots, n_i$, as follows: reject H_{ij}if $P_{ij} \le {}^{S\alpha}/_{mn_i}$.

3) For each rejected H_{ij} in step 2, decide the direction of the monotonic trend to be the same as that of $sign(T_{ij})$.

Step 1 and 2 identify first, the subregions and second, the locations with significant vegetation changes. The third step allows one to make a more detailed analysis by identifying the directions in which these significant changes have occurred. Impressively, this procedure controls the mdFDR at level α if the subregions are independent. A mathematical proof of this is given in the Appendix.

The results of implementing this procedure to our homogenous subregions are shown in Fig. 6. Sites with a significant increasing change in vegetation are plotted in green. Sites with significant negative vegetation change are plotted in red. The nonsignificant sites are represented by white. Using the temporal reassignment to form

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homogeneous subregions before implementing the multiple testing procedure detected 518 locations with significant vegetation changes. Compared to the procedure in Clements, et. al. (2014) based on arbitrary square subregions, this is an increase in 10 detected locations, which is indicative of a higher-powered testing procedure, while still maintaining control over Type I and Type III errors.

Geographically, the results show increasing vegetation trends in the Northern hemisphere as well as coastal Eastern Tanzania. Decreasing vegetation trends are mostly concentrated directly South of Lake Victoria. These findings are consistent with historical evidence and other climate change investigations done in this region.

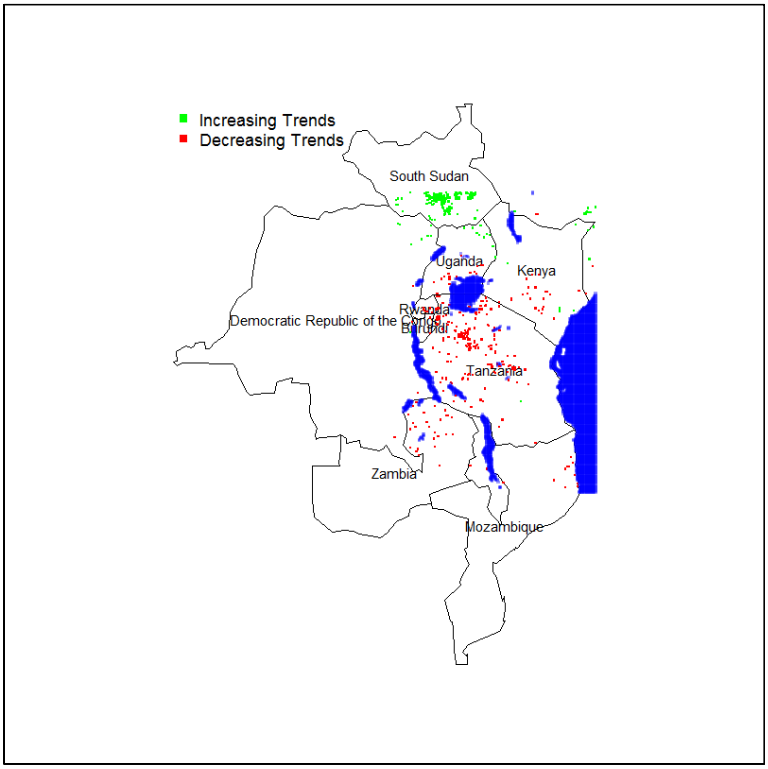

Figure 6 Pixels detected using the proposed heuristic reassignment solution with multiple testing procedures.

8 Data Availability

The data, titled "NDVI and Statistical Data for Generating Homogeneous Land Use Recommendations", may be accessed through figshare. The link to the archives is: https://figshare.com/s/ed0ba3a1b24c3cb31ebf and the DOI is https://figshare.com/articles/NDVI_and_Statistical_Data_for_Generating_Homogeneous_Land_Use_Recommendations/5897581.

9 Conclusions and Future Research

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It is important to consider neighboring pixel's vegetation when making costly land management decisions that would potentially relocate East African populations of people, livestock and crops. The motivation of this paper stems from the opportunity to optimize the pixel assignments based on neighboring pixel data, rather than using blocks in an arbitrary grid fashion, prior to using statistical methodologies to detect vegetation changes over regions in East Africa. Knowing information about the homogeneous cluster to which a particular pixel belongs can provide valuable insights and improved methodologies.

Although we demonstrated our methodology using NDVI data, the procedure can be used for any spatial-temporal data, even on finer scales. Overall, by using dynamic programming to formulate a multidimensional temporal assignment problem implemented by the heuristic procedure, we were able to reassign pixels to adjacent clusters based on similar NDVI values over time. The results of this analysis create more homogeneous regions of East Africa for decision makers to draw inferences regarding vegetation changes. We have demonstrated a powerful tool for homogeneous cluster creation of pixels undergoing land-cover change using temporal satellite data.

Efficient land use for economic sustainability and effective land use for environmental sustainability have become very important topics addressed by Cole, Et al. (2000) and Duveiller, Et al. (2007). This research may be directly extended to consider additional characteristics of land and identify appropriate land use as in Usongo & Nagahuedi (2008). This is especially important when considering the inclusion of multiple land purposes: residential, farm, riparian borders, industrial, commercial, etc.

Another avenue to explore in future research is to extend the proposed methodologies to other applications of spatio-temporal data. For example, monitoring and detecting transient sources in the night sky, specifically Type Ia supernovae transients, is an area of astronomical research that receives much attention. Spatio-temporal astronomy data has spatial dependencies that exist between pixels in astronomical images, which is well suited for a multidimensional temporal reassignment to create homogenous clusters.

With extension of this work to other special problems, finding optimal weights will become important and relevant work. Though the pixel assignment problems ultimately unveiled the appropriate weights through an iterative approach, problems with extended criteria provide a greater challenge in determining appropriate or optimal weights. We anticipate determination of optimal weights to be evaluated as future research as well.

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Appendix A

Proof. We prove that the mdFDR is controlled at desired level α, by borrowing some ideas in Clements, et. al. (2014). Let R be the total number of H_{ij}'s that have been rejected, and V and U, respectively, be the numbers of Types I and III errors that occurred out of these R rejections. Then

$$\text{mdFDR} = \text{FDR} + \text{dFDR} = E\left(\frac{V+U}{\max\{R,1\}}\right), \qquad (A1)$$

since $\text{FDR} = E\left(\frac{V}{\max\{R,1\}}\right)$ and $\text{dFDR} = E\left(\frac{U}{\max\{R,1\}}\right)$ is the directional FDR. Let us consider using H_{ij} as an indicator variable with $H_{ij} = 0$ (or 1), indicating that Brillinger's null hypothesis H_{ij}: $\beta_{ij} = 0$ is true (or false). Then,

$$V = \sum_{i=1}^{m} \sum_{j=1}^{n_i} I\left(H_{ij} = 0, P_{ij} \le S\alpha/mn_i\right) \qquad (A2)$$

where S is the number of significant subregions in the first stage of the procedure. Hence,

$$\text{FDR} = E\left(\frac{V}{\max\{R,1\}}\right) \qquad (A3)$$

$$= \sum_{i=1}^{m} \sum_{j=1}^{n_i} E\left(\frac{I\left(H_{ij} = 0, P_{ij} \le S\alpha/mn_i\right)}{\max\{R,1\}}\right) \qquad (A4)$$

$$\le \sum_{i=1}^{m} \sum_{j=1}^{n_i} I\left(H_{ij} = 0\right) E\left(\frac{I\left(P_{ij} \le \frac{S\alpha}{mn_i}\right)}{\max\{S,1\}}\right) \qquad (A5)$$

since $R \ge S$ [borrowing the idea from Guo and Sarkar (2012)]. Let $S^{(-i)}$ be the number of significant subregions that would have been obtained if we had completely ignored the i^{th} subregion and applied the first-stage BH method to the rest of the $m-1$ subregion p-values using the critical values $\frac{i\alpha}{m}, i = 2,3,\ldots,m$. Then, it can be shown that

$$\frac{I\left(P_{ij} \le S\alpha/mn_i\right)}{\max\{S,1\}} = \sum_{s=1}^{m} \frac{I\left(P_{ij} \le \frac{s\alpha}{mn_i}, S = s\right)}{s} \qquad (A6)$$

$$= \sum_{s=1}^{m} \frac{I\left(P_{ij} \le \frac{s\alpha}{mn_i}, S^{(-i)} = s-1\right)}{s} \qquad (A7)$$

Since we assume the m subregions are independent, taking expectation and inserting into FDR definition gives us

$$\mathrm{FDR} \le \sum_{i=1}^{m}\sum_{j=1}^{n_i} I(H_{ij}=0)\sum_{s=1}^{m}\frac{1}{s}\frac{s\alpha}{mn_i}\Pr\left(S^{(-i)}=s-1\right) \quad (A8)$$

$$= \alpha\sum_{i=1}^{m}\frac{1}{mn_i}\sum_{j=1}^{n_i} I(H_{ij}=0) \quad (A9)$$

$$= \frac{\alpha}{m}\sum_{i=1}^{m}\pi_{i0} \quad (A10)$$

where π_{i0} is the proportion of true null hypotheses among the total n_i null hypotheses in the i^{th} subregion.

We now work with the dFDR. Let $\delta_{ij} = \mathrm{sign}(\beta_{ij})$ representing the true sign of the Brillinger's monotonic trend parameter β_{ij} j^{th} location in the i^{th} subregion and T_{ij} is the test statistic. Now, U can be expressed as follows:

$$\mathrm{U} = \sum_{i=1}^{m}\sum_{j=1}^{n_i} I\left(H_{ij}=1, P_{ij} \le \frac{S\alpha}{mn_i}, T_{ij}\delta_{ij} < 0\right) \quad (A11)$$

from which we first have

$$\mathrm{dFDR} = E\left(\frac{\mathrm{U}}{\max\{R,1\}}\right) \quad (A12)$$

$$U = \sum_{i=1}^{m}\sum_{j=1}^{n_i} I(H_{ij}=1)E\left(\frac{\mathrm{I}\left(P_{ij} \le \frac{S\alpha}{mn_i}, T_{ij}\delta_{ij} < 0\right)}{\max\{R,1\}}\right) \quad (A13)$$

Making arguments similar to those used for the FDR, we then have

$$\mathrm{dFDR} \le \sum_{i=1}^{m}\sum_{j=1}^{n_i} I(H_{ij}=1)\sum_{s=1}^{m}\frac{1}{s}\Pr\left(P_{ij} \le \frac{s\alpha}{mn_i}, T_{ij}\delta_{ij} < 0\right)\Pr\left(S^{(-i)}=s-1\right) \quad (A14)$$

Notice that $P_{ij} = 2\left[1-\Phi\left(\left|T_{ij}\right|\right)\right]$, where Φ is the cumulative distribution function of the standard normal. Therefore, assuming without any loss of generality that $\beta_{ij} > 0$ when $H_{ij}=1$, we have, for such H_{ij},

$$\Pr\left(P_{ij} \le \frac{s\alpha}{mn_i}, T_{ij}\delta_{ij} < 0\right) \quad (A15)$$

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$$= \Pr_{\beta_{ij}>0}\left(|T_{ij}| \geq F^{-1}\left(1-\frac{s\alpha}{2mn_i}\right), T_{ij} < 0\right) \tag{A16}$$

$$= \Pr_{\beta_{ij}>0}\left(T_{ij} \leq -F^{-1}\left(1-\frac{s\alpha}{2mn_i}\right)\right) \tag{A17}$$

$$\leq \Pr_{\beta_{ij}=0}\left(T_{ij} \leq -F^{-1}\left(1-\frac{s\alpha}{2mn_i}\right)\right) \tag{A18}$$

$$= \frac{s\alpha}{2mn_i}.$$

The last inequality follows from the fact that, when $H_{ij}=1$, the distribution of T_{ij} is stochastically increasing in β_{ij}. Continuing, we have

$$\mathrm{dFDR} \leq \frac{\alpha}{2m}\sum_{i=1}^{m}\frac{1}{n_i}\sum_{j=1}^{n_i} I(H_{ij}=1) = \frac{\alpha}{2m}\sum_{i=1}^{m}\pi_{i1} \tag{A19}$$

where π_{i1} is the proportion of false null hypotheses among the total n_i null hypotheses in the i^{th} subregion. Thus, we combine and finally prove the desired result.

$$\mathrm{mdFDR} \leq \frac{\alpha}{m}\sum_{i=1}^{m}\left(\pi_{i0}+\frac{1}{2}\pi_{i1}\right) = \frac{\alpha}{m}\sum_{i=1}^{m}\left(\frac{1+\pi_{i0}}{2}\right) \tag{A20}$$

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Author Contribution

Nicolle Clements completed all multiple testing evaluation and statistical analysis. Virginia Miori completed all decision model development. Virginia Miori developed the heuristic approach; the heuristic was refined by Virginia Miori and Nicolle Clements. The development of computer code to implement the heuristic was completed by Brian Segulin.

Competing Interests

The authors declare that they have no conflict of interest.

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References

Balas, E. and Saltman, M.J.: An algorithm for the three-index assignment problem, Oper. Res., 39(1), 150–161, 1991.

Bandelt, H.J., Cramab, Y., and Spieksma, F.C.R.: Approximation algorithms for multi-dimensional assignment problems with decomposable costs, Discrete Applied Mathematics, 49, 20–25, 1994.

Bandelt, H.J., Maas, A., and Spieksma, F.C.R.: Local search heuristics for multi-index assignment problems with decomposable costs, The Journal of the Operational Research Society, 55(7), 694–704, 2004.

Brillinger, D.R.: Consistent detection of a monotonic trend superposed on a stationary time series, Biometrika, 76, 23–30, 1989.

Benjamini, Y. and Hochberg, Y.: Controlling the false discovery rate: A practical and powerful approach to multiple testing, Journal of the Royal Statistical Society, 57, 289-300, 1995.

Benjamini, Y., Krieger, K., and Yekutieli, D.: Adaptive linear step-up procedures that control the false discovery rate, Biometrika, 93, 491–507, 2006.

Benjamini, Y. and Yekutieli, D.: The control of the false discovery rate in multiple testing under dependency, Annals of Statistics, 29, 1165-1188, 2001.

Benjamini, Y. and Yekutieli, D.: False discovery rate-adjusted multiple confidence intervals for selected parameters, Journal of the American Statistical Association, 100, 71–93, 2005.

Blanchard, G. and Roquain, E.: Adaptive FDR control under independence and dependence. Journal of Machine Learning Research, 10, 2837–2871, 2009.

Cao, K., Batty, M., Huang, B., Liu, Y., and Chen, J.: Spatial multi-objective land use optimization: extensions to the non-dominated sorting genetic algorithm-II, International Journal of Geographical Information Science, 25(12), 1949-1969, 2011.

Cao, K., Huang, B., Wang, S., and Lin, H.: Sustainable land use optimization using boundary-based fast genetic algorithm, Computers, Environment and Urban Systems, 36, 257–269, 2012.

Chen, J., Jonsson, P., and Tamura, M.: A simple method for reconstructing a high-quality NDVI time-series data set based on the Savitzky–Golay filter, Remote Sensing of Environment, 91, 332–344, 2004.

Clements, N., Sarkar, S., Zhao, Z., and Kim, D.: Applying multiple testing procedures detect changes in East African vegetation, Annals of Applied Statistics, 8(1), 286-308, 2014.

Cole, J.E., Dunbar, R.B., McClanahan, T.R., and Muthiga, N.A.: Tropical pacific forcing of decadal SST variability in the western Indian Ocean over the past two centuries, Science, 287, 617–619, 2000.

Cressie, N. and Wikle, C.K.: Statistics for spatio-temporal data, Wiley, Hoboken (NJ), 2011.

Curran, P.J.: Multispectral remote sensing of vegetation amount, Progress in Physical Geography, 4, 315–341, 1980.

Duveiller, G., DeFourny, P., Desclee, B., and Mayaux, P.: Deforestation in Central Africa: Estimates at regional, national and landscape levels by advanced processing of systematically-disturbed Landsat extracts, Remote Sensing of Environment, 112, 1969–1981, 2007.

Foody, G.M.: Geographical weighting as a further refinement to regression modeling: An example focused on the NDVI–rainfall relationship, Remote Sensing of Environment, 88, 283–293, 2003.

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Manuscript under review for journal Earth Syst. Sci. Data
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Franz, L.S. and Miller, J.L.: Scheduling medical residents to rotations: Solving the large-scale multiperiod staff assignment problem, Oper. Res., 41(2), 269–279, 1993.

Frieze, A.M. and Yadegar, J.: An algorithm for solving 3-dimensional assignment problems with application to scheduling a teaching practice, The Journal of the Operational Research Society, 32(11), 989–995, 1981.

Gasson, R.: Goals and values of farmers, Journal of Agricultural Economics, 24(3), 521–537, 1973.

Gilbert, K.C. and Hofstra, R.B.: Multidimensional assignment problems, Decision Sciences, 19(2), 306–321, 1988.

Guo, W., Sarkar, S. and Peddada, S.: Controlling false discoveries in multidimensional directional decisions, with applications to gene expression data on ordered categories, Biometrics, 66, 485–492, 2009.

Gutin, G., Goldengorin, B. and Huang, J.: Worst case analysis of max-regret, greedy and other heuristics for multidimensional assignment and traveling salesman problems, Journal of Heuristics, 14, 169–181, 2008.

Harper, W.H. and Eastman, C.E.: An evaluation of goal hierarchies for small farm operators, American Journal of Agricultural Economics, 62(4), 742–747, 1980.

Hayashi, K.: Multicriteria analysis for agricultural resource management: A critical survey and future perspectives, European Journal of Operational Research, 122(2), 486–500, 2000.

Hayes, D.J. and Sader, S.A.: Comparison of change-detection techniques for monitoring tropical forest clearing and vegetation regrowth in a time series, Photogrammetric Engineering and Remote Sensing, 67, 1067–1075, 2001.

Hochberg, Y. and Tamhane, A.: Multiple comparison procedures. New York, New York: Wiley, 1987.

Hochberg, Y.: A sharper bonferroni procedure for multiple tests of significance, Biometrika, 75, 800-802, 1988.

Holland, B.S. and Copenhaver, M.D.: An improved sequentially rejective bonferroni test procedure, Biometrics, 43, 417-423, 1987.

Holm, S.: A simple sequential rejective multiple test procedure, Scandinavian Journal of Statistics, 6, 65-70, 1979.

Jackson, R.D., Slater, P.N., and Pinter, P.J.: Discrimination of growth and water stress in wheat by various vegetation indices through clear and turbid atmospheres, Remote Sensing of Environment, 13, 187–208, 1983.

Karapetyan, D. and Gutin, G.: Local search heuristics for the multidimensional assignment problem, Journal of Heuristics, 17, 201–249, 2011.

Krokhmal, P.A., Grundel, D.A., and Pardalos, P.M.: Asymptotic behavior of the expected optimal value of the multidimensional assignment problem, Mathematical Programing B, 109, 525–551, 2007.

Kuchma, T., Tarariko, O., and Syrotenko, O.: Landscape diversity indexes application for agricultural land use optimization, 6th International Conference on Information and Communication Technologies in Agriculture, Food and Environment, Procedia Technology, 8, 566 – 569, 2013.

Kutcher, G.P. and Norton, R.D.: Operations research methods in agricultural policy analysis, European Journal of Operational Research, 10(4), 333–345, 1982.

Kuroki, Y. and Matsui, T.: Approximation algorithm for multidimensional assignment problem minimizing the sum of squared errors, Mathematical Engineering Technical Reports 03, 2007.

Liu, Y., Peng, J., Jiao, L., and Liu, Y.: A heuristic land-use allocation model using patch-level operations and knowledge-informed rules, PLoS ONE, 11(6), 2016.

Memarian, H., Balasundram, S.K., Abbaspour, K.C., Talib, J.B., Sung, T.B., and Alias, M.S.: Integration of analytic hierarchy process and weighted goal programming for land use optimization at the watershed scale, Turkish Journal of Engineering & Environmental Sciences, 38, 139-158, 2014.

Miori, V.M.: A dynamic programming approach to the stochastic truckload routing problem, The Supply Chain in Manufacturing, Distribution and Transportation: Modeling, Optimization and Applications, CRC Press, 179-203, 2008.

Miori, V.M.: A multiple objective goal programming approach to the truckload routing problem, Journal of the Operational Research Society, 62, 1524-1532, 2011.

Miori, V.M.: The pollyanna problem: assignment of participants in a gift exchange, International Journal of Business Intelligence Research, 5(1), 1-12, 2014.

Norton, R.D. and Scandizzo, P.L.: Market equilibrium computations in activity analysis models, Oper. Res., 29(2), 243–262, 1981.

OCHA: Eastern Africa drought humanitarian report No. 3, UN Office for the Coordination of Humanitarian Affairs, 2011.

Önal, H. and McCarl, B.: Aggregation of heterogeneous firms in mathematical programming models, European Review of Agricultural Economics, 16(4), 499–513, 1989.

Phillips, N.V.: A weighting function for pre-emptive multicriteria assignment problems, The Journal of the Operational Research Society, 38(9), 787–802, 1987.

Pierskalla, W.P.: The multidimensional assignment problem, Oper. Res, 16(2), 422–431, 1968.

Poore, A.B. and Rijavec, N.: A lagrangian relaxation algorithm for multidimensional assignment problems arising from multitarget tracking, SIAM Journal on Optimization, 3(3), 544–563, 1993.

Robertson, A.J.: A set of greedy randomized adaptive local search procedure (GRASP) implementations for the multidimensional assignment problem, Computational Optimization and Applications, 19(2), 145–164, 2001.

Romero, C. and Rehman, T.: Multiple criteria analysis for agricultural decisions, Elsevier, Amsterdam, The Netherlands (original publication (1989), 2003.

Sadeghi, S.H.R., Jalili, K., and Nikkami, D. (2009). Land use optimization in watershed scale, Land Use Policy, 26, 186–193.

Sahebgharani, A.: Multi-objective land use optimization through parallel particle SWARM Algorithm: Case study Baboldasht district of Isfahah, Iran, Journal of Urban and Environmental Engineering, 10(1), 42-49, 2016.

Samuelson, P.A.: Spatial price equilibrium and linear programming, American Economic Review, 42(2), 283–303, 1952.

Sarkar, S.K.: Some probability inequalities for ordered MTP2 random variables: a proof of the Simes conjecture, Annals of Statistics, 26, 494-504, 1998.

Sarkar, S. K.: Some results on false discovery rate in stepwise multiple testing procedures, Annals of Statistics, 30, 239–257, 2002.

Sarkar, S. K.: Generalizing Simes' test and Hochberg's stepup procedure, Annals of Statistics, 36(1), 337–363, 2008.

Earth Syst. Sci. Data Discuss., https://doi.org/10.5194/essd-2018-18
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Discussion started: 24 April 2018

Sarkar, S.K. and Chang, C.K.: The Simes method for multiple hypothesis testing with positively dependent test statistics, Journal of the American Statistical Association, 92, 1601-1608, 1997.

Sarkar, S. and Zhou, T.: Controlling Bayes directional false discovery rate in random effects model, Journal of Statistical Planning and Inference, 138, 682–693, 2008.

Shaffer, J.: Multiplicity, directional type III errors, and the null hypothesis, Psychological Methods, 7, 356369, 2002.

Šidák, Z. K.: Rectangular confidence regions for the means of multivariate normal distributions, Journal of the American Statistical Association, 62 (318), 626–633, 1967.

Stewart, T.J., Janssen, R., and van Herwijnen, M.: A genetic algorithm approach to multiobjective landuse planning, Computers & Operations Research, 31, 2293–2313, 2004.

Storey, J., Taylor, J. and Siegmund, D.: Strong control, conservative point estimation and simultaneous conservative consistency of false discovery rates: a unified approach, Journal of the Royal Statistical Society, B. 66, 187–205, 2004.

Sunandar, A.D., Suhendang, E., Hendrayanto, Surati Jaya, I.N., Marimin.: Land use optimization in Asahan Watershed with linear programming and SWAT model, International Journal of Sciences: Basic and Applied Research, 18(1), 63-78, 2014.

Takayama, T. and Judge, G.G.: Spatial equilibrium and quadratic programming, Journal of Farm Economics, 46(1), 67–93, 1964.

Troung, V.A. and Roundy, R.O.: Multidimensional approximation algorithms for capacity-expansion problems, Oper. Res., 59(2), 313-327, 2011.

Tucker, C., Pinzon, J., Brown, M., Slayback, D., Pak, E., Mahoney, R., Vermote, E. and Saleous, N.: An extended AVHRR 8-km NDVI data set compatible with MODIS and SPOT vegetation NDVI data, International Journal of Remote Sensing, 26, 4485–4498, 2005.

Usongo, L. and Nagahuedi, J.: Participatory land-use planning for priority landscapes of the Congo Basin, Unasylva, 230, 17–24, 2008.

Vrieling, A., De Beurs, K.M., and Brown, M.E.: Recent trends in agricultural production of Africa based on AVHRR NDVI time series, Proceedings of the SPIE Conference: Remote Sensing for Agriculture, Ecosystems and Hydrology X, 2008.

Wang, C.H. and Guldmann, J.M.: A land-use allocation optimization model to mitigate potential seismic damages, Environment and Planning B: Planning and Design, 42, 730 – 753, 2015.

Weintraub, A. and Romero. C.: Operations research models and the management of agriculture and forestry resources: A review and comparison, Interfaces, 36(5), 446-457, 2017.

Wheeler, B.M. and Russell, J.R.M.: Goal programming and agricultural planning, Oper. Res. Quart, 28(1), 21–32, 1977.

White, D.J.: A special multi-objective assignment problem, The Journal of the Oper. Res. Society, 35(8), 759–767, 1984.

Williams, V., Jones, L., and Tukey, J.: Controlling error in multiple comparisons, with examples from state-to-state differences in educational achievement, Journal of Educational and Behaviorial Statistics, 24, 42–69, 1999.