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Insights into bioimpedance analyser via three-way dynamic panel threshold regression modelling

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Abstract

Bioimpedance refers to the measurement of the electrical impedance of biological tissue, and it has recently gained popularity as a tool for monitoring the food ripening process. In this work, we propose a novel application of a dynamic panel threshold regression model to identify meaningful physio-chemical transitions in fruit bioimpedance time series. The method is applied to an innovative three-way panel dataset comprising fruit bioimpedance measurements collected across a range of frequencies using two types of electrical impedance analysers: a bench-top device and a state-of-the-art portable one. Separate estimation is conducted for each device using a first-differenced generalised method of moments approach with instrumental variables. The analysis offers insights into ripening dynamics by estimating thresholds and identifying change points across the frequency spectrum. In addition, it produces novel evidence regarding the performance of the portable device, supporting its practical relevance for post-harvest monitoring, processing, and optimisation within the fruit supply chain. The three-way panel model is implemented in the R package `PanelTM`.

Keywords: Change point detection, Electrical impedance spectroscopy, Generalized method of moments, Panel data, Threshold model

JEL Code: C13, C18, C23, L66

1 Introduction

Bioimpedance refers to the measurement of the electrical impedance of biological tissue, that is, a physical quantity describing the ability of the tissue to oppose an external flow of electrical current (Grimnes and Martinsen, 2015; Ward and Brantlov, 2023). The measurement of bioimpedance involves applying a small electrical current to biological tissue and measuring the electrical response, often across a range of frequencies, a technique known as electrical impedance spectroscopy (EIS) (Grossi and Riccò, 2017). Since the electrical properties of

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tissue can be correlated with specific quality attributes, and different electrical frequencies cross cell membranes in different ways (Ibba et al., 2020), the analysis of electrical signals is useful to provide information about the properties of the analysed tissue (see e.g. El Khaled et al., 2017; Urzeniczok and Karpiel, 2024). Consequently, in recent years, bioimpedance and EIS have been gaining popularity in food quality control (Pliquett, 2010). For example, recent studies have demonstrated the potential of bioimpedance to monitor ripening stages in fruits such as lemons (Swain et al., 2025) and to assess the freshness of various fruits and vegetables (Kluza et al., 2025).

This paper focuses on EIS devices that measure the impedance of fruit over time to study dynamic changes in tissue electrical properties. We evaluate two EIS devices: a bench-top impedance analyser (IA) and a portable system called "FruitMeter" (FM) to assess any differences in the ability to detect physical changes in the fruit. The paper addresses statistical challenges in time-domain EIS data, since they present both serial and cross-sectional dependence, and are observed hundreds of times according to the range of frequencies applied. From Fig. 1 is evident that the variability among fruits, the type of bioimpedance analyser, and the temporal dynamics of the measurements conducted have an effect on bioimpedance. Since one of the main purposes of fruit bioimpedance analysis is to assess the ripening time, another challenge regards the development of a method to detect a possible point of change in the bioimpedance time series by exploiting thresholds varying across time series. Therefore, the development of a three-way dynamic panel threshold appears necessary.

Our proposal encompasses, on the one hand, panel regression models and, on the other, change-point detection methods. The reference literature is extensive, but to the best of our knowledge, from self-exciting threshold autoregressive models (Tong, 1990; Hansen, 2000) to the more recent dynamic panel model with threshold effect developed by Seo and Shin (2016), no panel models have been designed to work with three-way data and threshold parameters that are not common to all time series. Similarly, regarding change-point detection methods for panel data, existing approaches (see e.g. Li et al., 2015; Chen and Huang, 2017; Maciak et al., 2020) are not suitable for three-way structured data and have never been applied to bioimpedance data.

The proposed methodology builds upon the panel threshold model introduced by Seo and Shin (2016) in two key directions: (*i*) by adapting the original two-way structure to a three-way framework suitable for frequency-indexed bioimpedance panel data - specifically, allowing the threshold parameter to vary with the third dimension - and (*ii*) by introducing a measure to detect a change point in the estimated temporal dynamics. We apply our proposal to an innovative dataset concerning fruit bioimpedance curves over a range of frequencies. Here the purpose is twofold: (*i*) identifying the change point in bioimpedance time series that presumably indicates the onset of fruit spoilage and (*ii*) assessing the possible equivalence between a classic bench-top EIS and a novel portable EIS device.

The paper is organized as follows. In Sect. 2, we describe the innovative bioimpedance data that motivates our proposal. In Sect. 3, we present the

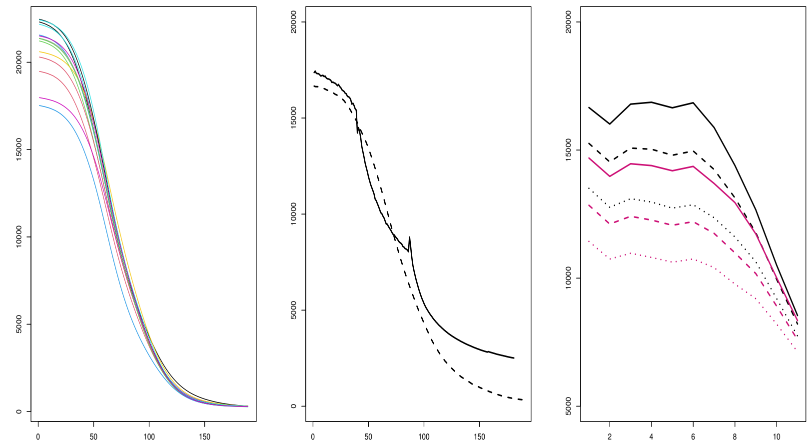

Figure 1: Bioimpedance spectra (x-axis: electrical frequency, y-axis: bioimpedance) for a subset of the banana sample analyzed, a fixed instant time ($t = 7$), and the IA (left); bioimpedance spectra - averaged over time and bananas - (x-axis: electrical frequency, y-axis: bioimpedance) for the EIS device considered, i.e. IA (dashed line) and FM (solid line) (middle); bioimpedance time series - averaged on bananas - (x-axis: time, y-axis: bioimpedance) for a small subset of the possible frequencies for the EIS considered, i.e. IA (black lines) and FM (other lines) (right).

three-way dynamic panel threshold model and a criterion to detect a change point. The real data analysis concerning fruit bioimpedance is shown in Sect. 4. Discussion and conclusion are presented in Sect. 5.

2 Bioimpedance Data

The innovative data we consider in this study consists of a collection of bioimpedance measurements of a production batch of 150 bananas observed for 11 days. The experiment was conducted by the Sensing Technologies Laboratory at the Free University of Bozen-Bolzano in the context of an interdisciplinary research project between the Faculty of Economics and Management and the Faculty of Engineering. In the experiment on fruit ripening, two bioimpedance analysers were used: a bench-top EIS device called "impedance analyser" (IA) that is a marketed equipment device, and an innovative portable custom-made device called "FruitMeter" (FM) (Ibba et al., 2021). Bench-top EIS devices are typically unwieldy and more powerful than a portable EIS device and are therefore generally more expensive and require more maintenance and expertise to operate, while portable EIS devices are small, lightweight instruments that can be easily transported and easily used in a wide range of situations and applications. With both the analysers, bioimpedance measurements were performed over a range of frequencies using two electrodes placed on the surface of each piece of fruit being measured (Ibba et al., 2020). A small alternating current was applied through one electrode, and the resulting voltage was measured at the other electrode and then used to calculate the impedance of the material at different frequencies. Since the voltage that generates the flow affects the measurement of bioimpedance, multiple electrical frequencies should be considered when assessing fruit quality (Ibba, 2021).

Bioimpedance measurements are provided at 189 frequencies ranging from 20 to 13668764.956 Hz for the IA and at 181 frequencies from 10 to 99000 Hz for the FM. It is to be noted that frequency values for the IA and FM are similar, but do not perfectly coincide. All the fruits were harvested simultaneously and placed on sale together, thus ensuring the homogeneity of the initial stage of ripening of the banana batch. The measurements were performed every day for 11 days, i.e. until the fruit visibly deteriorated, to monitor the progress of ripening with controlled room temperature and humidity. In Fig. 2, a preliminary representation of the data is shown for a set of frequencies ranging from the minimum to the maximum of the devices and considering three intermediate frequencies common to the two analysers used. Specifically, we have considered the frequencies $(10, 1000, 10000, 30000, 99000)$ for FM and the frequencies $(20, 1018.568, 10026.058, 29286.314, 13668764.956)$ for IA. Considering that our aim is not only to investigate the temporal dynamics of fruit bioimpedance by varying spectroscope frequency but also to compare the two analysers considered, frequencies $j < 20$ and $j > 99000$ Hz have been omitted. In addition, as shown in Fig. 2, we observe that bioimpedance time series tend to flatten at higher frequencies, regardless of the type of impedance analyser used. Bioimpedance measurements over time appear to be less informative in terms of the fruit ripening process and, for this reason, we have restricted the analysis to the set of frequencies in the interval $20 \leq j \leq 30000$ Hz. This selection led to 103 frequencies for the IA and 107 for the FM. In the end, the two post-processing data sets constitute three-way balanced panels with $n = 150$ bananas, $J = 103$, and $J = 107$ electrical frequencies for the IA and the FM, respectively, and $T = 11$ days. Finally, we have additional information regarding fruit weight for each day, which is a time-varying regressor that can be useful in describing the fruit ripening process.

3 Three-way Dynamic Panel Threshold Model

We define a three-way dynamic panel threshold regression model on $i = 1, \dots, n$ statistical units observed in $t = 1, \dots, T$ instants of time by varying a third way of $j = 1, \dots, J$ values

$$y_{ijt} = (1, \mathbf{x}'_{ijt})\phi_{1j}\mathbb{1}\left\{y_{ij(t-1)} \leq \gamma_j\right\} + (1, \mathbf{x}'_{ijt})\phi_{2j}\mathbb{1}\left\{y_{ij(t-1)} > \gamma_j\right\} + \varepsilon_{ijt} \quad (1)$$

where y_{ijt} is the value of the variable Y observed on the i-th statistical unit at time t for the j-th value of the considered third way, $\mathbf{x}_{ijt}$ is a vector of k_1 time-varying (exogenous or endogenous) regressors, which may include lagged

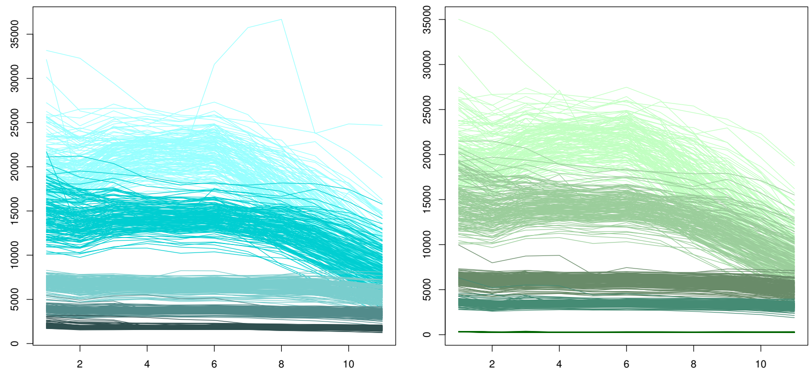

Figure 2: Bioimpedance time series (x-axis: time, y-axis: bioimpedance) of the 150 bananas observed as provided by the FM (left) and the IA (right) device by varying spectroscope frequency in $(10, 1000, 10000, 30000, 99000)$ Hz for FM and in $(20, 1018.568, 10026.058, 29286.314, 13668764.956)$ Hz for IA (from the lightest to the darkest color).

dependent variable, $\phi_{1j} = \left(\phi_{1j}^{(1)}, \ldots, \phi_{1j}^{(k_1+1)}\right)$ and $\phi_{2j} = \left(\phi_{2j}^{(1)}, \ldots, \phi_{2j}^{(k_1+1)}\right)$ are, respectively, the lower and upper regime intercept and slope parameters vectors of the j-th value, $\mathbb{1}$ is the indicator function that captures the change in regime and is defined by the threshold parameter γ_j that can vary by j, the lagged dependent variable $y_{ij(t-1)}$ is the endogenous transition variable, and ε_{ijt} is the error term that is defined as the sum of three components

$$\varepsilon_{ijt} = \mu_i + \lambda_j + \nu_{ijt}$$

where μ_i is the unobserved individual fixed effect, λ_j is the unobserved third-way fixed effect, and ν_{ijt} is a zero mean random error such that $E\left(\nu_{ijt}|\mathcal{F}_{t-1}\right) = 0$, where $\mathcal{F}_t$ is a natural filtration at time t such that ν_{ijt} is a martingale difference sequence.

3.1 GMM estimation method for the three-way model

The model in Eq. (1) can be estimated by adapting the generalised method of moments (GMM) in Seo and Shin (2016), which is based on the first difference transformation (FD) and the use of instrumental variables (IVs), to the three-way model case. Inspired by the motivating empirical applications (see Sect. 4), we assume that the J values of the third way are independent of each other, and represent, for instance, the categories or levels of a variable. This case occurs every time observations replicated on the same statistical units i at a fixed time t do not have any effect on each other, i.e. are independent.

The FD-GMM estimator for the three-way panel threshold model in Eq. (1) is developed through a procedure for the following first-differentiated model to deal with the correlation between regressors and the individual and category fixed effects

$$\Delta y_{ijt} = y_{ijt} - y_{ij(t-1)} = \beta_j' \Delta x_{ijt} + \delta_j' \mathbf{X}_{ijt}' \mathbb{1}_{ijt}(\gamma_j) + \Delta\varepsilon_{ijt}$$

where Δ is the first difference operator, $\beta_j = \left(\phi_{1j}^{(2)}, \ldots, \phi_{1j}^{(k_1+1)}\right)'$, $\delta_j = (\phi_{2j} - \phi_{1j})$,

$$\mathbf{X}_{ijt} = \begin{pmatrix} (1, \mathbf{x}_{ijt}') \\ \left(1, \mathbf{x}_{ij(t-1)}'\right) \end{pmatrix}, \ \mathbb{1}_{ijt}(\gamma_j) = \begin{pmatrix} \mathbb{1}\{y_{ij(t)} > \gamma_j\} \\ -\mathbb{1}\{y_{ij(t-1)} > \gamma_j\} \end{pmatrix},$$

and $\Delta\varepsilon_{ijt} = \varepsilon_{ijt} - \varepsilon_{ij(t-1)} = \nu_{ijt} - \nu_{ij(t-1)}$. Therefore, $\theta_j = (\beta_j', \delta_j', \gamma_j)'$ is the $(2k_1+2)$-dimensional vector of parameters to estimate for each level j, and the whole unknown parameters vector is $\theta = (\theta_1', \ldots, \theta_J')'$ and belongs to a compact set $\Theta \subset \mathbb{R}^{kJ}$ with $k = (2k_1 + 2)$.

In light of the independence among levels of the third way, we can estimate the parameters vector for each level j taken separately, i.e. estimate θ_j for each $j \in \{1, \ldots, J\}$. Indeed, the GMM objective function to minimise to find θ is a block diagonal matrix where each block is positive definite and can be minimised independently from the other blocks. We therefore estimate each θ_j, with $j = 1, \ldots, J$, taken separately. The idea is to use a two-step procedure where, in the first step, the GMM estimator of β_j and δ_j for a fixed γ_j is found through the grid search algorithm. Hence, $(\hat{\beta}_j', \hat{\delta}_j')' = (\hat{\beta}_j(\hat{\gamma}_j)', \hat{\delta}_j(\hat{\gamma}_j)')'$ and $(\hat{\beta}_j', \hat{\delta}_j', \hat{\gamma}_j)'$ are the first-step GMM parameters estimates. The second-step GMM estimators are given by the same procedure based on the grid search algorithm, updated by exploiting the first-step estimates. A detailed description of the estimation procedure for θ_j along with the asymptotic theory of the estimator and the test for threshold effect can be found in Seo and Shin (2016).

3.2 Change Point Detection

The three-way dynamic panel threshold model in Eq. (1) is also conceived to detect change points in panel data. Once the model proposed is estimated through the method developed in Sect. 3, the final goal is to compute the change point (CP) in each time series, that is the time at which a regime switch occurs. From the applied point of view, this involves testing structural change problems that occur naturally in many contexts; for example, in the context of fruit ripening control, where one is faced with the output of a production line and wants to detect any departure from an acceptable production standard. We propose to compute the change point as the minimum time at which the regime switch occurs, that is, the point at which the time series is greater than the estimated threshold parameter. We thus define the following measure

$$\widehat{\mathrm{CP}}_{ij} = \underset{t \in \{1, \ldots, T\}}{\arg\min} \{\mathbb{1}(y_{ijt} > \hat{\gamma}_j)\} \tag{2}$$

which provides the time of the regime change $\forall\, i, j$, i.e. for each time series and frequency of the spectroscopy, and, next, we summarise $\widehat{\mathrm{CP}}_{ij}$ over i as follows

$$\overline{\mathrm{CP}}_j = \sum_{i=1}^{n} \frac{\widehat{\mathrm{CP}}_{ij}}{n}. \tag{3}$$

In this way, the measures in Eq.s (2) and (3) make it possible to assess the time of the regime switch for each level j. It is worth noticing that Eq. (2) becomes the following: $\widehat{\mathrm{CP}}_{ij} = \underset{t\in\{1,\dots,T\}}{\arg\min}\ \{\mathbb{1}(y_{ijt} < \hat{\gamma}_j)\}$ when the first regime in the time series is the upper regime.

4 Empirical Analysis

Here we present the application of the three-way panel regression model presented in Sect. 3 on the bioimpedance data described in Sect. 2. We propose two alternative applications of Eq. (1) to the bioimpedance measurements of the bananas y_{ijt}: a model with no time-varying regressor and a model with one time-varying regressor, which is the weight of the fruit, say x_{it}. In both cases, the minimum allowable number of instrumental variables has been chosen. Hence, the first three lags of the variables considered - i.e., y_{ijt} for the model without regressors and y_{ijt} and x_{it} for the model with a time-varying regressor - have been used as IVs $\{z_{ijt}\}_{t=t_0}^{T}$, and observations at $t = 1, 2, 3$ have been excluded from the identification of the thresholds.

The FD-GMM estimates of the threshold parameters and of the difference between the slope parameters are shown in Fig. 3. Coherently with the spectroscopy, $\hat{\gamma}_j$ decreases as j increases. Overall, the two models led to similar estimated threshold values (Fig. 3, left). However, based on the Gaussian z-test, the estimated coefficients of the model including the weight of the bananas x_{it} are not significant. We have 107 p-values for FM ranging from 0.45 to 0.96 and 103 for IA ranging from 0.60 to 0.97, and higher p-values are associated with lower frequencies. This result is reflected in the corresponding estimated values of $\hat{\delta}_{Ij}$, which do not exhibit a clear pattern (Fig. 3, middle). In contrast, a more regular pattern can be observed for models without time-varying regressors. We thus conclude that the weight of the fruit is not a good explanatory variable for bioimpedance.

As far as the comparison of the two devices is concerned, the estimates overall appear very similar (Fig. 3, left). However, some dissimilarities emerge between the estimated $\hat{\gamma}_j$ of the two devices. The estimated threshold curves of the IA and the FM coincide for js up to approximately 4500 Hz, when the FM's curves abruptly increase. From that point on, the difference between the IA and the FM progressively reduces, but $\hat{\gamma}_j$ always appears slightly lower for the IA. This evidence can be traced back to a technical issue that emerged during the experiment with the FM: minor changes in the placement of the electrodes may have affected the data collection. Nevertheless, this technical issue does not impact the reliability of the instrument and does not affect statistical analysis. Therefore, we decided to keep all the data in order to show the differences between the IA and the FM more effectively. As discussed in Sect. 2 and shown in Fig. 2, for a fixed frequency j, the bioimpedance shows approximately the same trend for all bananas, while the time series tend to flatten out as frequencies increase. Nevertheless, the method developed always identifies the thresholds. In this respect, the presence of a threshold effect has been tested by means of the linearity test implemented in the R package `PanelTM` and described in Seo and Shin (2016) using 500 bootstrap replications. For both the analysers and both the models, estimated p-values are almost always greater than 0.97, and therefore the test supports the presence of a threshold effect irrespective of the frequency. When considering the model including x_{it}, a different result is obtained for four frequencies j - namely 4600, 4700, 4800, and 4900 Hz - of the FM. In such cases, the test does not reject the null hypothesis of linearity. However, it is worth noticing that this result is found in correspondence to frequencies j that were affected by the aforementioned technical issue in the FM experiment.

Finally, we identify the time of regime switches according to the procedure described in Sect. 3.2. The three-dimensional plots in Fig. 4 show the average time of regime switch for each j for the two models considered. Greater variability can be noted in the identified change points irrespective of the impedance analyser employed when the model with a time-varying regressor is used. This finding is in line with the non-significance of the estimated coefficients of the fruit's weight. Overall, these results suggest that there is a physio-chemical change in the bananas observed approximately at day 7 for both the IA and the FM data. The equivalence between the two devices considered can have important implications in the fruit harvesting and distribution chain for reasons directly related to the portability of the FrutiMeter. Having real-time information on the state of fruit ripening or spoilage would allow optimisation of the fruit supply chain starting from the time of fruit picking, which depends on both the state of fruit ripening and the destination of fruit delivery.

The proposed model was also applied in Di Lascio and Perazzini (2022) to a panel data of strawberry bioimpedance. In this case, the time series showed high heterogeneity in terms of bioimpedance regardless of the electrical frequency and the difference over regimes was not evident as in the banana data set. Nevertheless, the proposed method appeared to successfully identify thresholds and change points by varying the electrical frequencies. In any case, there is still a need for bioimpedance engineering studies to better understand what bioimpedance tells us about fruit ripeness, even though a correspondence between dynamics in the bioimpedance measurements and fruit deterioration is empirically observed. In this framework, our study could fuel future research aimed at contributing to the prediction of earlier stages of ripening, potentially facilitating the development of automated mechanisms for processing fruit within large-scale food distribution systems.

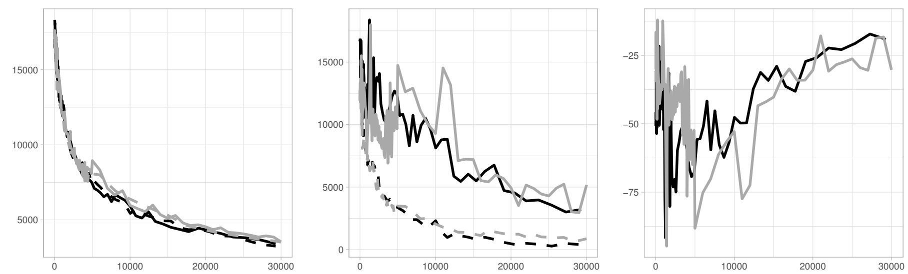

Figure 3: Logarithm of the estimated parameter (y-axis) considered per electrical frequency j (x-axis). Left: threshold parameters $\hat{\gamma}_j$. Middle: constants parameter $\hat{\delta}_{Ij}$. Right: weight parameter $\hat{\delta}_{Xj}$. The black line refers to the IA and the grey line to the FM. The dashed lines report results from the model without time-varying regressors, and solid lines represent estimates from the model with a time-varying regressor.

5 Discussion and Conclusion

In this paper, we have presented a three-way dynamic panel regression model with threshold effect. The third way is conceived as a variable influencing the identification of the different regimes and their thresholds. Our proposal is also intended as a change point detection method. We have defined a criterion to compute change points by varying the level of the third way. The introduced model is thus able to take into account serial and cross-sectional dependence and provide information on the time when an abrupt change occurs by varying the level of the third way. To estimate the proposed model, the well-known GMM estimation method in the instrumental variables framework has been used. The model and the change point detection criterion have been successfully applied to fruit bioimpedance panel data and implemented in the R software package `PanelTM`, which has been described in depth in Di Lascio and Perazzini (2025).

Our empirical findings support, on the one hand, the importance of further investigating the potential of bioimpedance to uncover physio-chemical dynamics in biological tissues and, on the other hand, the use of a portable device as a viable alternative for high-frequency bioimpedance analysis, which has traditionally been confined to laboratory environments. The latter result has important implications in the field of food engineering. Indeed, portable device for bioimpedance measurements offers several advantages over traditional benchtop analysers, such as enabling on-site data collection, requiring less setup time, and being easier to operate, making them particularly suitable for routine or large-scale monitoring without the need for specialised personnel.

This work was directly motivated by an application to bioimpedance data analysis, but it can be useful to all the other data that share some characteristics with that considered in this work. For example, in climate change studies, the temporal observation of debris flows, mudflows, and snow avalanches, due to

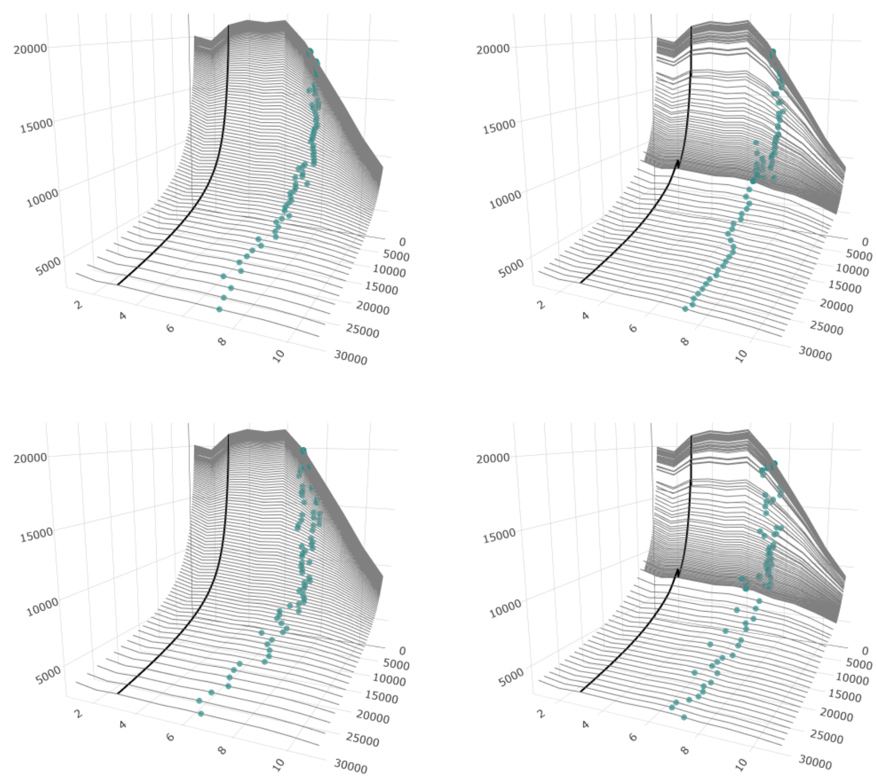

Figure 4: Average bananas bioimpedance (y-axis) per frequency j (z-axis) (grey lines) observed over time $t = 1, \ldots, 11$ (x-axis) and change points $\overline{\mathrm{CP}}_j$ (dots). The black line separates the observations used as instrumental variables from those used in the threshold estimation. Top: model without time-varying regressors. Bottom: model with a time-varying regressor. Left: IA. Right: FM.

the increasing frequency and intensity of heavy-to-extreme precipitation events, is crucial for assessing the hydrological response, e.g. land slope. In medical research, our threshold regression model may be used to study the response of patients before and after the administration of different levels of a drug for a given pathology. Other application domains include, for example, economics, where the identification of a shock that increases/decreases industrial production while decreasing the unemployment rate or producer prices is crucial to an industry's policy.

Finally, the introduced model can be thought of as a starting point when building new threshold regression models for multi-way data. Therefore, there are several possible future research directions. First of all, there are contexts in which the assumption of independence between the levels of the third way is unrealistic, even though this assumption allows model estimation to be implemented in parallel, thus reducing its computational burden. Relaxing this assumption is a great challenge that requires the minimisation of the GMM objective function $\hat{\mathbf{J}}(\theta)$, which is not block diagonal and should be minimised for all the J levels at the same time. Moreover, the consistency and efficiency of estimators for the J threshold parameters would also need to be proved. Another aspect that could deserve attention concerns the criterion to compute change points. An investigation of the statistical properties of the introduced measure or an alternative way to compute change points, especially when the time series dynamics are very complex, could be useful. In addition, an interesting extension of the model proposed would be to have parameters not homogeneous over i for applications where statistical units cannot be modelled through the same coefficients. Finally, a general extension of our proposal would consist of introducing multiple regimes, thresholds, and change points.

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