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Are African business cycles synchronized? Evidence from spatio-temporal modeling[☆]

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ABSTRACT

This paper investigates the business cycle synchronization in Africa, which is important for the definition of optimal monetary unions. Previous studies adopted either a cross-sectional or a time series approach, and this may have led to substantial variation in the findings for common business cycles across African countries. Considering fifty-two African economies, we study business cycles' synchronization with a novel spatio-temporal hierarchical approach founded on the gravity model. The introduction of the spatial dimension is particularly relevant for Africa, where infrastructure constraints make monetary unions less feasible due to higher trading costs. We find positive evidence for the Economic Community of West African States (ECOWAS) and the Common Monetary Area (CMA) feasibility, while our results do not support the Central Africa CFA and the East African Monetary Union (EAMU) monetary unions.

1. Introduction

The degree of convergence of business cycles is a key policy issue, in particular when it concerns the establishment and the sustainability of monetary unions. The Euro Area is an example of an established monetary union, and there is an increasing interest in a monetary integration process in Africa and in Asia. A monetary union involves that countries are subject to the same monetary policy. The Optimum Currency Area (OCA) theory (Mundell, 1961) states that, to be effective, an OCA must rely on strong economic integration that allows reduction of the negative effects of large country-specific shocks. Therefore, the effectiveness of an OCA is usually evaluated by the degree of business cycles' synchronization among its members. In our study we provide such an evaluation for African countries.

Business cycle synchronization is often studied using clustering techniques, see Artis and Zhang (2002) and Camacho et al. (2006), Ahlborn and Wortmann (2018) for European countries, Bénassy-Quéré and Coupet (2005), Tsangarides and Qureshi (2008) and Gammadigbe and Dioum (2022) for African countries and Quah and Crowley (2010) for countries in Asia. More precise, most studies adopt dissimilarity-based clustering methods, where the main focus is on how similarity among business cycles is measured. Inspired by the OCA theory, Artis and Zhang (2002), Bénassy-Quéré and Coupet (2005), Tsangarides and Qureshi (2008) and Quah and Crowley (2010) define the dissimilarity between two countries as the Euclidean distance across OCA-related variables. Examples of such variables are trade openness, inflation convergence, export diversification, correlation and output variables. These studies adopt a cross-sectional approach and do not consider temporal evolution of the variables. To our knowledge, Aguiar-Conraria and Soares (2011) are the first to adopt a time series clustering approach, as they consider distances between wavelet-domain spectra of real GDP series. To measure distance, Ahlborn and Wortmann (2018) consider a basic Euclidean distance among GDP time series while Franses and Wiemann (2020) propose a feature-based Dynamic Time Warping (DTW) distance among GDP time series.

In sum, the literature draws upon either cross-sectional or time series data. In our present study, we will propose a combined method, as it is likely that neighboring countries are likely affected by similar shocks and spatial spillovers. The first law of geography states that "*everything is related to everything else, but near things are more related than distant things*" (Tobler, 1970; Miller, 2004). Neighboring economies could be more related than more distant economies as they

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could be similarly affected by shocks and spatial spillovers, see Rey (2001), Le Gallo and Ertur (2003) and Hájek and Horváth (2016).

In the present paper, we introduce a spatio-temporal clustering method to examine dissimilarity across business cycles. Spatio-temporal clustering finds a theoretical economic foundation in the gravity model (e.g. see Ackah et al., 2012; Disdier and Head, 2008; Huang, 2007; Osabuohien et al., 2019; Wang et al., 2010). According to the gravity model, bilateral trade intensity depends on both the economic sizes and the geographical distance between two countries. In the words of Disdier and Head (2008) "*One of the best-established empirical results in international economics is that bilateral trade decreases with distance*". Notice that bilateral trade flow is one of the most important variables in the OCA definition (e.g. Calderon et al., 2007). The spatio-temporal approach developed in our paper aims at solving endogeneity issues compared to other clustering approaches, as the inclusion of the spatial contiguity constraint can be thought of as a way of instrumenting for bilateral trading flows, especially in light that long time series of countries' bilateral exposures are not available, especially for Africa. As trade intensity enhances the synchronization of business cycles, not including such a variable can lead to biased results.

The introduction of the spatial dimension is particularly relevant for Africa, where infrastructure deficits increase trading costs between distant countries. This lack of facilities makes the geographical distance even more important for the determination of bilateral trade intensity for Africa (see Tandrayen-Ragoobur et al., 2023; Akpan, 2014; Babu et al., 2022).

We apply our novel method to the synchronization of African economies. African economies represent an example of the relevance of spatial dimension in OCA definition as some of the proposed monetary unions, i.e. the West African Monetary Zone (WAMZ), the East African Monetary Union (EAMU) and the Southern African Monetary Union (SAMU), are clearly motivated by proximity arguments. Hence, our main hypothesis is that countries with membership of monetary unions show similar business cycle behavior. Our approach starts with an agnostic view by simply letting the algorithm tell us which countries show business cycles' similarities. Next, we look at the overlap between the clusters and the countries in the monetary unions. For the clustering task, following Camacho et al. (2006), Bénassy-Quéré and Coupet (2005), Quah and Crowley (2010) and Ductor and Leiva-Leon (2016), we adopt a hierarchical approach to study business cycles' synchronization.

The use of a spatio-temporal approach represents the main methodological novelty of our paper. We implement an algorithm using a soft contiguity constraint. Oliver and Webster (1989) and Bourgault et al. (1992) discuss clustering algorithms based on a modified dissimilarity matrix, obtained as a convex combination of geographical distances and the dissimilarity matrix computed from attribute variables. This approach requires the definition of suitable attribute and spatial weights, and this may be inconvenient. Chavent et al. (2018) recently proposed an objective approach for choosing the spatial and the attribute-space weights within a Ward (1963)-like clustering algorithm. The algorithm is called *ClustGeo* and is based on a two step procedure. In a first step a partition entirely based on the attribute-space dissimilarity is obtained with the aim of guessing an initial (suitable) number of clusters. Next, the optimal weight is chosen as the best compromise between loss in the attributes homogeneity and loss in spatial homogeneity. We extend *ClustGeo* to spatio-temporal data by considering the feature-based DTW distance proposed in Franses and Wiemann (2020) and Franses (2020) as the attribute-space dissimilarity.

Our main empirical findings are that the West CFA and Central CFA cannot form a single monetary union. We do however find positive evidence for the Common Monetary Agreement (CMA) among South African economies, where we suggest it could be extended with Zambia and Angola. Next, we obtain evidence not in support of the EAMU, although it seems that a monetary union involving north-east countries like Sudan, Eritrea and Ethiopia could be possible. Our results are robust to structural breaks.

The outline of our paper is as follows. Section 2 discusses the relevant literature about synchronization of African business' cycles while considering monetary unions. Section 3 discusses our spatio-temporal hierarchical clustering approach. Section 4 shows the results for African economies. Section 5 concludes with final remarks, limitations and suggestions for further research.

2. African business cycles and monetary unions

The monetary integration process in Africa has generated a large debate in the literature, with authors questioning about which regions can be considered for OCA formation, see Masson and Pattillo (2004a) and Asongu et al. (2017) for reviews. Monetary unions in Africa have been motivated by the desire to counteract perceived economic and political weakness of countries on the continent, as well as to help African countries in negotiating favorable trading arrangements with other countries (Masson and Pattillo, 2004b). A summary of monetary unions in Africa is shown in Fig. 1, which shows the three existing monetary unions, which are Common Monetary Area (CMA), West African CFA and Central African CFA. Fig. 1 does not include proposed unions not yet officially established.

The analysis of the feasibility of a monetary union is mainly based on an assessment of the degree of business cycles' synchronization of the involved countries. Some authors investigated the feasibility of using a single currency in the entire continent, the so-called African Monetary Union (AMU), but so far with negative results. Following the Clarida et al. (1999) framework, Karras (2007) find that the estimated cost and benefit measures exhibit substantial variability across the countries, and hence a single monetary union is not suggested. Tapsoba (2009) shows that business cycle synchronicity is scarce in Africa. However, by studying the relationship between business cycles' correlation and trade intensity via IV regression, Tapsoba (2009) also shows that trade intensity increases the synchronization of business cycles in Africa. Nevertheless, Tandrayen-Ragoobur et al. (2023) notice that the lack of infrastructural facilities, together with local political instabilities, represent an important barrier to bilateral trade development across all countries in the continent.

Most authors, therefore, study the feasibility of local monetary unions, which are partially motivated by proximity arguments along with similarity in the business cycles. Examples of proposed local monetary unions are the West African Monetary Zone (WAMZ), the East African Monetary Union (EAMU) and the Southern African Monetary Union (SAMU). Some of them exist officially (see Fig. 1), while others do not exist yet.

2.1. Central Africa

After independence, African countries made different decisions about exchange rates and monetary policies. Former British colonies moved to flexible exchange rates, while former French colonies formed the CFA monetary unions. The CFA encompasses two distinct monetary unions: the West African CFA (also known with French acronym UEMOA), including Benin, Burkina Faso, Cote d'Ivoire, Guinea Bissau, Mali, Niger, Senegal and Togo, and the Central African CFA, including Cameroon, Chad, Republic of Congo, Central African Republic, Equatorial Guinea and Gabon. Overall, most studies find evidence against the feasibility of the Central CFA monetary union.

Using cluster analysis, Bénassy-Quéré and Coupet (2005) demonstrate that the entire CFA franc zone cannot be viewed as a single optimum currency area, because Central CFA and West CFA countries do not belong to the same clusters. Carmignani (2010) studies whether the Central CFA monetary union has economic support. The author finds that business cycle synchronization increased only marginally

Fig. 1. Map of existing monetary unions in Africa.

over time for the involved countries, so that this monetary union does not seem to be effective in practice.

Finally, Loureiro et al. (2012) find that, while the composition of Central Africa CFA is not supported by strong integration of economies, the West CFA countries do have enough economic integration for sharing common monetary policy.

We note that Bénassy-Quéré and Coupet (2005) adopt a cross-sectional approach while investigating synchronization, while both Carmignani (2010) and Loureiro et al. (2012) measure it as the correlation coefficient computed on short time series data.

2.2. *West Africa: WAMZ and ECOWAS*

The empirical results for West Africa are mixed. The discussion about the creation of a monetary union involving non-CFA West African countries started in 2000. This potential monetary union in West Africa, called West African Monetary Zone (WAMZ), should include six mainly English-speaking countries, and these are Nigeria, Ghana, Liberia, Sierra Leone, Gambia and Guinea. The UEMOA and WAMZ countries represent two sub-regional blocks of the Economic Community of West African States (ECOWAS). The ECOWAS countries are currently planning to launch a single currency in 2027. It is called the Eco, but the earlier plans were derailed because of the COVID-19 pandemic.

The feasibility of monetary unions in West Africa, especially of the entire ECOWAS, attracted the interest of many researchers.

The results provided in Bénassy-Quéré and Coupet (2005) support the creation of WAMZ and suggest connecting the Gambia, Ghana and Sierra Leone to the West CFA union.

Using cluster analysis, Tsangarides and Qureshi (2008) show that, when west and central African countries are considered together, there are significant heterogeneities within the entire CFA zone, meaning that it cannot be considered as a single optimal monetary union. Furthermore, different from Bénassy-Quéré and Coupet (2005), the results highlight considerable dissimilarities in the economic characteristics of WAMZ members. Note that both Bénassy-Quéré and Coupet (2005) and Tsangarides and Qureshi (2008) adopt a cross-sectional clustering approach, but with a different variable selection. Using a time series approach based on cointegration analysis, Alagidede et al. (2012) highlight that WAMZ members have not synchronized business cycles.

Negative evidence is also highlighted in Coulibaly and Gnimassoun (2013). The authors study the feasibility of a monetary union in the entire West Africa (ECOWAS), by assessing convergence and co-movements between exchange rates with panel cointegration. The results show a lack of synchronization among ECOWAS countries. However, the authors find that the West Africa CFA area is the most homogeneous in terms of business cycle synchronization, and suggest Ghana, Gambia and Sierra Leone could join the union.

Considering synchronicity indices build on GDP growth time series, Simons and Jean Louis (2018) find positive evidence on the synchronization of the business cycles of WAMZ countries and identify the strong links with the Chinese economy as the main explanation.

Zouri (2020) shows that bilateral trade and financial integration positively affect synchronization of business cycles in the region, and hence that the weakness of intracommunity trade should not be a barrier to a monetary union. The author claims that the use of a single currency would increase business cycle synchronization by increasing bilateral trades.

In contrast, considering similarity across inflation rates and GDP growth rates, Loureiro and Baptista (2021) document that the adoption of a common currency by the entire ECOWAS region is not recommended because of lack of economic integration. Moreover, it is suggested to merge the currencies of Guinea, Liberia and Sierra Leone into a single currency and to make Gambia joining the West African CFA. However, the similarities across inflation rates are computed with average values during the restricted period 2000–2018. Similarly, business cycle synchronization is evaluated with the estimation of correlation coefficients for short time series.

2.3. Southern Africa

When we turn to Southern Africa, more coherent results are obtained. Along with Western and Central Africa monetary unions, Fig. 1 shows the presence of a third union among South African countries. The Common Monetary Area (CMA) was established in 1986 for South Africa, Swaziland and Lesotho. In 1992 the trilateral agreement has been replaced by the present multilateral monetary area with the entrance of Namibia.

Kabundi and Loots (2007), use the Generalized Factor Model of Forni et al. (2005) to investigate the co-movement of South African business cycles with those of the eleven countries belonging to Southern Africa Development Community (SADC). The results show strong and significant evidence of co-movement of South African with Swaziland, Botswana, Zimbabwe, Lesotho and Angola and a moderate synchronization with Mozambique, Mauritius and Namibia. Therefore, countries involved in the CMA share a satisfactory degree of cycle synchronization.

Tavlas (2009) contains a detailed review of studies dealing with the sustainability of the CMA. A systematic analysis of the relevant literature highlights that only a small group of countries satisfies the criteria necessary for monetary unification.

Combining Bayesian model averaging with dynamic panel analysis, Beck and Nzimande (2022) show that variables that positively affect business cycle synchronization, like migration, have an opposite effect in the SADC, thereby enlarging differences in the local business cycles instead of reducing them.

2.4. East Africa

The East African Community is interested in a monetary union for Burundi, Rwanda, Tanzania, Kenya and Uganda. The transition from flexible exchange rates to a monetary union is still in an initial convergence phase, where the partner states work towards achieving preconditions designed to limit the union's exposure to internal economic strains. The region has given itself 2024 to have established the East African Monetary Union (EAMU).

Using a system of simultaneous equations and GMM, Bangaké (2008) documents structural similarities only among the business cycles of Kenya, Tanzania and Uganda, thus suggesting that, at least partially, there is enough integration to construct the monetary union. Considering a structural VAR analysis, Kishor and Ssozi (2011) show that business cycle synchronization became weaker after 2000. This makes the authors to doubt the current feasibility of the union. Following a similar methodology, Mafusire and Brixiova (2013) document a lack of macroeconomic convergence.

Thomas and Paul (2013), using correlation and cointegration analysis, document the presence of huge asymmetric production structures and an absence of strong synchronization. However, the results are obtained considering a constrained period of about ten years.

Finally, in analogy with the analysis in Aguiar-Conraria and Soares (2011) for European business cycles, Umulisa and Habimana (2018) perform a cluster analysis based on wavelet spectra considering data in period 1989–2015. Documenting a general lack of business cycles' synchronization, the results indicate that Kenya, Tanzania, and Uganda form the core of the monetary union, whereas Burundi and Rwanda are at its periphery.

To wrap up the available literature, we see that various studies address the potential of monetary unions for countries in Africa. There is evidence in favor and there is evidence not in favor of such unions. What is common though across all studies is that thy either address similarities across the cross-sectional dimension or across the time series dimension. It may perhaps be that this separate focus drive the mixing results. In this paper we therefore propose to study common business cycles along the dimensions jointly.

3. Methodology: spatio-temporal hierarchical clustering

We put forward a Ward-like spatio-temporal hierarchical clustering algorithm. The Ward (1963) hierarchical clustering approach starts with considering an initial partition with N clusters of singletons. Then, at each step, the algorithm aggregates two clusters according to an objective function related to the within cluster inertia.

To be more precise, let us consider a set of N $(i = 1, \dots, N)$ statistical units and let $\mathbf{D} = [d_{ij}]$ be the $N \times N$ dissimilarity matrix associated with the N units, with d_{ij} being the dissimilarity measure between two units i and j. Let us define $\mathcal{P}_K = (C_1, \dots, C_K)$ a partition of the dataset into K clusters. In general we can express the within-clusters inertia C_k $(k = 1, \dots, K)$ as follows:

$$I\left(C_k\right) = \sum_{i\in C_k}\sum_{j\in C_k} \frac{w_i w_j}{2\sum_{i\in C_k} w_i} d_{ij}^2, \tag{1}$$

with w_i the weight associated to the ith statistical unit. Usually, in absence of any a priori information, it is common to set $w_i = 1/N$. In the standard Ward hierarchical clustering framework the dissimilarity matrix $\mathbf{D}$ is computed in the attribute space, that is, considering a set of P $(p = 1, \dots, P)$ variables describing the N statistical units. In the context of time series data, the attribute space is represented by the observation of an attribute over T $(t = 1, \dots, T)$ time periods. However, there can be cases where the consideration of the attribute space alone is not sufficient for clustering the N units. This is the case when both temporal and spatial dimensions should be considered together.

Following the notation used in Chavent et al. (2018), we define the spatio-temporal inertia of a C_k $(k = 1, \dots, K)$ cluster as the convex combination between the attribute inertia and the inertia of spatial clusters. In other words, in the case of spatio-temporal clustering, (1) becomes:

$$I\left(C_k\right) = (1-\alpha)\sum_{i\in C_k}\sum_{j\in C_k} \frac{w_i w_j}{2\sum_{i\in C_k} w_i} d_{ij,t}^2 + \alpha \sum_{i\in C_k}\sum_{j\in C_k} \frac{w_i w_j}{2\sum_{i\in C_k} w_i} d_{ij,g}^2, \tag{2}$$

where $d_{ij,t}^2$ is the squared distance between units i and j over the (temporal) attribute space and $d_{ij,g}^2$ is the squared distance in the geographical space. The smaller the inertia $I\left(C_k\right)$ is, the more homogenous are the observations in cluster C_k. Note that the spatio-temporal inertia (2) is a convex combination of temporal inertia and spatial inertia. Moreover, spatio-temporal inertia depends on the so-called *mixing parameter* α, which in our case can be interpreted as the relevance of spatial information relative to the temporal one.

To obtain a new partition $\mathcal{P}_K$ in K clusters from a given partition $\mathcal{P}_{K+1}$ in $K+1$ clusters, the idea is to aggregate the two clusters $\mathcal{A}$ and $\mathcal{B}$ of $\mathcal{P}_{K+1}$ such that the new partition has minimum within-cluster inertia, that is,

$$\min_{\mathcal{A},\mathcal{B}\in\mathcal{P}_{K+1}} W\left(\mathcal{P}_K\right) = \min_{\mathcal{A},\mathcal{B}\in\mathcal{P}_{K+1}} I\left(\mathcal{A}\cup\mathcal{B}\right) - I\left(\mathcal{A}\right) - I\left(\mathcal{B}\right). \tag{3}$$

The optimization problem is therefore achieved by defining the following aggregation measure between two clusters

$$\delta\left(\mathcal{A},\mathcal{B}\right) = I\left(\mathcal{A}\cup\mathcal{B}\right) - I\left(\mathcal{A}\right) - I\left(\mathcal{B}\right), \tag{4}$$

which is minimized at each step of the hierarchical clustering algorithm. In the first step the partition is $\mathcal{P}_N$ and the aggregation measures between the singletons are calculated as

$$\delta_{ij} = (1-\alpha)\frac{w_i w_j}{w_i + w_j} d_{ij,t}^2 + \alpha \frac{w_i w_j}{w_i + w_j} d_{ij,g}^2, \tag{5}$$

and stored in the $N \times N$ matrix $\Delta = [\delta_{ij}]$. For each subsequent step K, the aggregation between the new cluster $\mathcal{A} \cup \mathcal{B}$ and any cluster $\mathcal{D}$ of $\mathcal{P}_{K+1}$ are obtained thanks to the well-known (Lance and Williams, 1967) equation:

$$\delta(\mathcal{A} \cup \mathcal{B}, \mathcal{D}) = \frac{N_{\mathcal{A}} + N_{\mathcal{D}}}{N_{\mathcal{A}} + N_{\mathcal{B}} + N_{\mathcal{D}}} \delta(\mathcal{A}, \mathcal{D}) + \frac{N_{\mathcal{B}} + N_{\mathcal{D}}}{N_{\mathcal{A}} + N_{\mathcal{B}} + N_{\mathcal{D}}} \delta(\mathcal{B}, \mathcal{D}) - \frac{N_{\mathcal{D}}}{N_{\mathcal{A}} + N_{\mathcal{B}} + N_{\mathcal{D}}} \delta(\mathcal{A}, \mathcal{B}). \tag{6}$$

This clustering framework based on the inertia (2), which is a modification of the Ward hierarchical clustering including spatial constraints, has been defined as *ClustGeo* in Chavent et al. (2018) considering cross-sectional attribute space. In our study, we extend the ClustGeo framework to spatio-temporal modeling.

3.1. Measuring spatio-temporal similarity of business cycles

The measurement of spatio-temporal similarity starts by the definition of a proper distance measure for temporal data. Measuring time series similarity is a complicated task, which can be accomplished in many different ways. Following recent advances in the time series clustering literature, we adopt a feature-based Dynamic Time Warping (DTW) approach to measure intertemporal similarity of business cycles (Franses and Wiemann, 2020).

By considering two time series $\mathbf{x}_i$ $(t_i = 1, \dots, T_i)$ and $\mathbf{x}_j$ $(t_j = 1, \dots, T_j)$, the DTW is a distance-minimizing temporal alignment between the time series i and j with possibly $T_i \gtreqless T_j$. In other words, DTW seeks for a so-called warping path which is used to align the elements of the two temporal sequences such that their distance is minimized. By letting $d(x_{i,r}, x_{j,s})$ be the distance between two points r and s of the sequences $\mathbf{x}_i$ and $\mathbf{x}_j$, the DTW distance is given by the optimal alignment obtained with the minimization of the following the cumulative distance:

$$\Delta(r, s) = d(x_{i,r}, x_{j,s}) + \min\left[\Delta(r-1, s-1), \Delta(r-1, s), \Delta(r, s-1)\right]. \tag{7}$$

As argued by Franses and Wiemann (2020), the use of the simple DTW distance in the context of business cycles analysis is not perfectly appropriate because it ignores fluctuations associated with expansion and contraction periods. This happens because only the values at time t are considered, while subsequent and antecedent values are ignored.

For these reasons, following Franses and Wiemann (2020) and Xie and Wiltgen (2010), we consider an adaptive feature-based DTW distance. More in detail, we consider both global and local features of the time series data points associated with the two series. More specifically, the local feature of a particular observation r is originally defined by a 2-element vector that summarizes the growth rate between subsequent and antecedent time periods to capture local trends, which fits common business cycle analysis. The local feature of observation r of a series $\mathbf{x}_i$ is then given by

$$f_{\text{local}}\left(x_{i,r}\right) = \left[\frac{x_r - x_{r-1}}{x_{r-1}}, \frac{x_{r+1} - x_r}{x_r}\right]. \tag{8}$$

The global feature is adjusted in a similar manner as it is given by

$$f_{\text{global}}\left(x_{i,r}\right) = \left[\frac{x_r - \sum_{k=1}^{r-1} \frac{x_k}{r-1}}{\sum_{k=1}^{r-1} \frac{x_k}{r=1}}, \frac{x_r - \sum_{k=r+1}^{T_i} \frac{x_k}{T_i - r}}{\sum_{k=r+1}^{T_i} \frac{x_k}{T_i - r}}\right]. \tag{9}$$

We can define the following point distances:

$$d_{\text{local}}(x_{i,r}, x_{j,s}) = \left| f_{\text{local}}\left(x_{i,r}\right)_1 - f_{\text{local}}\left(x_{j,s}\right)_1 \right| + \left| f_{\text{local}}\left(x_{i,r}\right)_2 - f_{\text{local}}\left(x_{j,s}\right)_2 \right|, \tag{10}$$

and:

$$d_{\text{global}}(x_{i,r}, x_{j,s}) = \left| f_{\text{global}}\left(x_{i}\right)_1 - f_{\text{global}}\left(x_{j,s}\right)_1 \right| + \left| f_{\text{global}}\left(x_{i,r}\right)_2 - f_{\text{global}}\left(x_{j,s}\right)_2 \right|. \tag{11}$$

Note that the subscripts 1 and 2 indicate the position within the adaptive features' vectors. As a result, the DTW-based distance equals (7) where the quantity $d(x_{i,r}, x_{j,s})$ is substituted with the following distance:

$$d(x_{i,r}, x_{j,s}) = d_{\text{local}}(x_{i,r}, x_{j,s}) + d_{\text{global}}(x_{i,r}, x_{j,s}). \tag{12}$$

The main advantage of feature-based clustering procedures is that, different from model-based approaches, they do not rely on specific data generating processes (DGPs). Therefore, a clustering procedure which builds on the feature-DTW distance is free from model misspecification error. In other words, by considering a feature-DTW distance, we are agnostic about the DGP of the underlying time series in the clustering process, and we only look for the similarity across temporal patterns of the time series.

Once the temporal similarity measure is defined, it is important to introduce the spatial dissimilarity measure used in the spatio-temporal problem. Indeed, proximity in the temporal space does not evidently ensure proximity in the geographical space. Thus, in addition to the proximity in the attribute space, proximity in the geographical space must be taken into account.

Observations located close to one another in the geographical space can have similar characteristics. Hence, there is a need to obtain closely related or contiguous clusters of data locations with similar attribute values. The clustering can be achieved in different ways, depending mainly on the measure used to quantify proximity. To address these constraints, in this paper we consider a spatial (geographical) dissimilarity based on the geographical distances among the statistical units, measured in terms of latitude and longitude. More specific, the spatial dissimilarity considered is obtained as follows:

$$d_{ij,g} = \sqrt{\left(x_{i,\text{lat}} - x_{j,\text{lat}}\right)^2 + \left(x_{i,\text{long}} - x_{j,\text{long}}\right)^2}. \tag{13}$$

The dissimilarity (13), once considered in a given clustering algorithm, ensures that statistical units closer in the geographical space are clustered together. Obviously it is not the only way of approaching spatial dimension in clustering. Important properties such as spatial dependency and heterogeneity over the space are only partially considered in simple dissimilarity measures (see, e.g. Fouedjio, 2016; Mattera, 2022). Nevertheless, as shown in Chavent et al. (2018), if combined with another non-spatial dissimilarity, it can be successfully used to provide a soft spatial constraint to the final partition.

3.2. Choosing the mixing parameter

The main issue in the application of the ClustGeo framework lies in the objective definition of the mixing parameter α in (2). In what follows, we adopt the procedure proposed in Chavent et al. (2018), which is briefly summarized here for convenience.

The main goal when choosing α is to find a value representing the best compromise between loss in the temporal space and loss of geographical homogeneity. Indeed, it is known that in spatio-temporal modeling the temporal dimension is more important in discriminating the statistical units. Nevertheless, a certain amount of relevance has to be devoted to space in order to enhance some spatial clustering but still considering the partition implied by temporal dissimilarities.

In order to increase the geographical homogeneity without adversely affecting temporal homogeneity, Chavent et al. (2018) propose the following procedure. For a given number K_0 of clusters, we consider a grid of J values for $\alpha \in [0, 1]$:

$$\mathcal{V} = \left\{\alpha_1 = 0, \dots, \alpha_j, \dots, \alpha_J = 1\right\}.$$

For each value $\alpha_j \in \mathcal{V}$, the corresponding partition $\mathcal{P}_{K_0}$ in K_0 clusters is obtained using the Ward-like hierarchical clustering algorithm based on the inertia shown in (2). For each of the J partitions based on the alternative α_j values, the criterion

$$Q_{DTW}\left(\mathcal{P}_{K_0}\right) = 1 - \frac{W_{DTW}\left(\mathcal{P}_{K_0}\right)}{W_{DTW}\left(\mathcal{P}_1\right)} \tag{14}$$

Fig. 2. Countries included in the dataset.

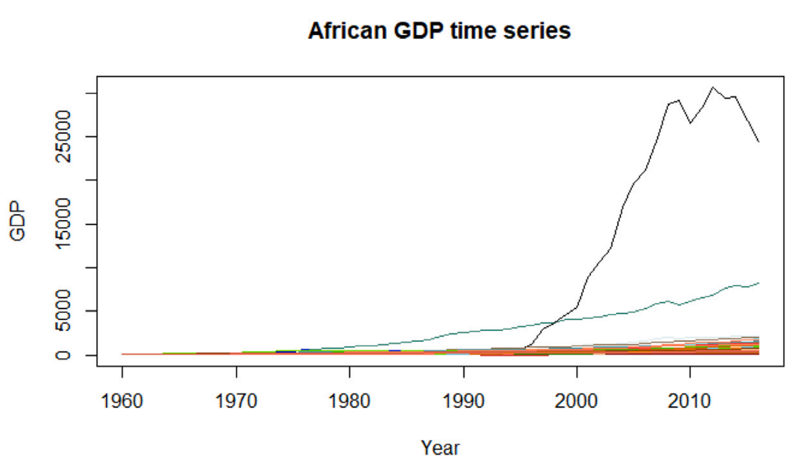

Fig. 3. GDP time series 1960–2016 of the countries in Fig. 2, indexed at 1960 = 100.

is evaluated. Note that $W_{DTW}\left(\mathcal{P}_1\right)$ is the total pseudo inertia associated with the DTW-based dissimilarity, while $W_{DTW}\left(\mathcal{P}_{K_0}\right)$ is the within-cluster inertia associated with the partition using only temporal information. Similarly, for each of the J partitions based on the alternative α_j values also the following criterion is assessed:

$$Q_{GEO}\left(\mathcal{P}_{K_0}\right) = 1 - \frac{W_{GEO}\left(\mathcal{P}_{K_0}\right)}{W_{GEO}\left(\mathcal{P}_1\right)} \tag{15}$$

where the numerator is the within-cluster inertia associated with the partition using only spatial information, while the denominator is the total pseudo inertia associated with the spatial dissimilarity matrix.

The plot of the points of Q_{DTW} and Q_{GEO} provide a visual way to observe the loss of temporal and spatial homogeneity of the partition by varying α_j. According to Chavent et al. (2018), the two plots allow the user to choose a suitable value for $\alpha \in \mathcal{U}$ as the point minimizing the distance between the two lines. The main problem of this procedure is that it depends on the choice of an initial value of K, which is set as the

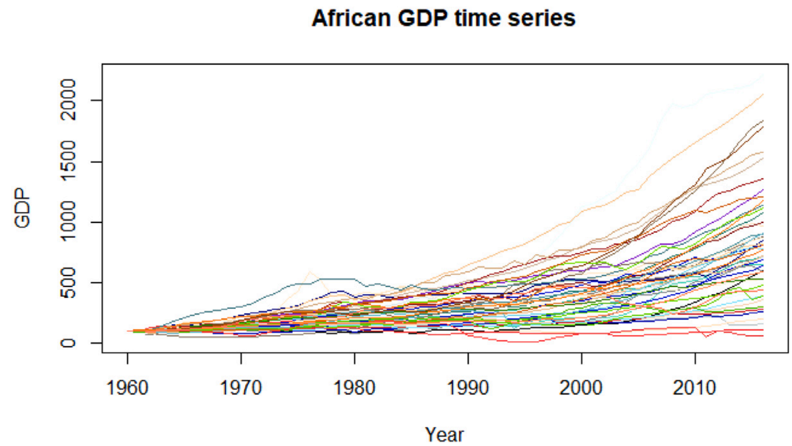

Fig. 4. GDP time series 1960–2016 of the countries in Fig. 2 – Botswana and Equatorial Guinea excluded.

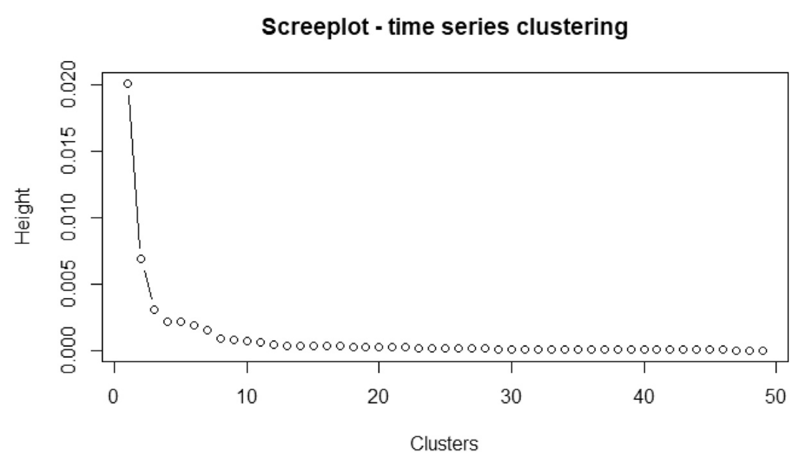

Fig. 5. Screeplot associated with spatio-temporal clustering.

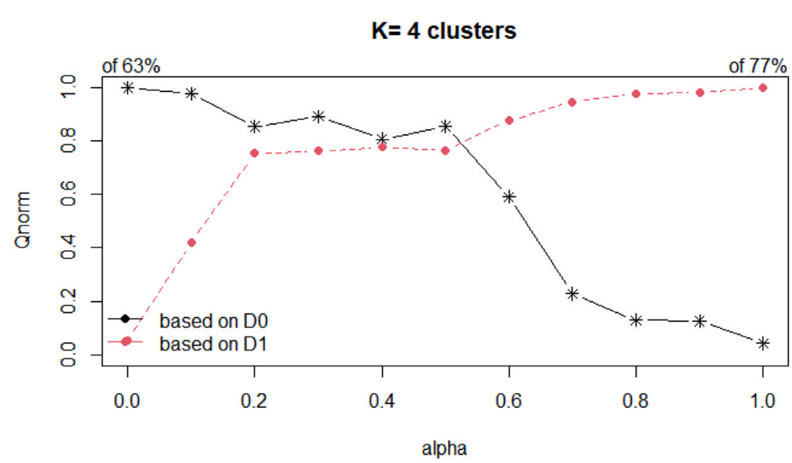

Fig. 6. Selection of the mixing parameter α, given $K = 4$ time series clusters. D0 and D1 are the temporal and spatial dissimilarity matrices, respectively.

number of clusters in the temporal space. Therefore, we first consider the partition associated with the time series approach and choose the initial K_0. Then a new K, perhaps with $K \neq K_0$, is chosen for the spatio-temporal partition.

4. Empirical analysis

We investigate business cycles' synchronization across African economies with our spatio-temporal methodology.

4.1. Data and clustering results

To study business cycles' similarity, we consider the GDP time series data 1960–2016 reconstructed by Franses and Vasilev (2019). The countries included in the dataset are shown in Fig. 2.

The GDP time series of the African countries are shown in Fig. 3.

Two outlier time series – Botswana and Equatorial Guinea – are highlighted in Fig. 2. We exclude these countries from the dataset to

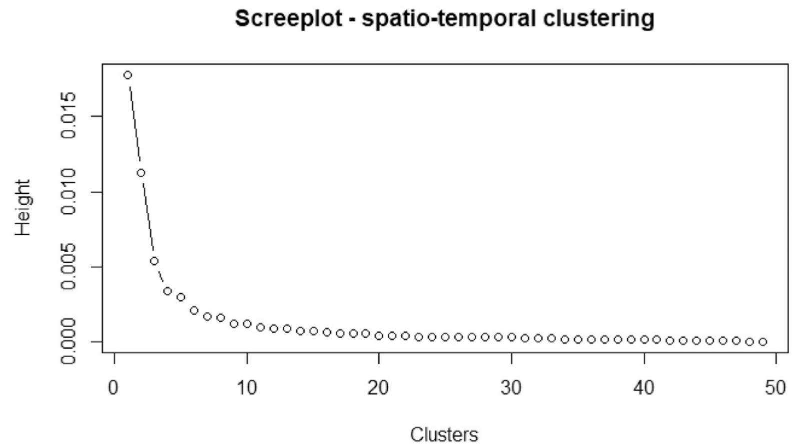

Fig. 7. Screeplot associated with spatio-temporal clustering.

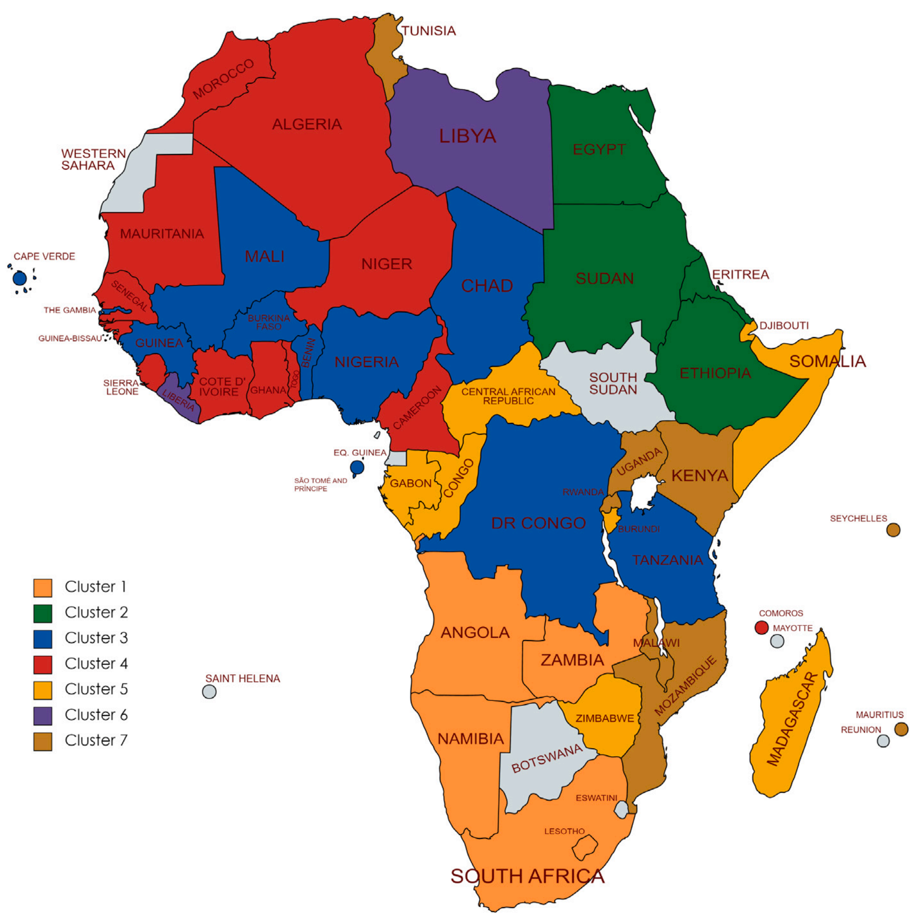

Fig. 8. Visualization of spatio-temporal clusters under feature-DTW ditance.

avoid the inclusion of noisy time series in the sample. The resulting GDP time series are shown in Fig. 4.

The resulting countries represent the set of statistical units to be clustered. Notice that, due to the nature of the distance (12), we resort to growth rates, see (8) and (9).

For spatio-temporal clustering, we first guess a suitable initial number of clusters considering the temporal dimension only. The screeplot of temporal DTW-based clustering is shown in Fig. 5.

From the scree plot we detect the elbow at $K_0 = 4$. Given the $K_0 = 4$ clusters, we adopt the Chavent et al. (2018) procedure for choosing the mixing parameter α. A set of values between 0 and 1 with a grid of 0.1 $\mathcal{U} = \{0, 0.1, 0.2, \ldots, 1\}$ is considered. The result is shown in Fig. 6.

According to Fig. 6, the best compromise is obtained with $\alpha = 0.4$. With this choice of the mixing parameter, Fig. 7 shows the scree plot associated with the clustering results.

According to the elbow criterion, we choose a partition into $K = 7$ clusters. The final partition is visualized in Fig. 8. Some details are provided below.

Most of South African countries belong to Cluster 1, that is, South Africa, Lesotho, Namibia, Angola and Zambia. Cluster 2 includes some

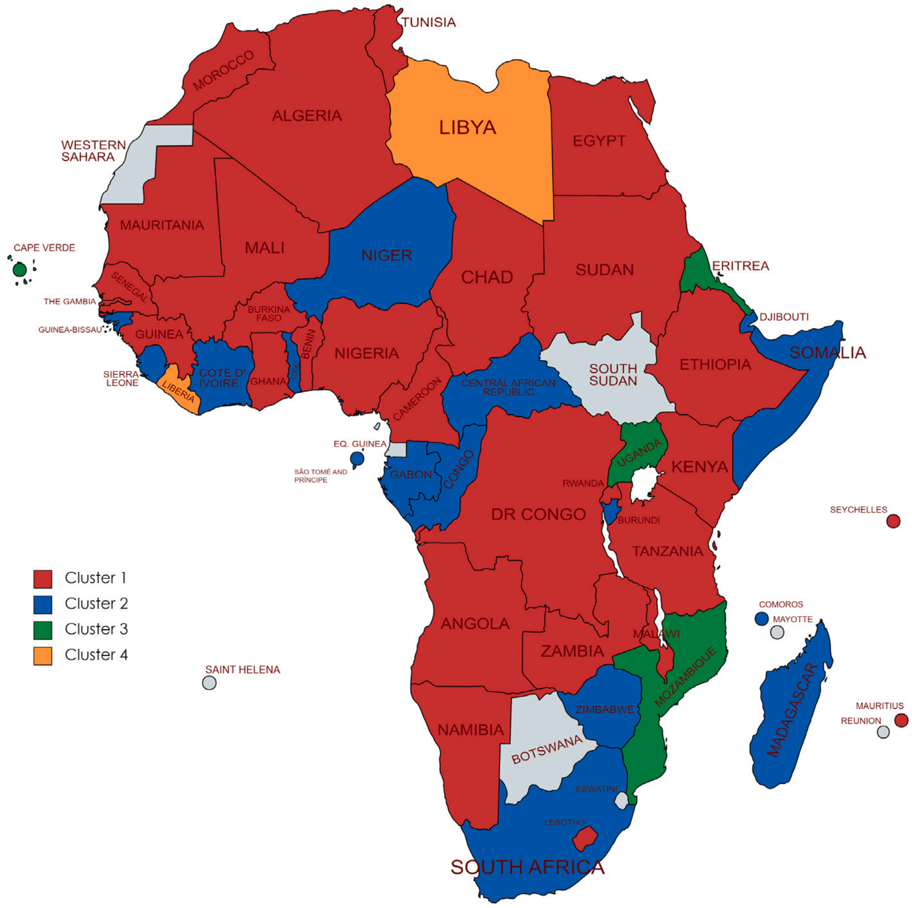

Fig. 9. Visualization of time series clusters under feature-DTW ditance.

countries in Northern East of continental Africa, amd these are Egypt, Sudan, Eritrea and Ethiopia.

Cluster 3 and Cluster 4 are the most numerous, with 10 and 11 Countries included, respectively. Both include mainly countries in the West and Northern West of Africa. In particular, Cluster 3 includes Gambia, Mali, Burkina Faso, Benin, Nigeria, Chad, DR Congo, Tanzania, Capo Verde and Sao Tome a Prince, while Cluster 4 groups together Algeria, Morocco, Niger, Mauritania, Senegal, Sierra Leone, Cote d'Ivoire, Ghana, Togo, Cameroon and Comoros.

Cluster 5, instead, includes some Central African countries like Congo, Gabon and Central African Republic. Other countries included in Cluster 5 are Burundi, Zimbabwe, Madagascar and Djibouti and Somalia in East Africa.

Cluster 6 has two countries, Lybia and Liberia, that share very peculiar business cycles although distant in space. Cluster 7 also includes countries with peculiar cycles in the Southern East of Africa, and these are Uganda, Mozambique, Kenya and Malawi. Island of Seychelles and Mauritius are also included.

4.2. Discussion

Our results highlight interesting points about the feasibility of currently established monetary unions in Africa and of new ones.

First of all, South Africa, Namibia and Lesotho, forming the Common Monetary Area, are grouped together in the Cluster 1, so they are likely to share synchronized business cycles. Our evidence supports claims of previous papers, like (Kabundi and Loots, 2007), in favor of CMA sustainability. However, our analysis also suggests that other countries in Southern Africa like Angola and Zambia share a common cycle with those of the CMA. Therefore, it would be feasible for the CMA to include also Angola and Zambia in the monetary union. Due to their spatial proximity, trade among these countries would be facilitated too. Furthermore, our results also indicate that the entire block of Southern African countries cannot form a single monetary union, due to lack of business cycle synchronization of Zimbabwe and Mozambique with those of Cluster 1.

Second, we do not find a perfect match between the countries placed in Cluster 5 with those of the Central African CFA. Gabon, Congo and Central African Republic share a common business cycle, although it seems that Cameroon and Chad do not. These results partially confirm the conclusions of Carmignani (2010) and Loureiro et al. (2012), which argue that the composition of Central Africa CFA is not supported by strong integration of the economies. The majority of the Central African CFA countries actually share a synchronized business cycle. Cameroon and Chad are the western countries of the Central Africa CFA monetary union, so they are spatially close to ECOWAS countries too. In presence of a business cycle more synchronized with ECOWAS countries, it seems reasonable for these two countries joining an alternative monetary union. Our findings are in line with those of Tsangarides and Qureshi (2008). Furthermore, in accordance with Bénassy-Quéré and Coupet (2005), we also find that the CFA cannot be seen as a single monetary union because Central CFA (Cluster 5) and West CFA (Cluster 4) countries do not belong to the same group. Interestingly, in Cluster 5 we observe that Gabon, Congo and Central African Republic are clustered together with Burundi, Madagascar, Somalia and Zimbabwe which are the poorest countries on the continent.[1]

[1] This statement refers to the GDP per capita (NY.GDP.PCAP.CD) of these countries in the year 2021. Data can be retrieved from the World Bank website.

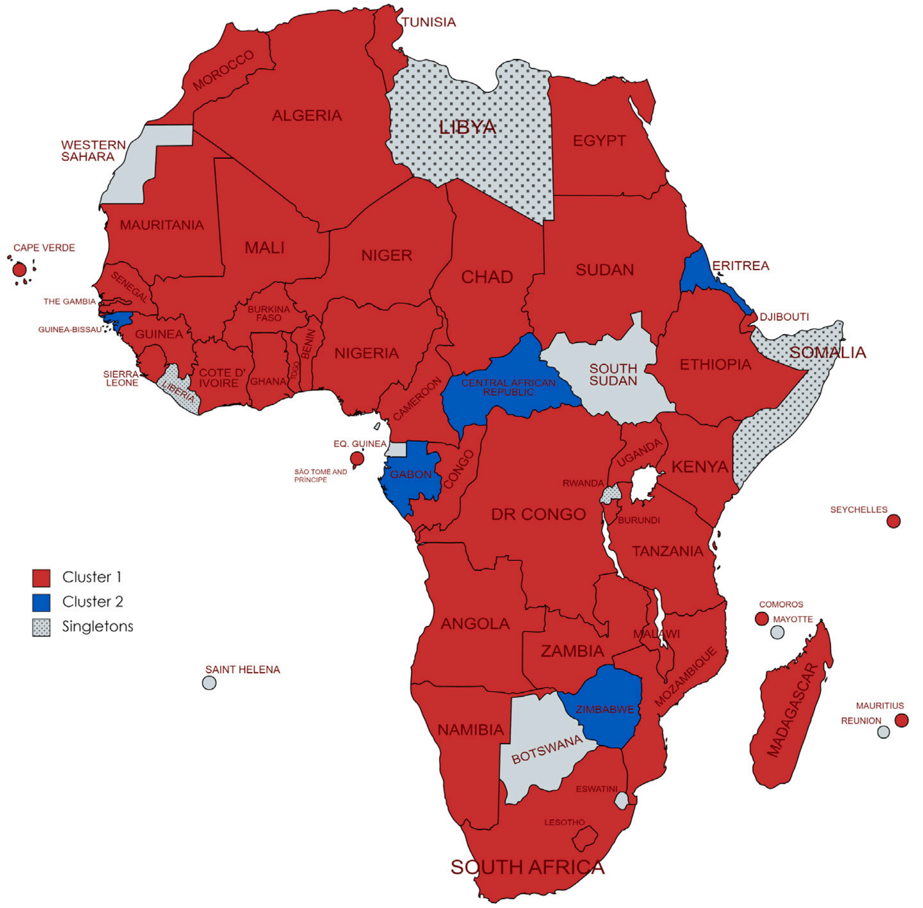

Fig. 10. Visualization of time series clusters under single-year based Euclidean distance.

Third, we observe two huge groups of countries, Cluster 3 and Cluster 4, in West Africa. These two clusters deserve a single investigation because they almost represent the ECOWAS countries. The ECOWAS is composed by two sub-groups, the English speaking (WAMZ) and the French speaking (UEMOA) countries. Most of French speaking countries in the UEMOA like Senegal, Guinea-Bissau, Cote d'Ivorie, Niger and Togo are grouped together in Cluster 4, but it seems that the business cycles of Benin, Burkina Faso and Mali, which are also UEMOA countries, are not synchronized with those in Cluster 4. Interestingly, the business cycles of Ghana and Sierra Leone, both WAMZ countries, are more synchronized with the UEMOA countries included in Cluster 4. Similarly, in Cluster 3 we have that countries belonging to the WAMZ like Nigeria, Gambia and Guinea are characterized by business cycles synchronized with Benin, Burkina Faso and Mali, that historically belong to the UEMOA. In sum, the obtained clusters show some overlap between the UEMOA and WAMZ countries. Considering spatial proximity and the overlap in terms of business cycles' synchronization, the clustering results seem to suggest that a monetary union of ECOWAS countries could perhaps be sustainable. As Zouri (2020) highlights, the creation of a monetary union in ECOWAS can also increase business cycles' synchronization by the increase of bilateral trades in the region. Our findings are thus in contrast with those of Coulibaly and Gnimassoun (2013) and Loureiro and Baptista (2021).

Fourth, clustering results provide evidence against the feasibility of the East African Monetary Union across Burundi, Rwanda, Tanzania, Kenya and Uganda, because Burundi and Tanzania do not show synchronized business cycles with the other countries. The lack of strong synchronization in these countries is documented also in Kishor and Ssozi (2011), Thomas and Paul (2013) and Mafusire and Brixiova (2013). A feasible monetary union should instead include a trilateral monetary agreement across Rwanda, Kenya and Uganda (see Cluster 7). Therefore, our results seem to reject the core–periphery pattern highlighted in Umulisa and Habimana (2018). Malawi and Mozambique are also included in Cluster 7, showing enough synchronization to join the virtual trilateral agreement of Rwanda, Kenya and Uganda. However, as Tanzania is a neighbor for both the blocks of Cluster 7, this union would be unfeasible in the absence of a trade agreement with Tanzania, although the presence of Seychelles in the union could facilitate trades. Indeed, Tanzania seems to have a business cycle more synchronized with its neighbor Congo and with West African economies (Cluster 3), so it should not join the union. In summary, our findings suggest that EAMU should include only Rwanda, Kenya and Uganda. The Seychelles Islands could also join this union.

Libya and Liberia, both placed in the Cluster 6, show very peculiar business cycles with respect to the other African countries. Due to their geographical distance, however, they cannot join into a monetary union. In other words, Cluster 6 can be considered as an outlier cluster.

Finally, our findings indicate the presence of a new feasible monetary union across some North-Eastern African countries, which has never been highlighted by previous studies. Such a union refers to Cluster 2 including Egypt, Sudan, Eritrea and Ethiopia. The business cycles of these countries are well synchronized, although the Egyptian economy is the most virtuous within the block. By excluding Egypt from the union, however, it seems that the creation of a trilateral agreement across these countries in Cluster 2 would be still recommendable.

In the end, it is interesting to highlight that our results do not suggest the creation of a monetary union across Northern African countries. Although spatially close, the business cycles of these countries are not enough synchronized.

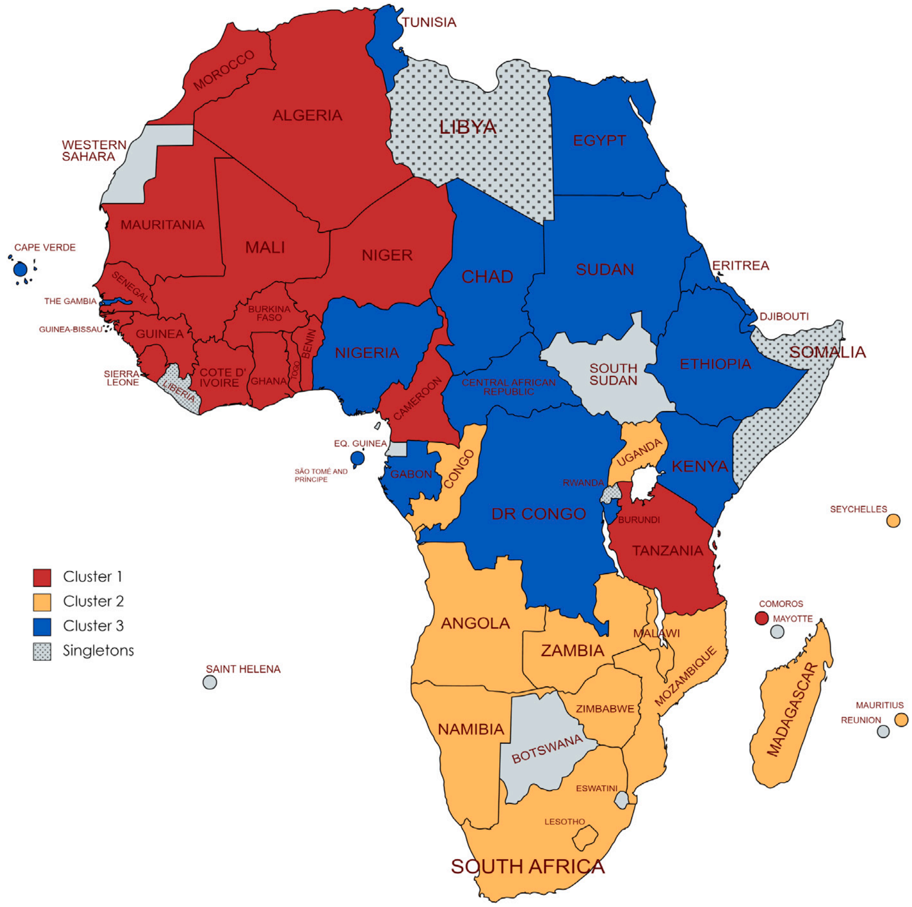

Fig. 11. Visualization of spatio-temporal series clusters under single-year based Euclidean distance.

4.3. Is the spatio-temporal approach useful?

We now analyze the effect of the introduction of the spatial dimension in our clustering problem. In the case of $\alpha = 0$ we obtain a partition only considering the temporal dimension. Such a partition into $K = 4$ clusters (see the scree plot in Fig. 5) is summarized in Fig. 9. In the supplementary material we show with simulations that ignoring the spatial dimension can lead to a smaller amount of clusters.

We can observe how the temporal partition is different from the partition obtained using the spatio-temporal approach. Fig. 9 confirms that Mozambique and Uganda share a similar cycle but, most importantly, that Cluster 6 of Fig. 8 coincides with Cluster 4 of Fig. 9. This means, in other words, that Lybia and Liberia share a common cycle, that is very different from other African countries.

The results highlighted in Fig. 9 are however inconvenient and difficult to justify economically. As mentioned, Africa is the least integrated continent in the world with a low level of intra-regional trade (Tandrayen-Ragoobur et al., 2023), mainly because of the lack of infrastructure that in turn increases bilateral trading costs (e.g. see Akpan, 2014; Babu et al., 2022). Therefore, suggestions of joining in the same monetary union distant countries would not be beneficial for Africa. In the case of Fig. 9, however, most of the countries belong to Cluster 1 which is not a reasonable result. Cluster 3 also includes distant countries, Eritrea, Mozambique and Uganda, not sharing any physical boundary. We also notice that there is almost no clear overlap of the obtained temporal partition with the currently existing monetary unions.

Overall, the use of a standard time series clustering does not seem to work well when dealing with the analysis of African business cycles. The results obtained with the proposed spatio-temporal approach, however, are more meaningful and explainable economically.

4.4. Within clusters cointegration analysis: results

Although the clusters obtained with the spatio-temporal approach seem to highlight some feasible monetary unions, it would be beneficial to provide support for the possible convergence of the economies placed in the clusters. We rely on the convergence definition in a pure time series context as proposed in Bernard and Durlauf (1995) for a group of countries which can be analyzed using the Johansen cointegration test.

Let n_c be the number of countries belonging to the cth cluster. If the rank $0 < r < n_c$ there are r cointegrating vectors and, hence, the group of time series is driven by $n_c - r$ common shocks. If $r = 0$ there are n_c stochastic trends and the long-run GDP levels are not related across countries. Following the convergence definition of Bernard and Durlauf (1995), for the individual output series to converge, there must be $n_c - 1$ cointegrating vectors. Table 1 shows the results of the Johansen cointegration test under trace statistics.

Before going into details of the main findings, we remark that the maximum size for cointegration analysis concerns $n_c = 11$ countries due to the availability of critical values. The only cluster with more than 11 countries is Cluster 4, so we removed Comoros from the cointegration analysis involving countries in this cluster because it is a small island placed very far from the countries.

For Cluster 2 we report the results of cointegration analysis without Egypt, and we find evidence of convergence. As explained in the discussion, the Egypt economy is much more advanced than those of Eritrea, Ehiopia and Sudan, so it would not be feasible for the first join a monetary union with the other three countries.

Moreover, Clusters 3 and 4 show evidence in favor of convergence, although the test statistics are significant at 90% of confidence. About

Table 1
Johansen cointegration test results within the clusters (trace statistics). First column indicates the estimate static, while the other columns indicate critical values of the test.

	Trace test	Critical values		
		10%	5%	1%
Cluster 1				
r ≤ 4	4.89	10.49	12.25	16.26
r ≤ 3	5.97	16.85	18.96	23.65
r ≤ 2	15.19	23.11	25.54	30.34
r ≤ 1	36.29**	29.12	31.46	36.65
r = 0	40.47**	34.75	37.52	42.36
Cluster 2				
r ≤ 2	5.84	10.49	12.25	16.26
r ≤ 1	23.21**	16.85	18.96	23.65
r = 0	30.81***	23.11	25.54	30.34
Panel C: Cluster 3				
r ≤ 10	10.10	10.49	12.25	16.26
r ≤ 9	24.99*	22.76	25.32	30.45
r ≤ 8	42.02*	39.06	42.44	48.45
r ≤ 7	63.74**	59.14	62.99	70.05
r ≤ 6	95.45**	83.20	87.31	96.58
r ≤ 5	131.01***	110.42	114.90	124.75
r ≤ 4	186.53***	141.01	146.76	158.49
r ≤ 3	244.27***	176.67	182.82	196.08
r ≤ 2	306.99***	215.17	222.21	234.41
r ≤ 1	427.00***	256.72	263.42	279.07
r = 0	578.92***	303.13	310.81	327.45
Cluster 4				
r ≤ 10	10.58	10.49	12.25	16.26
r ≤ 9	23.85*	22.76	25.32	30.45
r ≤ 8	43.78**	39.06	42.44	48.45
r ≤ 7	66.03**	59.14	62.99	70.05
r ≤ 6	94.24**	83.20	87.31	96.58
r ≤ 5	133.56***	110.42	114.90	124.75
r ≤ 4	174.59***	141.01	146.76	158.49
r ≤ 3	232.35***	176.67	182.82	196.08
r ≤ 2	301.69***	215.17	222.21	234.41
r ≤ 1	387.61***	256.72	263.42	279.07
r = 0	498.77***	303.13	310.81	327.45
Cluster 5				
r ≤ 7	5.99	10.49	12.25	16.26
r ≤ 6	14.70	22.76	25.32	30.45
r ≤ 5	27.36	39.06	42.44	48.45
r ≤ 4	45.99	59.14	62.99	70.05
r ≤ 3	73.76	83.20	87.31	96.58
r ≤ 2	111.87*	110.42	114.90	124.75
r ≤ 1	162.67***	141.01	146.76	158.49
r = 0	231.59***	176.67	182.82	196.08
Cluster 6				
r ≤ 1	5.10	10.49	12.25	16.26
r = 0	13.38	22.76	25.32	30.45
Cluster 7				
r ≤ 7	10.84	10.49	12.25	16.26
r ≤ 6	22.94	22.76	25.32	30.45
r ≤ 5	39.01	39.06	42.44	48.45
r ≤ 4	62.63*	59.14	62.99	70.05
r ≤ 3	93.15**	83.20	87.31	96.58
r ≤ 2	132.78***	110.42	114.90	124.75
r ≤ 1	192.65***	141.01	146.76	158.49
r = 0	268.58***	176.67	182.82	196.08

*Mean 10% significance.
**Mean 5% significance.
***Mean 1% significance.

Cluster 1, i.e. Common Monetary Union (CMU) in Southern Africa, we find absence of convergence. However, we do find the presence of a single cointegrating vector thus suggesting that there is a single long-run processes driving the GDP of this cluster. We can argue, therefore, that the GDPs of the Cluster 1 countries are likely subject to shocks in the South African GDP that is the main economy of the monetary union.

The groups not showing full cointegration are Clusters 5, 6 and 7. Cluster 5 corresponds to Central African CFA, for which we are not able to find convergence. We get the same result by considering a subset of Cluster 5 with Congo, Central African Republic and Gabon. Cluster 6 involves Lybia and Liberia that obviously cannot form a feasible monetary union (given also their huge distance in the space). The two GDP processes are also not cointegrated.

Cluster 7, in the end, involves some countries in the South East of Africa but also in this case we do not get evidence of convergence with cointegration analysis. The results are confirmed for possible subsets of this cluster, like a possible trilateral exchange across Uganda, Rwanda and Kenya or a bilateral agreement involving Malawi and Moambique.

In sum, by considering the convergence definition of Bernard and Durlauf (1995), we get some evidence supporting the feasibility of some monetary unions highlighted from our clusters. In particular, a monetary union in the West is highly recommended, while a new one in the North East of Africa seems promising. The CMU, in the end, seems to be feasible although a sort of "core–periphery" pattern can be found (Umulisa and Habimana, 2018), with South Africa being the core of the monetary union.

5. Robustness checks

5.1. Alternative measure for time series dissimilarity

In Section 3 we argued that the use of a simple single-year based distance in the context of business cycles analysis is not recommended because it ignores fluctuations associated with expansion and contraction periods. This is also true when dealing with the analysis of African business cycles, as the duration of the entire cyclical movements usually covers many years (e.g. see Rand and Tarp, 2002; Male, 2011).

Fig. 10 shows the time series clustering results with single-year distance. We are not able to discriminate the countries in our dataset considering this simple approach, as most of them belong to the same cluster and there are many singletons (i.e. countries forming a cluster by their own).

The consequence of this bad clustering quality is that with the introduction of the spatial contiguity constraint, we let the clusters be defined considering mainly the spatial dimension. Fig. 11 shows the spatial–temporal clustering approach under single-year distance.

By looking at only Fig. 10 we would erroneously suspect the presence of a single common business cycle for all the African countries, which is obviously not the case. Including the spatial dimension, we obtain a simple spatial clustering (West, Center-East and South) that is not reliable, especially in light of Fig. 10 findings.

Hence, we can argue that the feature-DTW distance is more useful for the analysis of the problem at hand. Indeed our approach is more suitable for recognizing similarities in the long-run movements rather than in the short run (e.g. few months or quarters), but the results we obtained are well explainable.

This suggests that the employed approach seems suitable for the analysis of African countries. Of course, the methodological approach proposed in this paper can be easily applied when quarterly data are available.

5.2. Splitting sample analysis

Many authors document structural breaks in various African GDP time series (e.g. McMillan et al., 2014). Particularly, most of the breaks occur around the early 1990s, which coincide with a number of significant events that took place during the period.

Considering data in the period 1960–1989 (see Fig. 12), it seems that the Common Monetary Area and ECOWAS were feasible looking

Fig. 12. Visualization of spatio-temporal series clusters: 1960–1989.

at temporal patterns before the 90's. The degree of synchronization across West African countries is surprising because the discussion about the creation of a common monetary union in the West started more than 10 years later than 1989. The ECOWAS, moreover, is not officially established yet.

Fig. 12 also suggests that the creation of monetary unions was not much adequate at that time. Indeed, the business cycles of Ivory Coast and Niger were not enough synchronized with the other former French colonies, while both English-speaking and French-speaking countries show synchronized business cycles. Although former French colonies share the Franc CFA since 1962, they were not all characterized by a common business cycle. This suggests that the endogeneity issue highlighted by Frankel and Rose (1998), that is, being in the same monetary union enhances business cycles synchronization, does not seem to hold for African countries.

Moreover, there is no evidence supporting the feasibility of the Central African CFA before the 90's. The absence of the synchronization across central African countries, which were sharing the same currency before 1960, provides some evidence against the endogeneity issue of Frankel and Rose (1998) for Africa. In sum, it seems that the adoption of a common currency does not improve synchronization across African countries alone. The role of bilateral trading or financial integration seems to be more relevant. However, we remain agnostic on this aspect as more research is needed to support this claim.

In the end, there are no concerns with respect to Common Monetary Area (CMA), which seems to be the only feasible among the already established monetary unions.

Considering data from 1990 to 2016 (see Fig. 13), we can also observe some interesting patterns. First of all, much more countries in West Africa seem to be synchronized concerning the past (see Fig. 12), thus providing stronger results in favor of ECOWAS feasibility. The business cycle synchronization of the ECOWAS countries with Niger and Chad is of particular relevance, as these two countries did not show synchronization with any of the West African economies before 1990.

Second, we get a further confirmation against the Central African CFA feasibility as the business cycles of these countries did not synchronize after 1990. Also in this case, therefore, we get evidence against the idea that OCA in Africa suffers from endogeneity issues.

Third, the composition of the Common Monetary Area in southern Africa remains stable considering data from 1990 onwards. More precise, it is particularly interesting how the composition of that cluster, without the inclusion of Mozambique, corresponds almost perfectly with the current countries involved in the CMA.

Finally, we observe from 1990 an increasing synchronization in the cluster with countries in the northern west of Africa, that is absent from Fig. 12. Therefore, the possible new monetary union we find with our full sample analysis seems to be quite recent. We would suggest institutions in Africa to seriously look into this possibility. The conclusions highlighted with the sample splitting analysis confirm the findings obtained with the full sample analysis, and our overall results are robust to structural breaks.

6. Final remarks

This paper dealt with the identification of African economies sharing similar business cycles. Business cycles' synchronization is particularly important for optimal monetary unions. We adopt an agnostic view while investigating this problem and use cluster analysis. Previous studies adopt either cross-sectional or time series clustering approaches, and they ignore the presence of spatial effects. The novelty introduced

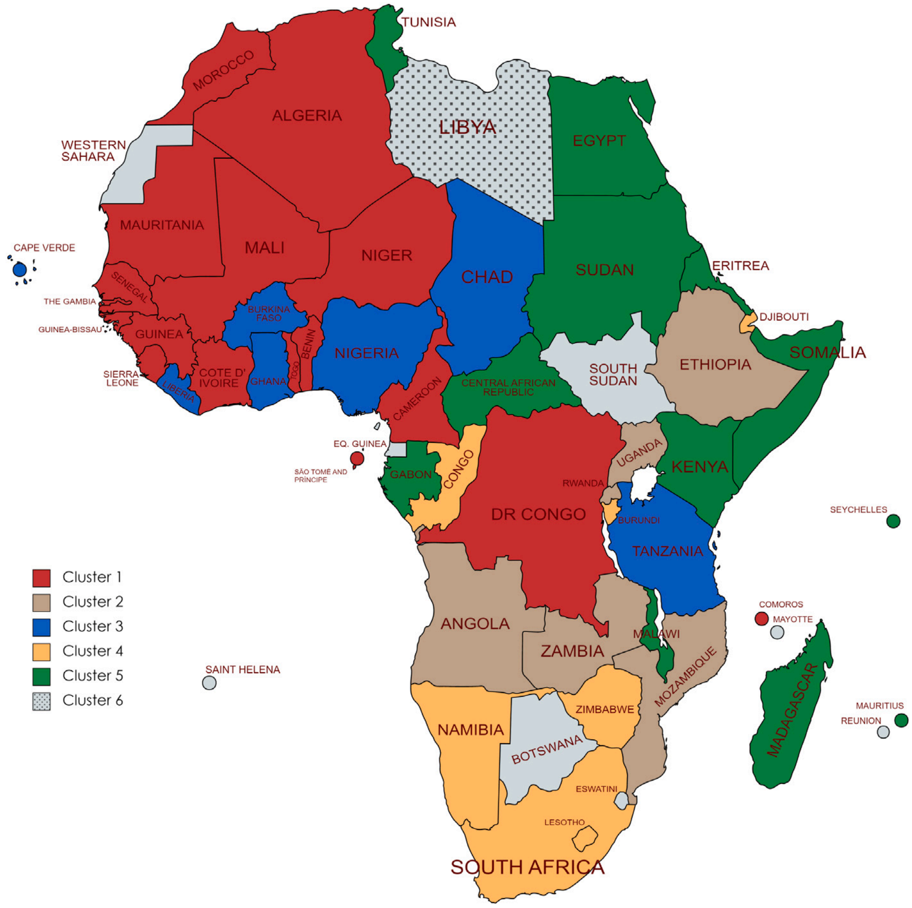

Fig. 13. Visualization of spatio-temporal series clusters: 1990–2016.

in our paper is the use of a spatio-temporal method for investigating business cycles' synchronization. This choice is motivated by the fact that neighboring countries are likely affected by similar shocks and spatial spillovers. Moreover, by enhancing spatial contiguity among the clusters, we exploit that monetary unions in Africa are also motivated by spatial proximity arguments.

The clustering method proposed in the paper extends *ClustGeo* of Chavent et al. (2018) to a spatio-temporal setting. Temporal similarity across business cycles is assessed with the feature-based DTW distance across GDP-based time series, as proposed by Franses and Wiemann (2020), while a soft spatial constraint is introduced with an Euclidean distance across geographical coordinates.

The main results can be summarized as follows.

First of all, we provide evidence in favor of CMA sustainability across Southern African countries. Our analysis also suggests that Angola and Zambia share a common cycle with those of the CMA, so that this union could be extended.

Second, we find that the West CFA and Central CFA cannot form a single monetary union due to a lack of synchronization in their business cycles. Moreover, our results also question the current composition of the West CFA since Gabon, Congo and Central African Republic share a common business cycle but Cameroon and Chad are more related with the ECOWAS economies.

Third, our results show that a monetary union across ECOWAS countries would be beneficial. Indeed, the obtained clustering results show some overlap between the UEMOA and WAMZ countries. Considering both overlaps and spatial proximity, we claim that the creation of a monetary union in ECOWAS could further increase business cycles' synchronization by increasing the size of bilateral trades.

Fourth, the clustering results provide evidence against the feasibility of the East African Monetary Union across Burundi, Rwanda, Tanzania, Kenya and Uganda, because Burundi and Tanzania do not show synchronized business cycles with the other countries. According to our results, a feasible monetary union should instead include a trilateral monetary agreement across Rwanda, Kenya, Uganda and, perhaps, with Seychelles Islands.

In the end, a completely new monetary union involving north-east countries – Sudan, Eritrea, Ethiopia – seems to be feasible according to our results. These countries share a common cycle and are neighbors.

The main weakness of our study is that business cycles' synchronization is studied considering the fluctuations of GDP growth rates time series, while also other variables can be used to investigate economic integration and the feasibility of monetary unions. In other words, our spatio-temporal clustering method could be extended to other time series. This aspect deserves future research. We have to note that this would not be straightforward in the case of Africa due to data availability constraints. Because full time series were not available, the GDP 1960–2016 series have been reconstructed in Franses and Vasilev (2019). A similar reconstruction operation should occur for additional relevant variables (Franses and Janssens, 2018) before conducting the analysis with a multivariate spatio-temporal clustering approach.

Another interesting issue is the inclusion of economic regimes in the clustering procedure. In our paper we considered a sample splitting analysis in the light of breaks that occurred around the 90s for various African economies. A suitable alternative approach could be, however, the consideration of a dissimilarity measure for time series that explicitly accounts for such economic regime changes, for example through Markow Switching models.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.econmod.2023.106485.

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