

The Spanish National Health Service: a Visual Study of Data Envelopment Analysis

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In recent years, the calculation of efficiency has been based on Data Envelopment Analysis (DEA) models. Public health is not an exception. Nevertheless, most of the studies are in hospitals rather than primary health care, such as walking centres and GP surgeries. DEA attempts to establish if the uses of resources of a particular unit of assessment (UOA) could have been better employed in other units of the same system. But what does this number mean? If two units are equally efficient, what are the different policies by which this level of efficiency is achieved? In the end, the efficiency score is the results of a choice of inputs and outputs established by the researchers, hence potentially biased and not practical from a managerial perspective or benchmarking. These issues are discussed in higher education institutions, microfinance institutions and airports previous studies. The approach combines the standard DEA analysis with multivariate statistical methods (DEA visualisation). Using the same methodology, we use data from the Madrid Health Service (SERMAS) regarding several inputs and outputs measures and explore by visualisation the special features of 82 public health centres within the Madrid province in 2018, before the COVID19 crisis.

Keywords: *DEA-Visualisation, Multidimensional Scaling (MDS); Efficiency, Public Health System, Benchmarking*

Highlights

DEA visualisation combined with Cluster Analysis highlights the mavericks within a group of UOA belonging to the same cluster (and potentially an outliers).

Classification: H54

1. Introduction

DEA visualisation has been applied previously in Higher Education Institution, micro-finance and airports. To the best of our knowledge this is the first time that this methodology is used in general practitioners surgeries and walking centres.

The paper is organised as follows. The following section presents a review of the literature on health efficiency. The methodology is described in Section 3, followed by the data in Section 4. The analysis and interpretation of the results follow next. Finally, the paper ends with a summary of findings.

2. Methodology

Charnes et al. (1978) developed non-parametric linear programming named Data Envelopment Analysis (DEA). The first approach was extended by Banker et al. (1984). DEA assesses the efficiency of a set of homogeneous units of assessment (UOAs) by benchmarking one against others (usually named decision-making units as having the power to decide among inputs and outputs, although this may not be the case, Ripoll-Zarraga 2018). DEA fundamental approaches are related to the path that an inefficient unit should follow to become efficient (frontier). This path can be radial or non-radial. Radial projections refer to the proportional reduction of the overall inputs (or increase in the overall outputs) to improve efficiency. Non-radial projections are other paths not based on percentages but a specific decrease of inputs (or increase of outputs). For further insights into radial projections, see Debreu (1951) and Farrell (1957), and non-radial Koopmans (1951) and Russell (1985), as well as Charnes et al. (1985), who introduced the additive model (non-oriented DEA). The basic approach has been modified to overcome relevant pitfalls for benchmark analysis (Dyson, 2001).

The literature in public health shows a significant number of studies in hospitals compared to walking centres and general medical practitioners. In hospitals efficiency benchmark, the use of constant and variable returns to scale and input and output-oriented models are balanced. In this study, the DEA model used follows the output-oriented and variable return to scale. The inputs are limited and restricted by the population in an area where the centre is located (assigned population). The population allocated to a centre is an external factor, i.e. not

controlled by the management; nevertheless, the medical and non-medical employees (resources) are determined by the number of citizens within an area. The model should reveal why centres with the same number of citizens as potential patients have more outputs than others.

Following Banker et al. (1984), efficiencies are estimated using the output-oriented DEA radial model and accounting for variable returns to scale by imposing the restriction $\sum \lambda = 1$,

Max ϕ s. t.

$$\phi y_i \leq Y\lambda \quad (1)$$

$$X\lambda \leq X_i$$

$$\sum \lambda = 1$$

The output-oriented model provides the solution for each unit of assessment to maximise the production (outputs) without exceeding the given resources (inputs).

The two-way table— DEA specifications by UOA— of efficiencies is analysed with the techniques of multivariate statistical analysis. These are Factor Analysis, Cluster Analysis, and Property Fitting. The first two help to determine similarities among a set of items, and Property fitting analyse proximities based on dimensions (underlying dimensions). This approach allows presenting the results graphically, i.e., it regresses a characteristic (based in similarities) of the observations to position on a map. Hence, to interpret the addition of information not used in the graphs (external analysis such as ratios). In the case the dependant variable is each DEA specification (attribute) and the independent variables the extracted factors (coordinates). Examples of this approach can be found in Gutierrez-Nieto et al. (2007), Sagarra et al. (2016) and Ripoll-Zarraga and Mar-Molinero (2020).

3. Data description

After the revision of the literature, five inputs and four outputs were selected for inclusion in the DEA model. The inputs are labelled with letters and the outputs with numbers.

Inputs	Outputs
A Doctors	1 Visits
B Nurses	2 Prescription Cost
C Admin	3 Vaccines
D Operating Costs	

Table 1: Inputs and Outputs in the DEA specifications

On the input side, the number of doctors, nurses and admin personnel are full-time or full-time equivalent. Interviews held at different centres have confirmed that they are unlikely to have part-time staff since there are no incentives to work in private centres. The operating costs correspond to fixed costs related to infrastructure, such as utilities, cleaning and maintenance, rent, etc. These are a proxy of depreciation since infrastructure data was not accessible, nor regarding the property (for example, if the premises are owned or rent). The outputs are the number of visits, vaccines and the average unitary cost of prescription per inhabitant. Expenses are usually inputs in other industries such as air transport to generate, for example, revenues (Ripoll-Zarraga et al. 2021; Ripoll-Zarraga and Mar-Molinero, 2020). Nevertheless, in public health, the number of prescriptions and prescription costs are outcomes of the medical activity potentially affected by limited resources (i.e., doctors).

The visits are the medical appointments, which patients attend annually. In this regard, this variable does not account for no-shows. The scheduled appointments with independence if the patients attend (or not) is unknown. One patient may have more than several scheduled appointments during the year, recurrent visits, which are enclosed. These appointments may include visits with the GP, a nurse, a paediatric doctor, and a combination. The rest of the services, including tests and treatments, are provided at hospitals. Overall the centres have GPs and nurses, but they may not have paediatric, provided that within the same catchment area, there is another centre with this service.

The unitary prescription cost is factual expenditure allocated (incurred) to the centre (i.e., not paid by the patient). There are two types of prescriptions according to the type of medicine prescribed: generic, which is usually produced by more than several laboratories and, specific. The generic is significantly cheaper compared to the specific medicine associated with a pharmaceutical brand. The national social security system covers partially or fully generic medicines (i.e., depending on characteristics such as age, unemployed, social benefits, etc.), whereas this is not the case for specifically labelled brand medicines. The larger the number of generic versus specific medicines prescribed, the centre is more efficient. Nevertheless, all the centres prescribed a similar percentage of generic medicines for 2018 (between 50% and 60%), hence, not providing enough discrimination for visualisation purposes. This variable was disregarded. Instead, the unitary cost per prescription is used. The unitary prescription cost will be lower to the extent than more generic medicine is prescribed, implying less public

expenditure. i.e., the cheaper the unitary prescription cost, the more efficient the centre will become.

The number of vaccines is the overall vaccines for flu and paediatrics. Other types of vaccines are not enclosed since being provided at the hospitals. Initially, the satisfaction was accounted for as a desirable output. Most of the centres have a high degree of satisfaction. Hence this variable provides low discriminatory power. Unsatisfied patients tend to change centres. Therefore, potential complaints are not raised and registered.

A measure of the overall revenues is not enclosed since these centres provide public health which in Spain is based on universality. The income refers to an annual allocated budget estimated according to the accrued expenses from the previous period. Hence, it depends on the overall expenses such as salaries, operating and prescription costs. Data is deflated by the GDP deflator base for Spain 2015 (World Bank and OECD national accounts data, December 2020).

Variable	Obs	Mean	Std. Dev	Min	Max
Doctor Costs (€)	262	1,382,541	537,545	235,466	3,218,039
Nurse Costs (€)	262	626,174	242,376	147,049	1,519,506
Admin Costs (€)	262	654,430	224,838	116,680	1,458,496
Operating Costs (€)	262	431,506	465,091	46,018	7,457,783
Prescriptions Costs (€)	262	4,105,786	1,604,356	541,792	9,258,504
Doctors	262	17.61	6.85	3	41
Nurses	262	12.77	4.94	3	31
Admin	262	11.22	3.85	2	25
Researchers	262	10.54	9.53	0	53
Patients	262	36,538.88	26,059.99	4,233	391,056
Visits	262	175,845.70	67,497.29	28,666	414,943
Vaccines	262	6,216.88	2,823.98	547	16,588
Prescriptions (per inhabitant)	262	24.77	5.74	10	42
Satisfaction (%)	262	89	5	58	98

Table 2: Descriptive Statistics Deflated GDP (2018)

The geographical distribution of the 262 health centres follows: 49 in the centre, 35 in the North (and 40 in the North-East), 31 in the South (and 39 in the South-East), 38 in the East and 30 in the West. Therefore, there are 75 centres in the North and 70 in the South overall.

Based on the demographic characteristics of the assigned population to each centre, from the 262 health centres located in Madrid province, we have extracted a sample based on senior citizens (i.e., more than 65 years old, which is the retirement age in Spain). Within this group, the centres sampled have between 5,000 and 15,000 senior citizens since centres with less than 5,000 have more youngsters and children with different illnesses and medical requirements. The final sample contains 82 centres that have a higher number of citizens older than 65 years old.

Non-sense combinations of inputs or outputs may be disregarded ex-ante. For example, where an appointment could be with any member of staff, prescriptions are prescribed only by doctors (A) but not by nurses (B) or admin staff (C). Consequently, the combination nurses-prescription unitary cost- (B2) or admin-prescription unitary cost (C2) is not understood as a feasible DEA specification. In the same way, having only doctors (A), nurses (B) and admin staff (C) without a running infrastructure (D) are not possible. To capture the impact of having works and refurbishment, hence infrastructure under-used, the combinations of at least two types of staff without accounting for operating costs (D) is enclosed in the analyses (e.g., AB, AC and BC). Some studies may disregard centres with only a nurse (B) or admin (C) since all the centres have prescriptions during 2018, but accounting for centres with only doctors (A). The same applies to the outputs: the prescription unitary cost (2) individually or combined with vaccines (23), or the vaccines (3) since will require at least one visit with a patient (1). With this regard, both types of outputs will require not only an appointment with the patient (1). Nevertheless, in this study, all the possible DEA combinations are enclosed. Searching for intrinsic characteristics of the data is difficult to determine a priori, we prefer not to disregard any information. Additionally, the algorithm will exclude these non-sense combinations within the factorial analysis. Following this rationale, there are 15 combinations of inputs to align with seven different combinations of outputs providing 105 different DEA specifications. The summary of the different DEA specifications based on all the combinations of inputs and outputs is shown in Appendix A.

4. Results

The initial analysis generates a table with 105 DEA specifications (i.e., efficiency scores) for 82 observations (health centres). Some relevant intrinsic characteristics of the health centres may be learnt through facie evidence of the data. However, multi-statistical analysis helps to

reveal special features by visualisation (graphical form). Following Serrano-Cinca et al. (2004, 2005), the initial matrix contains observations and variables. The health centres are treated as observations (82 rows) and the DEA specifications as variables (105 columns). This matrix is transformed into another matrix containing in rows and columns observations: centres and principal components. We use multi-statistical analysis, in particular, factor analysis, to reduce the dimensionality of the data according to similar behaviour of the observations across the variables. Some specifications may generate similar efficiency scores across the observations. Therefore these are allocated in a specific component (factor). We performed an initial un-rotated principal component analysis on the data, which provides more than two extracted factors (eigenvalue higher than one per Kaiser criterion). A second-factor analysis is performed by rotating the axes (varimax) to obtain a better visualisation, hence, identification of the dimensions. Seven factors were extracted using the Kaiser criterion, the same as per Jolliffe (1972), a less strict option (i.e., eigenvalue > 0.70). In this case, there are no factors with eigenvalues between 0.70 and 1. The results are shown in Table 3.

Table 3. Factor Analysis. Variance explained.

Component	Initial Solution			Rotated Solution		
	Eigenvalue	% of Variance	Cumulative %	Eigenvalue	% of Variance	Cumulative %
1	59.63	60.85	60.85	34.21	34.91	34.91
2	19.08	19.47	80.32	24.29	24.78	59.69
3	10.00	10.20	90.52	23.53	24.01	83.70
4	3.21	3.27	93.79	6.48	6.61	90.31
5	2.01	2.05	95.84	3.72	3.79	94.10
6	1.45	1.48	97.32	2.80	2.86	96.96
7	1.16	1.18	98.50	1.51	1.54	98.50
8	0.44	0.45	98.95			

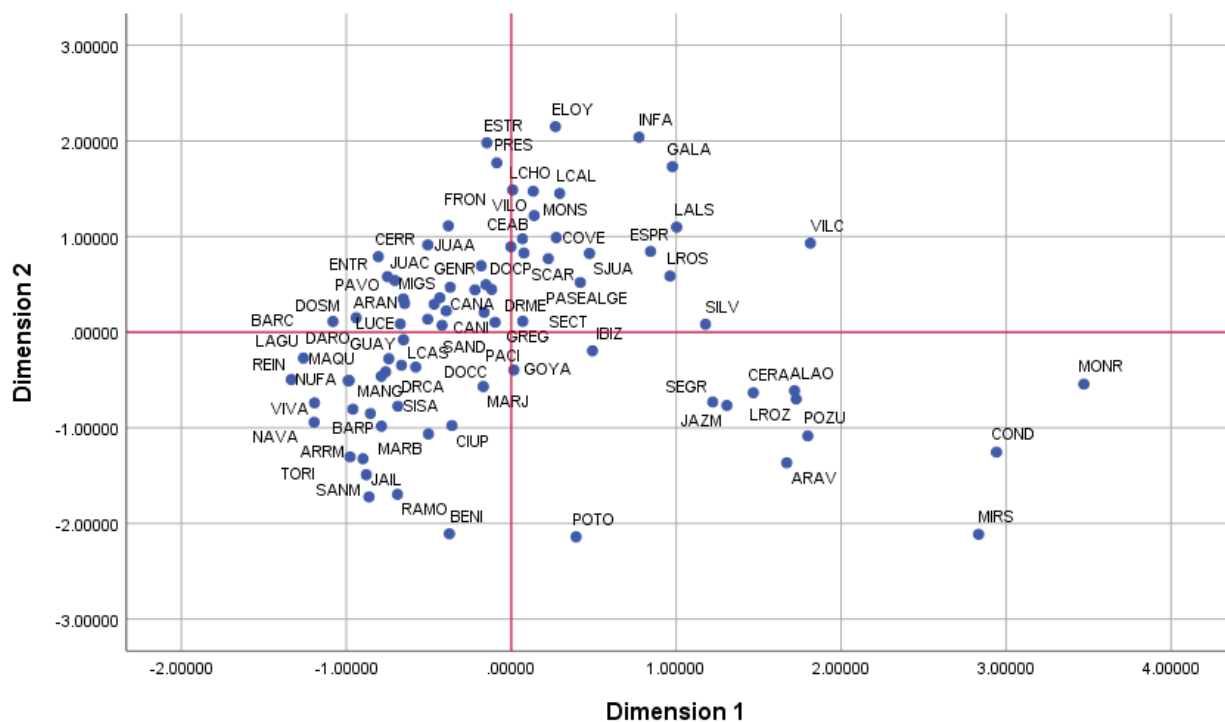
The first two components explain 80% of the variability of the data (un-rotated solution). The first factor explains 61%, being the most relevant factor; factor two 19%, factor three 10%, and the rest add a marginal effect (between 0.4% and 3%). However, these factors may reveal outliers or mavericks, which are worth investigating. Indeed the rotated solution provides less relevance in Factor 1 (35%) and more explanatory power to factors two and three (25% and 24%). Note that factor eight is not relevant for both solutions. Altogether the first three factors

explain over 90% (un-rotated solution): a high percentage means that the information contained (resumed) in the extracted components is good enough to reveal intrinsic characteristics of the units of assessment and inefficiency sources. Overall the first three components are relevant to identify features of the health centres. Hence, to provide managerial recommendations.

The factor loading matrix is used to provide meaning to each factor (see Appendix A.3.). We have removed loadings lower than 0.4 to facilitate the interpretation. With few exceptions, the correlations between the DEA specifications within the first factor are positive and high. Then, this factor is interpreted usually as overall efficiency. Nevertheless, we are using a rotated matrix. Hence, the variability of the data is distributed between Factor 1 and Factor 2, as previously discussed.

The next stage is to allocate each UOA according to each extracted component (factors). The factor analysis provides the coordinates in the common map; for each UOA, the common map provides the location related to each component (component matrix). We use the rotated solution. The second matrix, which contains observations in rows (82 centres), and columns (seven extracted factors), is shown in Appendix A.3. The following map shows the location of the UOA according to the first two components.

Figure 1. Common Map. Factors 1 and 2.

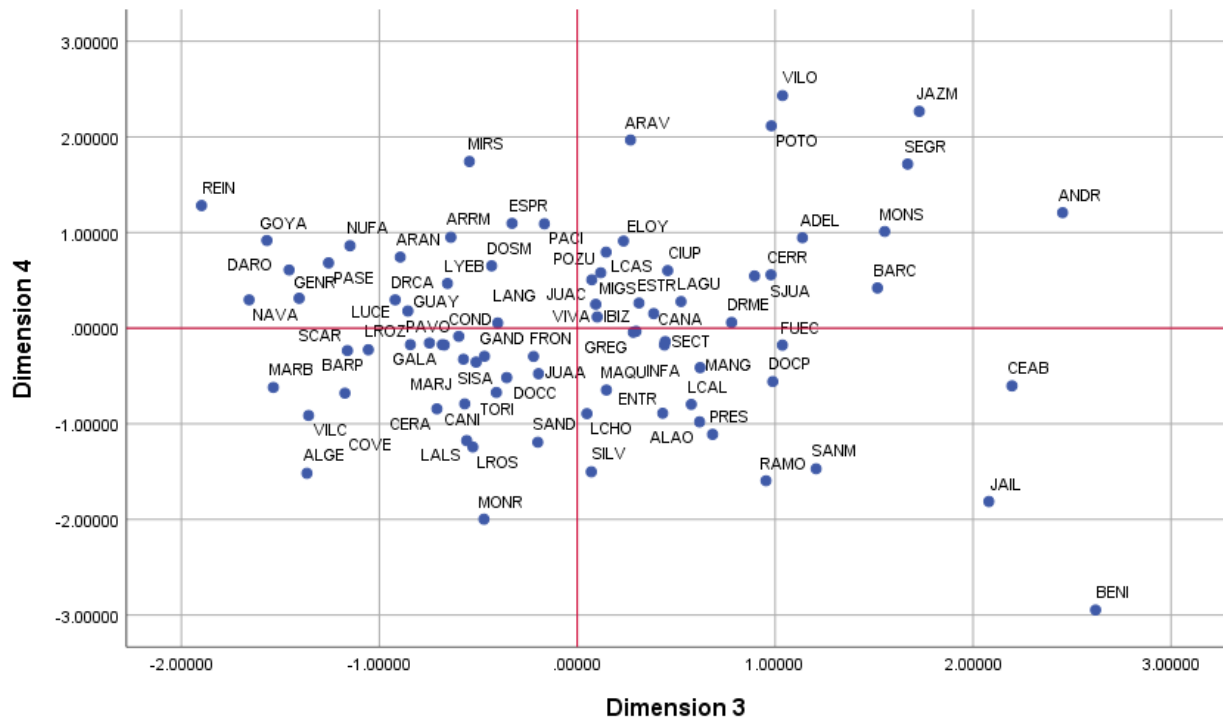


The component matrix shows that for Factor 1 combinations with only output 2 (Prescription Cost) loads the highest factor scores with the independence of the inputs used (0.93 D2 to 0.98, for example, A2, B2, C2, BC2), suggesting that this factor is the efficiency of the centre in prescribing generics. The maximum load corresponds to A2 (0.9816), which is the combination of Doctors (A) and Prescription Cost (2). Considering the location of the centres concerning Factor 1 (see Figure 1), Monterrozas (MONR), Condes de Barcelona (COND), and Mirasierra (MIRS) are the centres with better performance. Indeed, these centres incur the lowest unitary prescription cost (80.31, 89.16, and 91.29, respectively). The most efficient centre is MONR since having the lowest unitary prescription cost overall. The centres located on the opposite side, such as Barcelona (BARC) and Las Aguilas (LAGU), are the most inefficient as per respective values 200 (euros/prescription) and 227 respectively. Reina Victoria (REIN) is also located nearby these two centres but incur a small cost (125). This location may be indicating that it is a maverick, which will be analysed later. Consequently, we name Factor 1 as the Efficiency Overall (i.e., in prescribing generics). As previously discussed, lower prescription cost implies a higher weight of generic medicines, hence, more efficiency. Taking our attention to Factor 2, the better positioned are Eloy Gonzalo (ELOY), Infanta Mercedes (INFA), Estrecho de Corea (ESTR) compared to Benita de Avila (BENI), Potosi (POTO) or Mirasierra (MIRS), which have the lowest values of Factor 2. There is no clear pattern across the data, but the component loading matrix shows that D3 (Operating Costs-Vaccines) load higher scores compared to other combinations of inputs and outputs. Indeed, ELOY, INFA and ESTR have the highest ratio Operating Costs-Vaccines (70.08, 69.12 and 73.36) compared to POTO (48.59), BENI (50.24), MIRS (50.24) or RAMO (41.54). This factor seems to refer to the economic inefficiency of centres for vaccines or nurses efficiency (i.e., to administrate vaccines). In other words, the centres with less number of vaccines per one euro spent in operating costs are located at the top of the chart. These centres incur high operating costs according to the number of vaccines per year. Alternatively, these incur less operating costs by barely administrating vaccines to the citizens due to the allocated population: all the centres in the extreme of the axis of Dimension 2 contain a similar allocated population (from 6,000 to 6,500).

For Factor 3 combinations with output 2 (Prescription Cost) or input D (Operating Costs) load low factor scores, compared to other including 1 (Visits), 3 (Vaccines) or their combination 13, and A (Doctors), B (Nurses) and C (Admin) or their combinations. A13 and A23 load the

highest factor scores (both 0.9432). Figure 2 shows Benita de Avila (BENI), Andres Mellado (ANDR), Cea Bermudez (CEAB), Jaime Vera-Leganés (JAIL) as the worst centres regarding Factor 3 compared to Reina Victoria (REIN), for example. All these centres have a similar number of vaccines administered per year. Nevertheless, REIN has a significant lower medical staff compared to the other centres: BENI (6,350 vaccines in 2018 and 30 doctors, 24 nurses), ANDR (5,494 vaccines, 21 doctors, 15 nurses), CEAB (5,010 vaccines, 12 doctors, eight nurses), JAIL (6,302 vaccines, ten doctors, eight nurses). Since REIN seems a potential maverick (6,238 vaccines, three doctors, three nurses), we pay attention to other centres located on the left-hand side of the Axis X (Factor 3). These are DARO (13, 276 vaccines, 19 doctors, 12 nurses), GOYA (14,096 vaccines, 36 doctors, 28 nurses), NAVA (14,071 vaccines, six doctors, five nurses), GENR (11,600 vaccines, 33 doctors, 27 nurses) and MARB (15,740 vaccines, 18 doctors, 15 nurses). Consequently, Factor 3 is reflecting the efficiency of medical staff to administrate vaccines. Overall, centres with more medical staff (e.g., nurses) should administrate more vaccines. MARB is the centre administrating more vaccines but at the expenses of having a significant number of medical staff. MARB could improve its efficiency by administrating more vaccines rather than the actual number. Another solution involves transferring patients from other centres (i.e., if no further allocated population requires to be vaccinated in 2018). CEAB is the centre with the lowest number of vaccines administered in 2018 and having only eight nurses in the centre. Therefore, it may be little room for improvement.

Figure 2. Common Map. Factors 3 and 4.



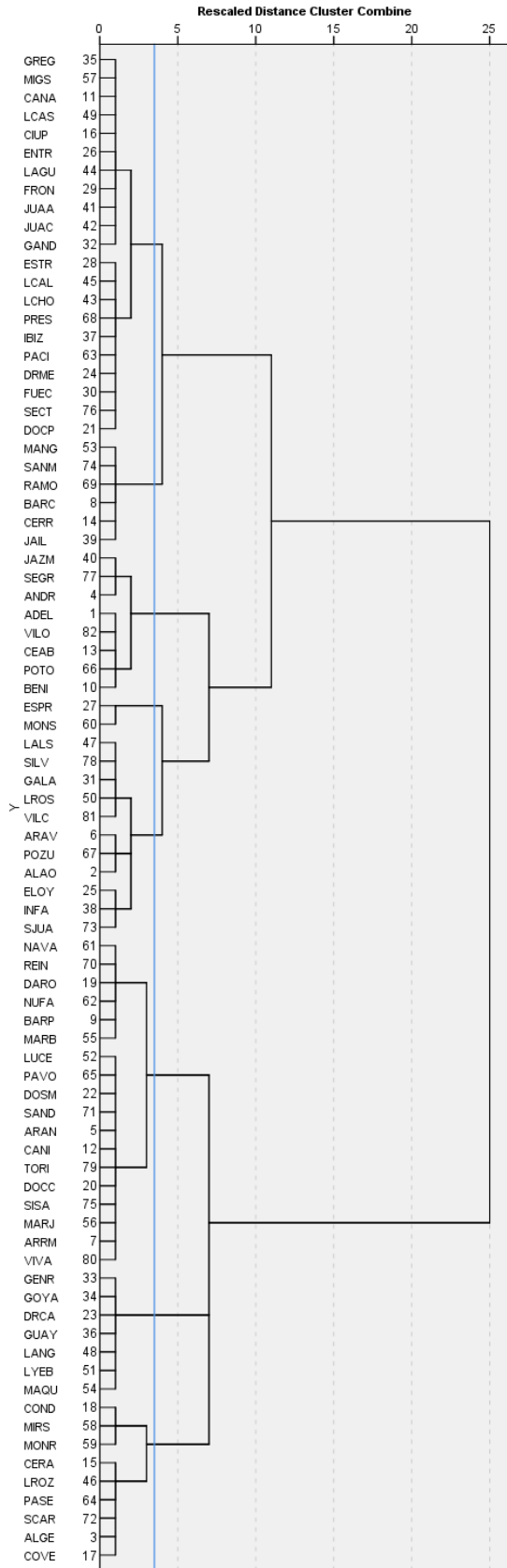
For Factor 4, D1 (Operating Costs-Visits) is the combination that loads the highest factor score (0.6245), and combined with any other input, e.g., BD1 (0.6047), ABD1 (0.6037), AD1 (0.6021), BCD1 (0.6019), and ABCD1 (0.6009). Centres such as VILO, JAZM, POTO, ARAV, MIRS or SEGR, have high operating costs about the number of patients who went to the centres in 2018. These centres are located in the positive values of Factor 4 (Axis Y). The more visits that a centre has for the same level of costs (fix), the more efficient it is. Consequently, this factor indicates the use of infrastructure to generate visits; centres with idle infrastructure will have higher factor values and efficient centres the lowest values. For example, the VILO (2.87 euros of operating costs per patient), JAZM (2.87), POTO (2.70) incur more operating costs per patient compared to RAMO (1.72) or JAIL (2.00). This relationship is not straight forward as per MONR located at the lowest values for Factor 4, incurs 2.70 euros per patient or BENI (2.07). The specifications that load highest on Factor 5 exclude input D (Operating Costs), suggesting that the personnel efficiency independently of the type of activity (i.e., visits, prescribing generic medicines or administrating vaccines) is captured by Factor 5. Factor 4 seems that has higher factor scores for combinations with output 1 (Visits) and input D (Operating Costs). Also, for D1 with output 2 (Prescription Cost), but no with other combinations since the scores are not relevant. Similarly with Factor 4, the relationship is not straight forward. The interpretation of factors is difficult since each centre is a point in a space of 105 dimensions (the DEA specifications estimated). Although two centres may appear each other, this may not be the case in space. The visualisation is in two

dimensions rather than multidimensionality. To help the interpretation of the intrinsic meaning of the factors, we conduct a cluster analysis.

The previous visualisation goes one step forward, accounting for clusters to visualise common patterns for centres (within the same cluster and across the DEA specifications). For the cluster analysis, the data is not required to be standardised: the efficiency scores are allocated from 0 to 100% (input-oriented). In the Cluster Analysis, the matrix used contains the UOA as the observations and the DEA specifications as the variables as the initial matrix. We use the Ward method to maximise homogeneity within each cluster but heterogeneity between clusters. Using the dendrogram, we identify the most relevant clusters to use in the analysis. The dendrogram reveals between seven to nine clusters (see Figure 3).

Figure 3. Dendrogram. Ward Method.

Dendrogram using Ward Linkage



After performing the Cluster Analysis, we visualise the observations classified into their respective cluster and according to the seven previous extracted factors. For example, for Factors 1 and 7 (see Figure 4), we can observe that REIN, which is in cluster four, is located at a significant distance from its group, hence, being a maverick as confirmed by the previous analysis¹. For Factor 7, it is located far away from its cluster and at a significant distance from the other centres allocated to other clusters. REIN is the centre with the lowest number of doctors, nurses and admin team overall. The other centres allocated in cluster 4, have few members of staff but not as little as REIN. Consequently, one source of inefficiency relies on having lower personnel to perform similar activities than the rest of the centres in the same group (cluster 4). Of course, not all the centres allocated in cluster 4 have low staff²; we must remember other intrinsic characteristics relate to this cluster and must be analysed. On the other hand, REIN is not efficient in prescribing generic medicines (Factor 1), as per incurring in 125.27 (euros/prescription). NAVA (cluster 4) is another centre efficient in most of the DEA specifications. Nevertheless, sources of inefficiency are shown regarding Dimensions 1 and with less relevance regarding Dimension 7, according to its position in the common map. MARB (cluster 4) highly efficient in all the DEA specifications except for combinations with only the output 2 (Prescription Cost) where becoming approximately 28% inefficient and very inefficient for C12 (Admin-Visits-Prescription Cost). However, according to the map for Dimensions 1 and 2, it is not performing accordingly, the same as per Factors 3 and 4. According to the intrinsic information contained in the extracted factors, MARB will require to improve its efficiency in prescribing generic medicines rather than specific ones, to increase the number of administrated vaccines (the nurse efficiency) to have better use of infrastructure. Hence, to reduce the unitary fix costs.

Figure 4. Common Map. Cluster Analysis (Factors 1 and 7)

¹ REIN is the most efficient centre for all the combinations of inputs and outputs (DEA specifications) except for DEA specifications accounting for the input D only (Operating Costs).

² For example, the dendrogram shows that in a first aggregation NAVA (six doctors, five nurses and six admin), REIN (three, three, and two), DARO (19, 12, 12), NUFA (17, 13, 10), BARP and MARB (18, 15, 12) are allocated together. Then others form LUCE (22, 14, 11) to VIVA (eight, six, five).

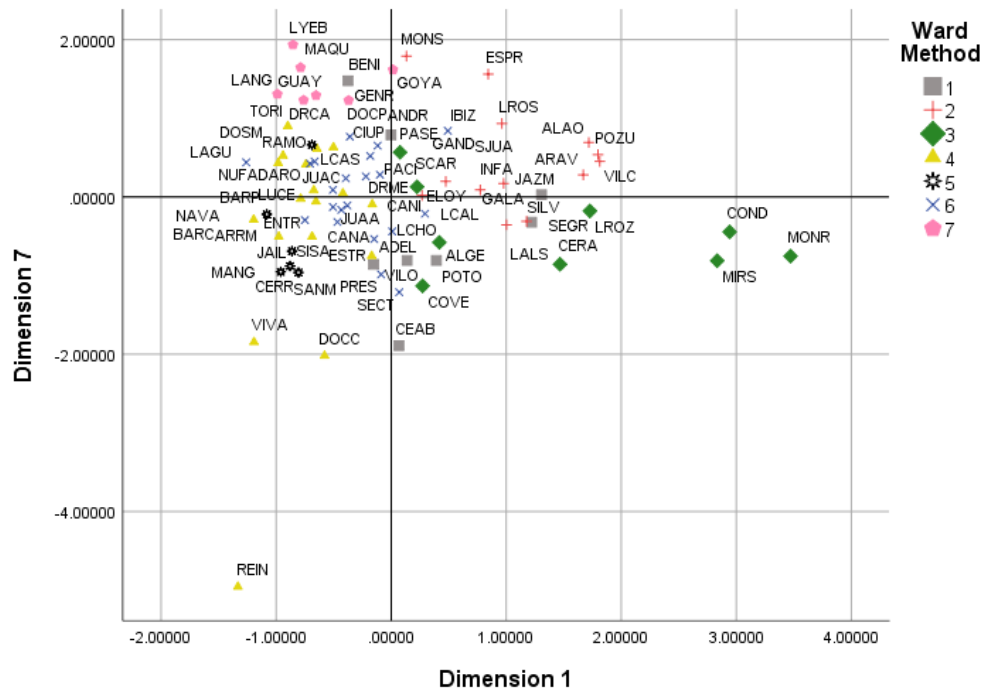
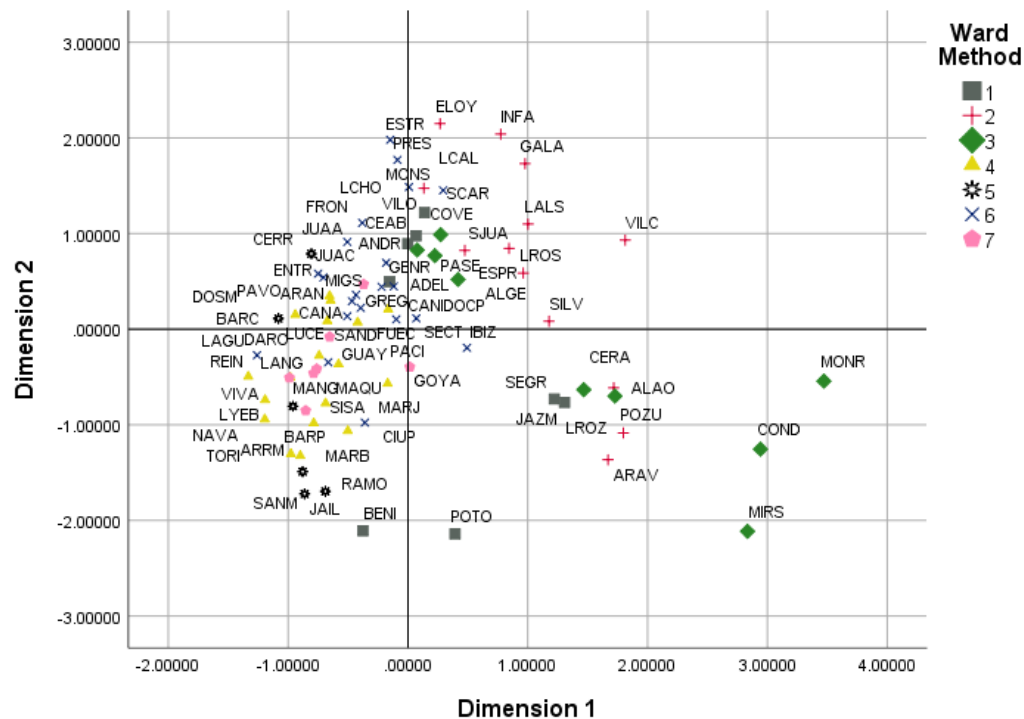


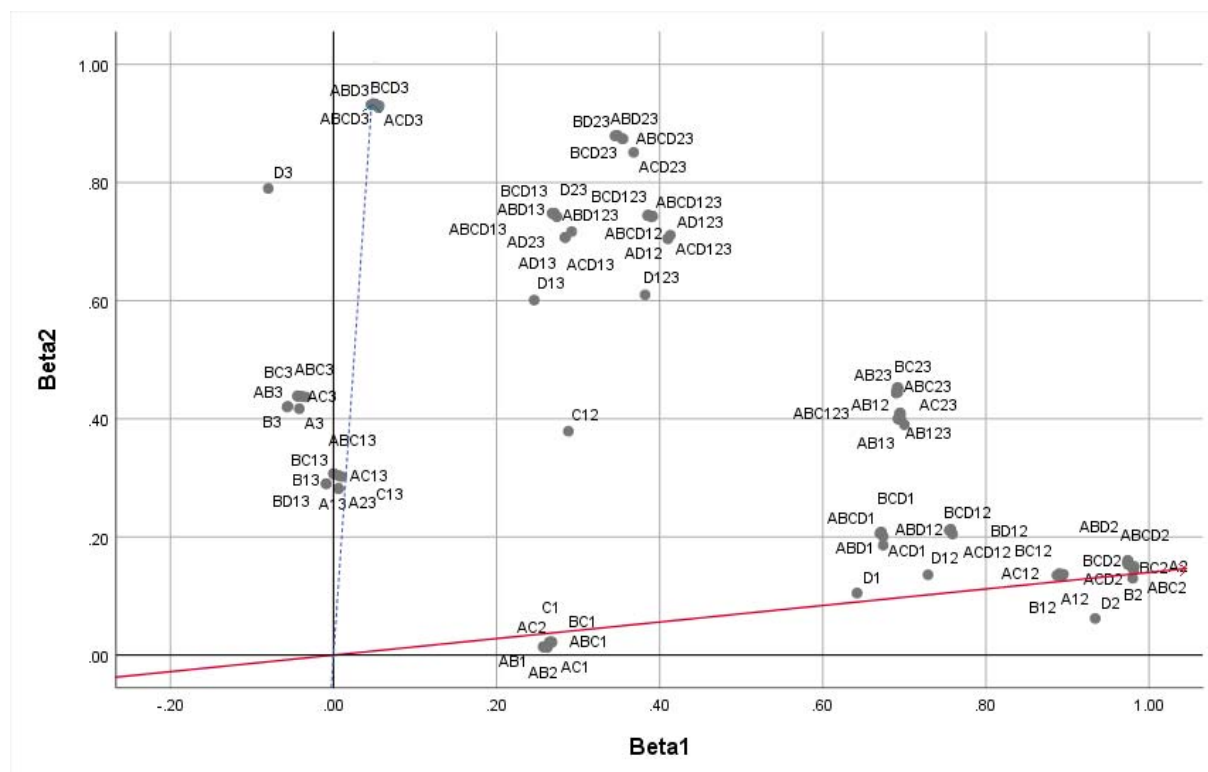
Figure 5. Common Map. Cluster Analysis (Factors 1 and 2)



Visualising the relative position of each UOA in maps helps to assess potential sources of inefficiency, which still is not that clear since, in the end, to name a dimension is a subjective process. We use property fitting (ProFit) to assess the relative position of the observations

according to the underlying meaning of the dimensions: i.e., one regression for each DEA specification (dependent variable, attribute) using the coordinates of the extracted factors as independent variables. Property Fitting provides standardised coefficients (Betas), which are direction cosines, and these are used to draw arrows representing the attributes on the map. The coefficients are the relative contribution of each axis of the map to the prediction of the attribute (dimension): i.e., the direction where the attribute increases along. The positive values of the direction cosines provide the coordinates of the head of the arrow (direction), which points in the direction of increasing attribute values. The middle of the arrow is always located in the centre (0, 0).

Figure 6. ProFit for Dimensions 1 and 2.



For dimension 1, we can observe that the DEA specifications closest to the arrowhead are A2, B2 and BC2 as per the value of the coefficients obtained through ProFit (0.98164, 0.98116 and 0.98100, respectively). Each DEA specification is a point in space, to mean that although the visualisation shows some points close to each other, this is only due to mapping in two dimensions. These two points could be very far away. Hence, the closest a point (DEA specification) is to the arrowhead, the more relevant the dimension. It seems that the common variable for these combinations is Output 2 (Prescription Cost). Through visualisation, it can

be observed that for combinations containing only Output 1 (Visits), Dimension 1 is not relevant, but when combining output 1 with 2, 3 or both, the relevance increases (i.e., the DEA specifications are closer to the end of the vector). Hence, the relevance of using a visit to either prescribe a medicine (2) or to administer vaccines (3). For dimension 2 the DEA specifications closer to the end of the arrow are: ABD3 (0.93307), ABCD3 (0.93304), BCD3 (0.93210), BD3 (0.93184). All these specifications seem to contain BD3 as common variables (Nurses-Operating Costs-Vaccines). These combinations confirm the previous analysis as per naming the first dimension as the overall efficiency (i.e., to prescribe generic medicines); and the second dimension as the economic efficiency of centres in administering vaccines (by nurses). In the same way by using ProFit (see Appendix A.9 and A.10), we confirm: the name of dimension three as the efficiency of medical staff to generate visits and administer vaccines, dimension four the use of infrastructure to generate visits, dimension five the efficiency of medical staff (i.e. in prescribing medicines or administering vaccines), dimension six technical efficiency per visit and dimension seven, the efficiency of non-medical staff in dealing with visits to prescribe generic medicines. For each centre, further analysis can be performed. For example, to determine why centres allocated in clusters 4 and 5 are very inefficient overall (dimension 1) compared to clusters 1, 2 and 3.

5. Conclusions

The traditional DEA model will benchmark the UOA according to inputs and outputs are chosen by the researcher. Nevertheless, one unit is efficient or inefficient according to using all the inputs to produce the outputs overall, not disregarding specific activities (intrinsic characteristics) where inefficient units become efficient. Not only DEA visualisation identifies sources of inefficiency, and therefore, draws managerial recommendations, but it visualises outliers and mavericks. In the extreme case, REIN is efficient in any combination of inputs and outputs, which in the traditional DEA would have no question searching for further needs. By combining DEA with Cluster analysis, a common pattern of the UOA behaviour can be determined.

Further analysis will account for other age groups as infants since we may have disregarded a significant population requiring more vaccines, potentially changing this first picture. Additionally, future research will account for the proportion of chronics, as per accounting for patients permanent condition or including population older than 65. Again, these may

affect the relative position of the centres, therefore other sources of inefficiency. The overall patient satisfaction was initially analysed as desirable output. Beyond the potential issues that using percentages in DEA can generate, small centres or old deco facilities may be unfairly treated as 'worse' in comparison to large centres, even though not having delays in the service. The visual aspect of a centre becomes a marketing customer-oriented factor, which is not related to the quality of the service provided, and it is misspecified as technical inefficiency.

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Appendix A

Appendix A.1. DEA Specifications models

DEA Specifications	Inputs	Outputs
ABCD123 Traditional DEA model	ABCD (Number of Doctors, Nurses, & Admin Staff, Operating Costs)	123 (Visits, Prescription Unitary Cost, Vaccines)
A1, A2, A3	A (Number of Doctors)	1 (Visits)
B1, B2, B3	B (Number of Nurses)	2 (Prescription Unitary Cost)
C1, C2, C3	C (Admin Staff)	3 (Vaccines)
D1, D2, D3	D (Operating Costs)	12 (Visits, Prescription Unitary Cost)
A12, A13, A23, A123		13 (Visits, Vaccines)
B12, B13, B23, B123		23 (Prescription Unitary Cost, Vaccines)
C12, C13, C23, C123		123 (Visits, Prescription Unitary Cost, Vaccines)
D12, D13, D23, D123		
AB1, AB2, AB3, AB12, AB13, AB23, AB123	AB (Number of Doctors & Nurses)	
AC1, AC2, AC3, AC12, AC13, AC23, AC123	AC (Number of Doctors & Admin)	
AD1, AD2, AD3, AD12, AD13, AD23, AD123	AD (Number of Doctors, Operating Costs)	
BC1, BC2, BC3, BC12, BC13, BC23, BC123	BC (Number of Nurses & Admin)	
BD1, BD2, BD3, BD12, BD13, BD23, BD123	BD (Number of Nurses, Operating Costs)	
CD1, CD2, CD3, CD12, CD13, CD23, CD123	CD (Admin, Operating Costs)	
ABC1, ABC2, ABC3, ABC12, ABC13, ABC23, ABC123	ABC (Number of Doctors, Nurses & Admin)	
ABD1, ABD2, ABD3, ABD12, ABD13, ABD23, ABD123	ABD (Number of Doctors & Nurses, Operating Costs)	
ACD1, ACD2, ACD3, ACD12, ACD13, ACD23, ACD123	ACD (Number of Doctors & Admin, Operating Costs)	
BCD1, BCD2, BCD3, BCD12, BCD13, BCD23, BCD123	BCD (Number of Nurses & Admin, Operating Costs)	
ABCD1, ABCD2, ABCD3, ABCD12, ABCD13, ABCD23, ABCD123	ABCD (Number of Doctors, Nurses, & Admin Staff, Operating Costs)	

15 Input combinations and seven Output combinations (105 DEA specifications)

Appendix A.2: DEA Efficiencies based on 105 DEA Specifications

Health Centres	ABCD123	ABCD12	ABCD13	ABCD23	ABCD1	ABCD2	ABCD3	ABC123	ABC12	ABC13	ABC23	ABC1	ABC2	ABC3
ADEL	127%	127%	127%	127%	135%	137%	129%	136%	139%	230%	136%	259%	139%	230%
ALAO	119%	119%	119%	119%	133%	189%	119%	165%	178%	190%	165%	235%	190%	190%
ALGE	106%	106%	106%	129%	106%	161%	130%	116%	116%	116%	131%	116%	161%	138%
ANDR	133%	133%	147%	133%	154%	136%	147%	149%	150%	287%	149%	327%	150%	287%
ARAN	114%	114%	118%	114%	118%	129%	127%	114%	114%	145%	114%	145%	129%	149%
ARAV	110%	110%	110%	110%	153%	186%	110%	157%	178%	167%	157%	256%	186%	167%
ARRM	100%	100%	100%	100%	113%	107%	100%	100%	105%	129%	100%	167%	107%	129%
BARC	104%	104%	122%	104%	122%	104%	141%	106%	106%	229%	106%	229%	106%	240%
BARP	100%	100%	100%	101%	101%	115%	105%	103%	105%	120%	103%	128%	115%	120%
BENI	100%	100%	100%	100%	100%	100%	100%	120%	120%	248%	120%	269%	120%	248%
CANA	119%	119%	120%	120%	120%	127%	129%	124%	125%	196%	124%	203%	128%	196%
CANI	110%	110%	110%	123%	110%	136%	127%	125%	125%	154%	125%	154%	136%	160%
CEAB	128%	128%	128%	138%	128%	141%	138%	142%	142%	272%	142%	272%	142%	291%
CERR	115%	115%	123%	117%	123%	117%	147%	117%	117%	217%	117%	217%	117%	236%
CERA	111%	111%	111%	114%	122%	187%	114%	135%	158%	135%	135%	160%	187%	135%
CIUP	110%	110%	110%	110%	125%	125%	110%	120%	125%	178%	120%	225%	125%	178%
COVE	114%	114%	114%	134%	114%	156%	138%	133%	133%	135%	138%	135%	156%	153%
COND	109%	109%	109%	109%	141%	234%	109%	127%	177%	127%	127%	177%	234%	127%
DARO	104%	104%	112%	104%	112%	123%	114%	104%	104%	113%	104%	113%	123%	115%
DOCC	103%	103%	103%	109%	103%	116%	111%	115%	115%	154%	115%	154%	116%	166%
DOCP	122%	122%	123%	126%	123%	134%	136%	135%	136%	224%	135%	224%	142%	227%
DOSM	108%	108%	116%	108%	116%	115%	130%	108%	108%	157%	108%	157%	115%	166%
DRCA	105%	105%	111%	105%	111%	122%	115%	105%	106%	135%	105%	136%	122%	135%
DRME	125%	125%	126%	126%	126%	135%	132%	132%	135%	215%	132%	226%	137%	215%
ELOY	141%	141%	141%	151%	141%	162%	157%	151%	153%	221%	151%	221%	162%	224%
ENTR	103%	103%	105%	114%	105%	114%	149%	110%	110%	174%	115%	174%	115%	227%
ESPR	134%	134%	134%	134%	143%	179%	134%	151%	159%	180%	151%	209%	179%	180%

(continued)

Health Centres	ABCD123	ABCD12	ABCD13	ABCD23	ABCD1	ABCD2	ABCD3	ABC123	ABC12	ABC13	ABC23	ABC1	ABC2	ABC3
ESTR	127%	127%	127%	139%	127%	144%	165%	137%	137%	202%	140%	202%	144%	239%
FRON	114%	114%	114%	126%	114%	133%	150%	121%	121%	166%	126%	166%	133%	202%
FUEC	116%	116%	120%	118%	120%	123%	130%	122%	123%	218%	122%	222%	123%	218%
GALA	134%	134%	134%	147%	134%	187%	147%	153%	153%	174%	155%	174%	187%	182%
GAND	116%	116%	116%	126%	116%	142%	136%	124%	124%	162%	127%	162%	142%	177%
GENR	112%	112%	115%	116%	115%	141%	129%	112%	112%	122%	116%	122%	141%	136%
GOYA	110%	110%	110%	110%	124%	152%	110%	112%	119%	112%	112%	126%	152%	112%
GREG	118%	118%	119%	121%	119%	129%	128%	124%	126%	191%	124%	197%	130%	191%
GUAY	109%	109%	112%	110%	112%	127%	121%	110%	110%	141%	111%	141%	127%	145%
IBIZ	121%	121%	121%	121%	129%	156%	121%	140%	148%	187%	140%	217%	157%	187%
INFA	139%	139%	139%	156%	139%	175%	156%	162%	162%	226%	162%	226%	175%	232%
JAIL	100%	100%	100%	100%	100%	100%	100%	101%	101%	231%	101%	241%	101%	231%
JAZM	124%	124%	124%	124%	163%	171%	124%	168%	180%	231%	168%	339%	180%	231%
JUAA	110%	110%	110%	122%	110%	127%	148%	117%	117%	162%	122%	162%	127%	202%
JUAC	115%	115%	120%	117%	120%	123%	137%	118%	118%	184%	118%	184%	123%	193%
LCHO	116%	116%	116%	137%	116%	145%	157%	132%	132%	179%	138%	179%	145%	221%
LAGU	100%	100%	112%	100%	112%	100%	131%	100%	100%	185%	100%	185%	100%	197%
LCAL	125%	125%	125%	143%	125%	152%	153%	144%	144%	210%	147%	210%	153%	236%
LROZ	111%	111%	111%	114%	130%	194%	115%	136%	165%	136%	136%	171%	194%	136%
LALS	122%	122%	122%	138%	122%	177%	142%	153%	153%	166%	155%	166%	177%	173%
LANG	102%	102%	109%	102%	109%	112%	118%	103%	103%	153%	103%	153%	112%	155%
LCAS	112%	112%	118%	112%	123%	120%	118%	115%	119%	176%	115%	203%	121%	176%
LROS	122%	122%	122%	131%	122%	180%	131%	146%	146%	164%	146%	164%	180%	167%
LYEB	102%	102%	108%	102%	113%	117%	108%	103%	107%	139%	103%	155%	117%	139%
LUCE	106%	106%	106%	111%	106%	122%	127%	109%	109%	135%	112%	135%	122%	152%
MANG	103%	103%	106%	103%	107%	105%	112%	105%	105%	189%	105%	190%	106%	189%
MAQU	104%	104%	107%	108%	107%	116%	121%	109%	110%	174%	109%	174%	116%	179%

(continued)

Health Centres	ABCD123	ABCD12	ABCD13	ABCD23	ABCD1	ABCD2	ABCD3	ABC123	ABC12	ABC13	ABC23	ABC1	ABC2	ABC3
MARB	100%	100%	100%	100%	100%	128%	100%	100%	100%	100%	100%	100%	128%	100%
MARJ	106%	106%	106%	112%	111%	134%	112%	122%	125%	145%	122%	160%	134%	145%
MIGS	119%	119%	119%	121%	119%	129%	127%	124%	125%	186%	124%	193%	129%	186%
MIRS	100%	100%	100%	100%	152%	222%	100%	116%	190%	116%	116%	199%	222%	116%
MONR	116%	116%	116%	119%	133%	256%	119%	139%	171%	139%	139%	171%	256%	139%
MONS	141%	141%	148%	141%	148%	148%	150%	154%	159%	265%	154%	285%	160%	265%
NAVA	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
NUFA	101%	101%	111%	101%	112%	114%	113%	101%	103%	122%	101%	128%	114%	122%
PACI	121%	121%	121%	121%	130%	141%	121%	132%	136%	173%	132%	204%	141%	173%
PASE	126%	126%	126%	127%	126%	158%	129%	127%	127%	142%	127%	142%	158%	142%
PAVO	107%	107%	107%	115%	107%	124%	133%	111%	111%	140%	115%	140%	124%	163%
POTO	100%	100%	100%	100%	144%	138%	100%	134%	143%	181%	134%	282%	143%	181%
POZU	112%	112%	112%	112%	142%	191%	112%	158%	179%	164%	158%	230%	191%	164%
PRES	115%	115%	115%	136%	115%	138%	170%	133%	133%	195%	138%	195%	139%	261%
RAMO	100%	100%	100%	100%	100%	105%	100%	108%	110%	184%	108%	209%	110%	184%
REIN	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
SAND	104%	104%	104%	118%	104%	124%	130%	117%	117%	157%	119%	157%	124%	179%
SCAR	119%	119%	119%	130%	119%	158%	131%	128%	128%	138%	131%	138%	158%	148%
SJUA	135%	135%	135%	135%	139%	160%	136%	153%	158%	225%	153%	256%	161%	225%
SANM	100%	100%	100%	100%	100%	100%	100%	102%	102%	202%	102%	202%	102%	203%
SISA	102%	102%	102%	108%	105%	117%	109%	110%	111%	146%	110%	154%	117%	146%
SECT	117%	117%	117%	120%	122%	142%	120%	136%	138%	197%	136%	211%	142%	197%
SEGR	121%	121%	121%	121%	156%	169%	121%	166%	176%	231%	166%	323%	176%	231%
SILV	119%	119%	119%	126%	122%	176%	126%	158%	163%	181%	158%	192%	176%	181%
TORI	100%	100%	100%	100%	100%	108%	100%	100%	105%	140%	100%	154%	108%	140%
VIVA	100%	100%	104%	100%	104%	100%	109%	100%	100%	158%	100%	158%	100%	161%
VILC	129%	129%	129%	131%	129%	221%	131%	133%	133%	133%	134%	133%	221%	134%
VILO	140%	140%	140%	140%	155%	151%	140%	149%	155%	236%	149%	287%	155%	236%

Health Centres	ABD123	ABD12	ABD13	ABD23	ABD1	ABD2	ABD3	ACD123	ACD12	ACD13	ACD23	ACD1	ACD2	ACD3
ADEL	127%	132%	127%	127%	135%	138%	129%	131%	134%	138%	131%	139%	137%	139%
ALAO	119%	133%	119%	119%	133%	190%	119%	121%	134%	121%	121%	134%	189%	121%
ALGE	106%	106%	106%	129%	106%	161%	130%	106%	106%	106%	130%	106%	163%	130%
ANDR	133%	135%	147%	133%	154%	136%	147%	133%	135%	147%	133%	154%	136%	147%
ARAN	114%	114%	118%	114%	118%	129%	127%	114%	114%	118%	114%	118%	129%	127%
ARAV	110%	153%	110%	110%	153%	186%	110%	114%	156%	114%	114%	156%	189%	114%
ARRM	100%	105%	100%	100%	114%	107%	100%	100%	105%	100%	100%	113%	107%	100%
BARC	105%	105%	122%	105%	122%	105%	141%	104%	104%	122%	104%	122%	104%	141%
BARP	100%	102%	100%	101%	102%	115%	105%	100%	101%	100%	102%	101%	116%	105%
BENI	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
CANA	120%	120%	121%	122%	121%	128%	129%	119%	119%	120%	120%	120%	127%	129%
CANI	110%	110%	110%	123%	110%	136%	127%	111%	111%	111%	126%	111%	140%	128%
CEAB	128%	128%	128%	138%	128%	141%	138%	135%	135%	135%	140%	135%	142%	154%
CERR	115%	115%	123%	117%	123%	117%	147%	115%	115%	123%	117%	123%	117%	147%
CERA	111%	122%	111%	114%	122%	187%	114%	112%	122%	112%	114%	122%	188%	114%
CIUP	110%	119%	110%	110%	125%	125%	110%	111%	120%	111%	111%	126%	127%	111%
COVE	114%	114%	114%	134%	114%	156%	138%	115%	115%	115%	136%	115%	157%	138%
COND	109%	141%	109%	109%	141%	234%	109%	109%	142%	109%	109%	142%	237%	109%
DARO	104%	104%	112%	104%	112%	123%	114%	105%	105%	113%	106%	113%	128%	117%
DOCC	103%	103%	103%	109%	103%	116%	111%	110%	110%	110%	119%	110%	122%	121%
DOCP	122%	122%	123%	126%	123%	134%	136%	122%	122%	123%	126%	123%	134%	136%
DOSM	108%	108%	116%	109%	116%	117%	130%	108%	108%	116%	108%	116%	115%	130%
DRCA	105%	106%	111%	105%	111%	122%	115%	105%	106%	111%	105%	111%	122%	115%
DRME	125%	125%	126%	126%	126%	137%	132%	125%	125%	126%	126%	126%	135%	132%
ELOY	141%	141%	141%	151%	141%	162%	157%	141%	141%	141%	151%	141%	164%	157%
ENTR	103%	103%	105%	116%	105%	116%	149%	103%	103%	105%	114%	105%	114%	149%
ESPR	134%	143%	134%	134%	143%	179%	134%	134%	143%	134%	134%	143%	181%	134%

(continued)

Health Centres	ABD123	ABD12	ABD13	ABD23	ABD1	ABD2	ABD3	ACD123	ACD12	ACD13	ACD23	ACD1	ACD2	ACD3
ESTR	127%	127%	127%	139%	127%	144%	165%	127%	127%	127%	139%	127%	144%	165%
FRON	114%	114%	114%	127%	114%	135%	150%	114%	114%	114%	126%	114%	133%	150%
FUEC	116%	116%	120%	118%	120%	123%	130%	118%	118%	122%	120%	122%	125%	134%
GALA	134%	134%	134%	147%	134%	187%	147%	134%	134%	134%	147%	134%	187%	147%
GAND	116%	116%	116%	126%	116%	142%	136%	116%	116%	116%	126%	116%	142%	136%
GENR	112%	112%	115%	116%	115%	141%	129%	112%	112%	115%	116%	115%	141%	129%
GOYA	110%	119%	110%	110%	124%	152%	110%	110%	119%	110%	110%	124%	152%	110%
GREG	119%	119%	119%	122%	119%	131%	129%	118%	118%	119%	121%	119%	129%	128%
GUAY	109%	109%	112%	110%	112%	127%	121%	109%	109%	112%	110%	112%	127%	121%
IBIZ	121%	129%	121%	121%	129%	158%	121%	121%	129%	121%	121%	129%	156%	121%
INFA	139%	139%	139%	156%	139%	175%	156%	139%	139%	139%	156%	139%	178%	156%
JAIL	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
JAZM	124%	163%	124%	124%	163%	173%	124%	125%	164%	125%	125%	164%	171%	125%
JUAA	110%	110%	110%	123%	110%	129%	148%	110%	110%	110%	122%	110%	127%	148%
JUAC	115%	115%	120%	117%	120%	123%	137%	115%	115%	120%	117%	120%	125%	137%
LCHO	116%	116%	116%	139%	116%	146%	157%	116%	116%	116%	137%	116%	145%	157%
LAGU	100%	100%	112%	100%	112%	100%	131%	100%	100%	112%	100%	112%	100%	131%
LCAL	125%	125%	125%	143%	125%	156%	153%	125%	125%	125%	143%	125%	152%	153%
LROZ	111%	130%	111%	114%	130%	194%	115%	114%	132%	114%	115%	132%	197%	115%
LALS	122%	122%	122%	138%	122%	177%	142%	124%	124%	124%	142%	124%	182%	143%
LANG	102%	102%	109%	102%	109%	112%	118%	102%	102%	109%	102%	109%	112%	118%
LCAS	113%	116%	118%	113%	123%	121%	118%	112%	116%	118%	112%	123%	120%	118%
LROS	122%	122%	122%	131%	122%	180%	131%	122%	122%	122%	131%	122%	180%	131%
LYEB	102%	107%	108%	102%	113%	117%	108%	102%	107%	108%	102%	113%	117%	108%
LUCE	107%	107%	107%	112%	107%	122%	128%	106%	106%	107%	111%	107%	122%	127%
MANG	103%	103%	106%	104%	107%	105%	112%	103%	103%	108%	103%	108%	105%	116%
MAQU	104%	104%	107%	108%	107%	116%	121%	104%	104%	107%	108%	107%	116%	121%

(continued)

Health Centres	ABD123	ABD12	ABD13	ABD23	ABD1	ABD2	ABD3	ACD123	ACD12	ACD13	ACD23	ACD1	ACD2	ACD3
MARB	100%	100%	100%	100%	100%	128%	100%	100%	100%	100%	100%	100%	128%	100%
MARJ	106%	111%	106%	112%	111%	134%	112%	108%	111%	108%	114%	111%	135%	114%
MIGS	119%	119%	119%	121%	119%	129%	127%	122%	122%	122%	124%	122%	134%	132%
MIRS	100%	152%	100%	100%	152%	222%	100%	100%	152%	100%	100%	152%	225%	100%
MONR	116%	133%	116%	119%	133%	256%	119%	118%	134%	118%	119%	134%	260%	119%
MONS	141%	142%	148%	141%	148%	148%	150%	141%	142%	148%	141%	148%	148%	150%
NAVA	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
NUFA	101%	103%	112%	101%	113%	115%	114%	101%	103%	111%	101%	112%	114%	113%
PACI	121%	130%	121%	121%	130%	141%	121%	121%	130%	121%	121%	130%	141%	121%
PASE	126%	126%	126%	127%	126%	158%	129%	126%	126%	126%	127%	126%	158%	129%
PAVO	108%	108%	108%	115%	108%	124%	134%	107%	107%	107%	115%	107%	124%	133%
POTO	100%	139%	100%	100%	144%	143%	100%	100%	138%	100%	100%	145%	138%	100%
POZU	112%	142%	112%	112%	142%	191%	112%	117%	146%	117%	117%	146%	196%	117%
PRES	115%	115%	115%	137%	115%	139%	170%	115%	115%	115%	136%	115%	138%	170%
RAMO	100%	100%	100%	100%	100%	105%	100%	100%	100%	100%	100%	100%	105%	100%
REIN	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
SAND	104%	104%	104%	118%	104%	124%	130%	105%	105%	105%	120%	105%	128%	132%
SCAR	119%	119%	119%	130%	119%	158%	131%	119%	119%	119%	130%	119%	159%	131%
SJUA	135%	139%	135%	135%	139%	160%	136%	138%	141%	138%	138%	141%	162%	138%
SANM	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
SISA	102%	105%	102%	108%	105%	117%	109%	104%	106%	104%	109%	106%	117%	110%
SECT	117%	122%	117%	120%	122%	142%	120%	127%	127%	127%	133%	127%	146%	133%
SEGR	121%	156%	121%	121%	156%	171%	121%	127%	159%	127%	127%	159%	169%	127%
SILV	119%	122%	119%	126%	122%	176%	126%	121%	123%	121%	127%	123%	176%	127%
TORI	100%	100%	100%	100%	100%	108%	100%	100%	100%	100%	100%	100%	108%	100%
VIVA	100%	100%	104%	100%	104%	100%	109%	100%	100%	105%	100%	105%	100%	115%
VILC	129%	129%	129%	131%	129%	221%	131%	129%	129%	129%	131%	129%	221%	131%
VILO	140%	149%	140%	140%	155%	154%	140%	142%	149%	145%	142%	158%	151%	146%

Health Centres	BCD123	BCD12	BCD13	BCD23	BCD1	BCD2	BCD3	AB123	AB12	AB13	AB23	AB1	AB2	AB3
ADEL	127%	132%	127%	127%	135%	137%	129%	136%	136%	230%	136%	259%	139%	230%
ALAO	119%	133%	119%	119%	133%	189%	119%	165%	165%	191%	165%	236%	190%	191%
ALGE	106%	106%	106%	129%	106%	161%	130%	116%	116%	116%	131%	116%	161%	138%
ANDR	133%	135%	147%	133%	154%	136%	147%	149%	149%	287%	149%	327%	150%	287%
ARAN	114%	114%	118%	114%	118%	129%	127%	114%	114%	145%	114%	145%	129%	149%
ARAV	110%	153%	110%	110%	153%	186%	110%	157%	157%	167%	157%	256%	186%	167%
ARRM	100%	105%	100%	100%	113%	108%	100%	101%	101%	133%	101%	168%	107%	133%
BARC	104%	104%	122%	104%	122%	104%	143%	106%	106%	230%	106%	230%	106%	242%
BARP	100%	101%	100%	101%	101%	115%	105%	103%	103%	120%	103%	128%	115%	120%
BENI	100%	100%	100%	100%	100%	100%	100%	120%	120%	248%	120%	269%	120%	248%
CANA	119%	119%	120%	120%	120%	127%	130%	124%	124%	200%	124%	204%	128%	200%
CANI	110%	110%	110%	123%	110%	136%	127%	125%	125%	154%	125%	154%	136%	160%
CEAB	128%	128%	128%	138%	128%	141%	138%	142%	142%	272%	142%	272%	142%	291%
CERR	115%	115%	123%	117%	123%	117%	148%	117%	117%	217%	117%	217%	117%	238%
CERA	111%	122%	111%	114%	122%	187%	114%	137%	137%	137%	137%	161%	187%	137%
CIUP	110%	119%	110%	110%	125%	125%	110%	120%	120%	178%	120%	225%	125%	178%
COVE	114%	114%	114%	134%	114%	156%	138%	133%	133%	135%	138%	135%	156%	153%
COND	109%	141%	109%	109%	141%	234%	109%	127%	127%	127%	127%	177%	234%	127%
DARO	104%	104%	112%	104%	112%	123%	114%	104%	104%	113%	104%	113%	123%	115%
DOCC	103%	103%	103%	109%	103%	116%	111%	115%	115%	154%	115%	154%	116%	166%
DOCP	122%	122%	123%	126%	123%	134%	136%	135%	135%	224%	135%	224%	142%	227%
DOSM	108%	108%	116%	108%	116%	115%	130%	108%	108%	157%	109%	157%	117%	166%
DRCA	105%	106%	111%	105%	111%	122%	115%	105%	105%	135%	105%	136%	122%	135%
DRME	125%	125%	126%	126%	126%	135%	132%	133%	133%	217%	133%	227%	137%	217%
ELOY	141%	141%	141%	151%	141%	162%	157%	151%	151%	221%	151%	221%	162%	224%
ENTR	103%	103%	105%	114%	105%	114%	149%	110%	110%	174%	116%	174%	116%	227%
ESPR	134%	143%	134%	134%	143%	179%	134%	151%	151%	180%	151%	209%	179%	180%

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Health Centres	BCD123	BCD12	BCD13	BCD23	BCD1	BCD2	BCD3	AB123	AB12	AB13	AB23	AB1	AB2	AB3
ESTR	127%	127%	127%	139%	127%	144%	165%	137%	137%	202%	140%	202%	144%	239%
FRON	114%	114%	114%	126%	114%	133%	150%	121%	121%	166%	127%	166%	135%	202%
FUEC	116%	116%	120%	118%	120%	123%	130%	122%	122%	218%	122%	222%	123%	218%
GALA	134%	134%	134%	147%	134%	187%	147%	153%	153%	174%	155%	174%	187%	182%
GAND	116%	116%	116%	126%	116%	142%	136%	124%	124%	162%	127%	162%	142%	177%
GENR	112%	112%	115%	116%	115%	141%	129%	112%	112%	122%	116%	122%	141%	136%
GOYA	110%	119%	110%	110%	124%	152%	110%	112%	112%	112%	112%	126%	152%	112%
GREG	118%	118%	119%	121%	119%	129%	128%	125%	125%	195%	125%	198%	132%	195%
GUAY	109%	109%	112%	110%	112%	127%	121%	110%	110%	141%	111%	141%	127%	145%
IBIZ	121%	129%	121%	121%	129%	156%	121%	141%	141%	187%	141%	217%	159%	187%
INFA	139%	139%	139%	156%	139%	175%	156%	162%	162%	226%	162%	226%	175%	232%
JAIL	100%	100%	100%	100%	100%	100%	100%	101%	101%	231%	101%	241%	101%	231%
JAZM	124%	163%	124%	124%	163%	171%	124%	170%	170%	237%	170%	341%	181%	237%
JUAA	110%	110%	110%	122%	110%	127%	148%	117%	117%	162%	123%	162%	129%	202%
JUAC	115%	115%	120%	117%	120%	123%	137%	118%	118%	184%	118%	184%	123%	193%
LCHO	116%	116%	116%	137%	116%	145%	157%	133%	133%	179%	139%	179%	146%	221%
LAGU	100%	100%	112%	100%	112%	100%	131%	100%	100%	185%	100%	185%	100%	197%
LCAL	125%	125%	125%	143%	125%	152%	153%	145%	145%	210%	148%	210%	156%	236%
LROZ	111%	130%	111%	114%	130%	194%	115%	136%	136%	136%	136%	171%	194%	136%
LALS	122%	122%	122%	138%	122%	177%	142%	153%	153%	166%	155%	166%	177%	173%
LANG	102%	102%	109%	102%	109%	112%	118%	103%	103%	153%	103%	153%	112%	155%
LCAS	112%	116%	118%	112%	123%	120%	118%	115%	115%	177%	115%	203%	121%	177%
LROS	122%	122%	122%	131%	122%	180%	131%	146%	146%	164%	146%	164%	180%	167%
LYEB	102%	107%	108%	102%	113%	117%	108%	103%	103%	139%	103%	155%	117%	139%
LUCE	106%	106%	106%	111%	106%	122%	127%	109%	109%	136%	112%	136%	122%	153%
MANG	103%	103%	106%	103%	107%	105%	112%	105%	105%	191%	105%	191%	106%	192%
MAQU	104%	104%	107%	108%	107%	116%	121%	109%	109%	174%	109%	174%	116%	179%

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Health Centres	BCD123	BCD12	BCD13	BCD23	BCD1	BCD2	BCD3	AB123	AB12	AB13	AB23	AB1	AB2	AB3
MARB	100%	100%	100%	100%	100%	129%	100%	100%	100%	100%	100%	100%	128%	100%
MARJ	106%	111%	106%	112%	111%	134%	112%	123%	123%	147%	123%	160%	134%	147%
MIGS	119%	119%	119%	121%	119%	129%	127%	124%	124%	186%	124%	193%	129%	186%
MIRS	100%	152%	100%	100%	152%	222%	100%	117%	117%	117%	117%	199%	222%	117%
MONR	116%	133%	116%	119%	133%	256%	119%	139%	139%	139%	139%	171%	256%	139%
MONS	141%	142%	148%	141%	148%	148%	150%	154%	154%	265%	154%	285%	160%	265%
NAVA	100%	100%	100%	100%	100%	103%	100%	100%	100%	100%	100%	100%	100%	100%
NUFA	101%	103%	111%	101%	112%	114%	113%	101%	101%	124%	101%	128%	115%	124%
PACI	124%	131%	124%	124%	131%	144%	124%	132%	132%	173%	132%	204%	141%	173%
PASE	126%	126%	126%	127%	126%	158%	129%	127%	127%	142%	127%	142%	158%	142%
PAVO	107%	107%	107%	115%	107%	124%	133%	111%	111%	141%	115%	141%	124%	164%
POTO	100%	138%	100%	100%	144%	138%	100%	136%	136%	186%	136%	284%	143%	186%
POZU	112%	142%	112%	112%	142%	191%	112%	158%	158%	164%	158%	230%	191%	164%
PRES	115%	115%	115%	136%	115%	138%	170%	133%	133%	196%	138%	196%	139%	263%
RAMO	100%	100%	100%	100%	100%	105%	100%	110%	110%	190%	110%	211%	113%	190%
REIN	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
SAND	104%	104%	104%	118%	104%	124%	130%	117%	117%	157%	119%	157%	124%	179%
SCAR	119%	119%	119%	130%	119%	158%	131%	128%	128%	138%	131%	138%	158%	148%
SJUA	135%	139%	135%	135%	139%	160%	136%	153%	153%	225%	153%	256%	161%	225%
SANM	100%	100%	100%	100%	100%	100%	100%	102%	102%	203%	102%	203%	102%	207%
SISA	102%	105%	102%	108%	105%	117%	109%	110%	110%	146%	110%	154%	117%	146%
SECT	117%	122%	117%	120%	122%	142%	120%	136%	136%	197%	136%	211%	142%	197%
SEGR	121%	156%	121%	121%	156%	169%	121%	167%	167%	234%	167%	324%	176%	234%
SILV	119%	122%	119%	126%	122%	177%	126%	158%	158%	181%	158%	192%	176%	181%
TORI	100%	100%	100%	100%	100%	109%	100%	100%	100%	140%	100%	154%	108%	140%
VIVA	100%	100%	104%	100%	104%	100%	109%	100%	100%	181%	100%	181%	100%	188%
VILC	129%	129%	129%	131%	129%	221%	131%	133%	133%	133%	134%	133%	221%	134%
VILO	140%	149%	140%	140%	155%	151%	140%	150%	150%	238%	150%	289%	155%	238%

Health Centres	AC123	AC12	AC13	AC23	AC1	AC2	AC3	AD123	AD12	AD13	AD23	AD1	AD2	AD3
ADEL	138%	141%	230%	138%	259%	141%	230%	133%	135%	140%	133%	140%	143%	141%
ALAO	165%	178%	190%	165%	235%	192%	190%	123%	135%	123%	123%	135%	196%	123%
ALGE	116%	116%	116%	132%	116%	163%	138%	107%	107%	107%	131%	107%	164%	131%
ANDR	153%	154%	287%	153%	327%	154%	287%	133%	135%	147%	133%	154%	136%	147%
ARAN	114%	114%	145%	114%	145%	129%	149%	114%	114%	118%	114%	118%	129%	127%
ARAV	157%	180%	168%	157%	257%	190%	168%	116%	158%	116%	116%	158%	192%	116%
ARRM	100%	105%	129%	100%	167%	107%	129%	100%	105%	100%	100%	115%	107%	100%
BARC	106%	106%	229%	106%	229%	106%	240%	105%	105%	122%	105%	122%	105%	141%
BARP	103%	105%	120%	103%	128%	116%	120%	102%	103%	102%	103%	103%	117%	105%
BENI	120%	120%	248%	120%	269%	120%	248%	100%	100%	100%	100%	100%	100%	100%
CANA	124%	125%	196%	124%	203%	128%	196%	120%	120%	121%	122%	121%	128%	129%
CANI	126%	126%	155%	127%	155%	140%	164%	112%	112%	112%	126%	112%	140%	128%
CEAB	144%	144%	274%	144%	274%	144%	297%	135%	135%	135%	141%	135%	144%	154%
CERR	117%	117%	217%	117%	217%	117%	236%	115%	115%	123%	117%	123%	117%	147%
CERA	135%	158%	135%	135%	160%	188%	135%	113%	123%	113%	115%	123%	188%	115%
CIUP	121%	128%	182%	121%	226%	129%	182%	111%	120%	111%	111%	126%	127%	111%
COVE	133%	133%	136%	139%	136%	157%	155%	115%	115%	115%	136%	115%	157%	138%
COND	128%	178%	128%	128%	178%	237%	128%	109%	142%	109%	109%	142%	237%	109%
DARO	105%	105%	115%	106%	115%	128%	119%	105%	105%	113%	106%	113%	128%	117%
DOCC	122%	122%	155%	122%	155%	122%	167%	110%	110%	110%	119%	110%	122%	121%
DOCP	135%	136%	224%	135%	224%	142%	227%	122%	122%	123%	126%	123%	134%	136%
DOSM	108%	108%	157%	108%	157%	115%	166%	108%	108%	116%	109%	116%	117%	130%
DRCA	105%	106%	135%	105%	136%	122%	135%	105%	106%	111%	105%	111%	122%	115%
DRME	132%	135%	215%	132%	226%	137%	215%	125%	125%	126%	126%	126%	137%	132%
ELOY	152%	153%	221%	152%	221%	164%	224%	141%	141%	141%	151%	141%	164%	157%
ENTR	110%	110%	174%	115%	174%	115%	227%	103%	103%	105%	116%	105%	116%	149%
ESPR	151%	159%	180%	151%	209%	181%	180%	134%	143%	134%	134%	143%	181%	134%

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Health Centres	AC123	AC12	AC13	AC23	AC1	AC2	AC3	AD123	AD12	AD13	AD23	AD1	AD2	AD3
ESTR	137%	137%	202%	140%	202%	144%	239%	127%	127%	127%	141%	127%	146%	165%
FRON	121%	121%	166%	126%	166%	133%	202%	114%	114%	114%	127%	114%	135%	150%
FUEC	126%	127%	225%	126%	225%	128%	225%	118%	118%	122%	120%	122%	125%	134%
GALA	153%	153%	174%	155%	174%	187%	182%	134%	134%	134%	147%	134%	187%	147%
GAND	124%	124%	162%	127%	162%	142%	177%	116%	116%	116%	126%	116%	142%	136%
GENR	112%	112%	122%	116%	122%	141%	136%	112%	112%	115%	116%	115%	141%	129%
GOYA	112%	119%	112%	112%	126%	152%	112%	110%	119%	110%	110%	124%	152%	110%
GREG	124%	126%	191%	124%	197%	130%	191%	119%	119%	119%	122%	119%	132%	129%
GUAY	110%	110%	141%	111%	141%	127%	145%	109%	109%	112%	110%	112%	127%	121%
IBIZ	140%	148%	187%	140%	217%	157%	187%	121%	129%	121%	121%	129%	159%	121%
INFA	163%	163%	226%	163%	226%	178%	232%	139%	139%	139%	156%	139%	178%	156%
JAIL	101%	101%	232%	101%	242%	101%	232%	100%	100%	100%	100%	100%	100%	100%
JAZM	168%	180%	231%	168%	339%	180%	231%	125%	164%	125%	125%	164%	173%	125%
JUAA	117%	117%	162%	122%	162%	127%	202%	110%	110%	110%	123%	110%	129%	148%
JUAC	118%	118%	184%	118%	184%	125%	193%	115%	115%	120%	117%	120%	125%	137%
LCHO	132%	132%	179%	138%	179%	145%	221%	116%	116%	116%	139%	116%	148%	157%
LAGU	100%	100%	185%	100%	185%	100%	197%	100%	100%	112%	100%	112%	100%	131%
LCAL	144%	144%	210%	147%	210%	153%	236%	125%	125%	125%	143%	125%	156%	153%
LROZ	138%	166%	138%	138%	172%	197%	138%	114%	132%	114%	115%	132%	197%	115%
LALS	154%	154%	168%	157%	168%	182%	178%	124%	124%	124%	142%	124%	182%	143%
LANG	103%	103%	153%	103%	153%	112%	155%	102%	102%	109%	102%	109%	112%	118%
LCAS	115%	119%	176%	115%	203%	121%	176%	113%	117%	118%	113%	123%	126%	118%
LROS	146%	146%	164%	146%	164%	180%	167%	122%	122%	122%	131%	122%	180%	131%
LYEB	103%	107%	139%	103%	155%	117%	139%	102%	107%	108%	102%	113%	117%	108%
LUCE	109%	109%	135%	112%	135%	122%	152%	107%	107%	107%	114%	107%	128%	128%
MANG	105%	105%	189%	105%	190%	106%	189%	103%	103%	109%	104%	109%	105%	116%
MAQU	109%	110%	174%	109%	174%	116%	179%	104%	104%	107%	108%	107%	116%	121%

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Health Centres	AC123	AC12	AC13	AC23	AC1	AC2	AC3	AD123	AD12	AD13	AD23	AD1	AD2	AD3
MARB	100%	100%	100%	100%	100%	128%	100%	100%	100%	100%	100%	100%	128%	100%
MARJ	122%	125%	145%	122%	160%	135%	145%	110%	113%	110%	114%	113%	135%	115%
MIGS	127%	129%	190%	127%	194%	134%	190%	123%	123%	123%	126%	123%	134%	134%
MIRS	116%	190%	116%	116%	199%	225%	116%	100%	154%	100%	100%	154%	226%	100%
MONR	141%	172%	141%	141%	172%	260%	141%	118%	134%	118%	119%	134%	260%	119%
MONS	154%	159%	265%	154%	285%	160%	265%	141%	142%	148%	141%	148%	148%	150%
NAVA	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
NUFA	101%	103%	122%	101%	128%	114%	122%	102%	104%	113%	102%	113%	116%	114%
PACI	132%	136%	173%	132%	204%	141%	173%	121%	130%	121%	121%	130%	141%	121%
PASE	127%	127%	142%	127%	142%	158%	142%	126%	126%	126%	127%	126%	158%	129%
PAVO	111%	111%	140%	115%	140%	124%	163%	108%	108%	108%	116%	108%	125%	134%
POTO	134%	143%	181%	134%	282%	143%	181%	100%	140%	100%	100%	146%	143%	100%
POZU	160%	180%	168%	160%	232%	196%	168%	117%	146%	117%	117%	146%	196%	117%
PRES	133%	133%	195%	138%	195%	139%	261%	115%	115%	115%	139%	115%	141%	170%
RAMO	108%	110%	184%	108%	209%	110%	184%	100%	100%	100%	100%	100%	105%	100%
REIN	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
SAND	117%	117%	158%	120%	158%	128%	183%	105%	105%	105%	120%	105%	132%	132%
SCAR	128%	128%	138%	131%	138%	159%	148%	119%	119%	119%	130%	119%	162%	131%
SJUA	155%	159%	229%	155%	257%	163%	229%	138%	141%	138%	138%	141%	162%	138%
SANM	102%	102%	202%	102%	202%	102%	203%	100%	100%	100%	100%	100%	100%	100%
SISA	110%	111%	146%	110%	154%	117%	146%	104%	106%	104%	109%	106%	117%	110%
SECT	140%	142%	202%	140%	212%	146%	202%	127%	127%	127%	133%	127%	146%	133%
SEGR	166%	177%	231%	166%	323%	177%	231%	127%	159%	127%	127%	159%	171%	127%
SILV	158%	163%	182%	158%	192%	176%	182%	121%	123%	121%	127%	123%	176%	127%
TORI	100%	105%	140%	100%	154%	108%	140%	100%	100%	100%	100%	100%	108%	100%
VIVA	100%	100%	158%	100%	158%	100%	161%	100%	100%	111%	100%	111%	100%	120%
VILC	133%	133%	133%	134%	133%	221%	134%	129%	129%	129%	131%	129%	221%	131%
VILO	150%	155%	236%	150%	287%	155%	236%	146%	152%	149%	146%	160%	159%	149%

Health Centres	BC123	BC12	BC13	BC23	BC1	BC2	BC3	BD123	BD12	BD13	BD23	BD1	BD2	BD3
ADEL	136%	139%	230%	136%	259%	139%	230%	127%	132%	127%	127%	135%	138%	129%
ALAO	165%	178%	190%	165%	235%	190%	190%	119%	133%	119%	119%	133%	190%	119%
ALGE	116%	116%	116%	131%	116%	161%	138%	106%	106%	106%	129%	106%	161%	130%
ANDR	149%	150%	287%	149%	327%	150%	287%	133%	135%	147%	133%	154%	136%	147%
ARAN	114%	114%	145%	114%	145%	129%	149%	114%	114%	118%	114%	118%	129%	127%
ARAV	157%	178%	167%	157%	256%	186%	167%	110%	153%	110%	110%	153%	186%	110%
ARRM	100%	105%	129%	100%	167%	108%	129%	100%	106%	100%	100%	114%	109%	100%
BARC	107%	107%	229%	107%	229%	107%	240%	106%	106%	122%	106%	122%	106%	143%
BARP	103%	105%	120%	103%	128%	115%	120%	100%	102%	100%	101%	102%	115%	105%
BENI	120%	120%	248%	120%	269%	120%	248%	100%	100%	100%	100%	100%	100%	100%
CANA	124%	125%	196%	124%	203%	128%	196%	120%	120%	121%	123%	121%	129%	131%
CANI	125%	125%	154%	125%	154%	136%	160%	110%	110%	110%	123%	110%	136%	127%
CEAB	142%	142%	272%	142%	272%	142%	291%	128%	128%	128%	138%	128%	141%	138%
CERR	118%	118%	217%	118%	217%	118%	236%	115%	115%	123%	118%	123%	118%	148%
CERA	135%	158%	135%	135%	160%	187%	135%	111%	122%	111%	114%	122%	187%	114%
CIUP	120%	125%	178%	120%	225%	125%	178%	110%	119%	110%	110%	125%	125%	110%
COVE	133%	133%	135%	138%	135%	156%	153%	114%	114%	114%	134%	114%	156%	138%
COND	127%	177%	127%	127%	177%	234%	127%	109%	141%	109%	109%	141%	234%	109%
DARO	104%	104%	113%	104%	113%	123%	115%	104%	104%	112%	104%	112%	123%	114%
DOCC	115%	115%	154%	115%	154%	116%	166%	103%	103%	103%	109%	103%	116%	111%
DOCP	135%	136%	224%	135%	224%	142%	227%	122%	122%	123%	126%	123%	134%	136%
DOSM	108%	108%	157%	108%	157%	115%	166%	108%	108%	116%	109%	116%	117%	130%
DRCA	105%	106%	135%	105%	136%	122%	135%	105%	106%	111%	105%	111%	122%	115%
DRME	132%	135%	215%	132%	226%	137%	215%	125%	125%	126%	126%	126%	137%	132%
ELOY	151%	153%	221%	151%	221%	162%	224%	141%	141%	141%	151%	141%	162%	157%
ENTR	110%	110%	174%	115%	174%	115%	227%	103%	103%	105%	116%	105%	116%	149%
ESPR	151%	159%	180%	151%	209%	179%	180%	134%	143%	134%	134%	143%	179%	134%

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Health Centres	BC123	BC12	BC13	BC23	BC1	BC2	BC3	BD123	BD12	BD13	BD23	BD1	BD2	BD3
ESTR	137%	137%	202%	140%	202%	144%	239%	127%	127%	127%	139%	127%	144%	165%
FRON	121%	121%	166%	126%	166%	133%	202%	114%	114%	114%	127%	114%	135%	150%
FUEC	122%	123%	218%	122%	222%	123%	218%	116%	116%	120%	118%	120%	123%	130%
GALA	153%	153%	174%	155%	174%	187%	182%	134%	134%	134%	147%	134%	187%	147%
GAND	124%	124%	162%	127%	162%	142%	177%	116%	116%	116%	126%	116%	142%	136%
GENR	112%	112%	122%	116%	122%	141%	136%	112%	112%	115%	116%	115%	141%	129%
GOYA	112%	119%	112%	112%	126%	152%	112%	110%	119%	110%	110%	124%	152%	110%
GREG	124%	126%	191%	124%	197%	130%	191%	119%	119%	119%	122%	119%	131%	129%
GUAY	110%	110%	141%	111%	141%	127%	145%	109%	109%	112%	110%	112%	127%	121%
IBIZ	140%	148%	187%	140%	217%	157%	187%	121%	129%	121%	121%	129%	158%	121%
INFA	162%	162%	226%	162%	226%	175%	232%	139%	139%	139%	156%	139%	175%	156%
JAIL	101%	101%	231%	101%	241%	101%	231%	100%	100%	100%	100%	100%	100%	100%
JAZM	168%	180%	231%	168%	339%	180%	231%	124%	163%	124%	124%	163%	173%	124%
JUAA	117%	117%	162%	122%	162%	127%	202%	110%	110%	110%	123%	110%	129%	148%
JUAC	118%	118%	184%	118%	184%	123%	193%	115%	115%	120%	117%	120%	123%	137%
LCHO	132%	132%	179%	138%	179%	145%	221%	116%	116%	116%	139%	116%	146%	157%
LAGU	100%	100%	185%	100%	185%	100%	197%	100%	100%	112%	100%	112%	100%	131%
LCAL	144%	144%	210%	147%	210%	153%	236%	125%	125%	125%	143%	125%	156%	153%
LROZ	136%	165%	136%	136%	171%	194%	136%	111%	130%	111%	114%	130%	194%	115%
LALS	153%	153%	166%	155%	166%	177%	173%	122%	122%	122%	138%	122%	177%	142%
LANG	103%	103%	153%	103%	153%	112%	155%	102%	102%	109%	102%	109%	112%	118%
LCAS	115%	119%	176%	115%	203%	121%	176%	113%	116%	118%	113%	123%	121%	118%
LROS	146%	146%	164%	146%	164%	180%	167%	122%	122%	122%	131%	122%	180%	131%
LYEB	103%	107%	139%	103%	155%	117%	139%	102%	107%	108%	102%	113%	117%	108%
LUCE	109%	109%	135%	112%	135%	122%	152%	107%	107%	107%	112%	107%	122%	128%
MANG	105%	106%	189%	105%	190%	106%	189%	103%	103%	106%	104%	107%	106%	112%
MAQU	109%	110%	174%	109%	174%	116%	179%	104%	104%	107%	108%	107%	116%	121%

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Health Centres	BC123	BC12	BC13	BC23	BC1	BC2	BC3	BD123	BD12	BD13	BD23	BD1	BD2	BD3
MARB	100%	100%	100%	100%	100%	129%	100%	100%	100%	100%	100%	100%	129%	100%
MARJ	122%	125%	145%	122%	160%	134%	145%	106%	111%	106%	112%	111%	134%	112%
MIGS	124%	125%	186%	124%	193%	129%	186%	119%	119%	119%	121%	119%	129%	127%
MIRS	116%	190%	116%	116%	199%	222%	116%	100%	152%	100%	100%	152%	222%	100%
MONR	139%	171%	139%	139%	171%	256%	139%	116%	133%	116%	119%	133%	256%	119%
MONS	154%	159%	265%	154%	285%	160%	265%	141%	142%	148%	141%	148%	148%	150%
NAVA	100%	100%	100%	100%	100%	103%	100%	100%	100%	100%	100%	100%	103%	100%
NUFA	101%	103%	122%	101%	128%	114%	122%	101%	103%	112%	101%	113%	115%	114%
PACI	133%	139%	175%	133%	205%	144%	175%	124%	131%	124%	124%	131%	144%	124%
PASE	127%	127%	142%	127%	142%	158%	142%	126%	126%	126%	127%	126%	158%	129%
PAVO	111%	111%	140%	115%	140%	124%	163%	108%	108%	108%	115%	108%	124%	134%
POTO	134%	144%	181%	134%	282%	144%	181%	100%	139%	100%	100%	144%	143%	100%
POZU	158%	179%	164%	158%	230%	191%	164%	112%	142%	112%	112%	142%	191%	112%
PRES	133%	133%	195%	138%	195%	139%	261%	115%	115%	115%	137%	115%	139%	170%
RAMO	108%	110%	184%	108%	209%	110%	184%	100%	100%	100%	100%	100%	105%	100%
REIN	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
SAND	117%	117%	157%	119%	157%	124%	179%	104%	104%	104%	118%	104%	124%	130%
SCAR	128%	128%	138%	131%	138%	158%	148%	119%	119%	119%	130%	119%	158%	131%
SJUA	153%	158%	225%	153%	256%	161%	225%	135%	139%	135%	135%	139%	160%	136%
SANM	104%	104%	202%	104%	202%	104%	203%	100%	100%	100%	102%	100%	105%	102%
SISA	110%	111%	146%	110%	154%	117%	146%	102%	105%	102%	108%	105%	117%	109%
SECT	136%	138%	197%	136%	211%	142%	197%	117%	122%	117%	120%	122%	142%	120%
SEGR	166%	176%	231%	166%	323%	176%	231%	121%	156%	121%	121%	156%	171%	121%
SILV	158%	163%	181%	158%	192%	177%	181%	119%	122%	119%	126%	122%	177%	126%
TORI	100%	105%	140%	100%	154%	109%	140%	100%	100%	100%	100%	100%	109%	100%
VIVA	100%	100%	158%	100%	158%	100%	161%	100%	100%	104%	100%	104%	100%	109%
VILC	133%	133%	133%	134%	133%	221%	134%	129%	129%	129%	131%	129%	221%	131%
VILO	149%	155%	236%	149%	287%	155%	236%	140%	149%	140%	140%	155%	154%	140%

Health Centres	CD12 3	CD12 CD13	CD23	CD1	CD2	CD3	A123	A12	A13	A23	A1	A2	A3	B123	B12	B13	
ADEL	131%	134 %	138%	131 %	139%	137%	139 %	141 %	144 %	238 %	141 %	262 %	144 %	238 %	136 %	139 %	230 %
ALAO	121%	134 %	121%	121 %	134%	189%	121 %	168 %	180 %	197 %	168 %	238 %	197 %	197 %	165 %	178 %	191 %
ALGE	106%	106 %	106%	130 %	106%	163%	130 %	117 %	117 %	117 %	133 %	117 %	164 %	141 %	116 %	116 %	116 %
ANDR	133%	135 %	147%	133 %	154%	136%	147 %	153 %	154 %	287 %	153 %	327 %	154 %	287 %	149 %	150 %	287 %
ARAN	114%	114 %	118%	114 %	118%	129%	127 %	114 %	114 %	145 %	114 %	145 %	129 %	149 %	114 %	114 %	145 %
ARAV	114%	156 %	114%	114 %	156%	189%	114 %	159 %	183 %	173 %	159 %	259 %	192 %	173 %	157 %	178 %	167 %
ARRM	100%	105 %	100%	100 %	113%	108%	100 %	101 %	105 %	133 %	101 %	168 %	107 %	133 %	102 %	106 %	134 %
BARC	104%	104 %	123%	104 %	123%	104%	144 %	106 %	106 %	230 %	106 %	230 %	106 %	242 %	107 %	107 %	230 %
BARP	100%	101 %	100%	102 %	101%	116%	105 %	104 %	107 %	123 %	104 %	129 %	117 %	123 %	103 %	106 %	120 %
BENI	100%	100 %	100%	100 %	100%	100%	100 %	120 %	120 %	248 %	120 %	269 %	120 %	248 %	120 %	120 %	248 %
CANA	119%	119 %	120%	120 %	120%	127%	130 %	124 %	126 %	200 %	124 %	204 %	128 %	200 %	125 %	127 %	201 %
CANI	112%	112 %	112%	126 %	112%	142%	128 %	126 %	126 %	155 %	127 %	155 %	140 %	164 %	125 %	125 %	154 %
CEAB	136%	136 %	139%	141 %	139%	142%	170 %	144 %	144 %	274 %	144 %	274 %	144 %	297 %	142 %	142 %	272 %
CERR	115%	115 %	124%	117 %	124%	117%	152 %	117 %	117 %	217 %	117 %	217 %	117 %	238 %	118 %	118 %	217 %
CERA	112%	122 %	112%	114 %	122%	189%	114 %	139 %	159 %	139 %	139 %	161 %	188 %	139 %	137 %	158 %	137 %

CIUP	111%	120 %	111%	111 %	126%	127%	111 %	121 %	128 %	182 %	121 %	226 %	129 %	182 %	120 %	125 %	178 %
COVE	116%	116 %	116%	139 %	116%	162%	142 %	133 %	133 %	136 %	139 %	136 %	157 %	155 %	133 %	133 %	135 %
COND	109%	142 %	109%	109 %	142%	239%	109 %	129 %	178 %	129 %	129 %	178 %	237 %	129 %	127 %	177 %	127 %
DARO	105%	105 %	113%	106 %	113%	128%	117 %	105 %	105 %	115 %	106 %	115 %	128 %	119 %	104 %	104 %	113 %
DOCC	112%	112 %	112%	127 %	112%	137%	138 %	122 %	122 %	155 %	122 %	155 %	122 %	167 %	115 %	115 %	154 %
DOCP	122%	122 %	123%	126 %	123%	134%	136 %	135 %	136 %	224 %	135 %	224 %	142 %	227 %	135 %	136 %	224 %
DOSM	108%	108 %	116%	108 %	116%	115%	130 %	108 %	108 %	157 %	109 %	157 %	117 %	166 %	108 %	108 %	157 %
DRCA	105%	106 %	111%	105 %	111%	122%	115 %	105 %	106 %	135 %	105 %	136 %	122 %	135 %	105 %	106 %	135 %
DRME	125%	125 %	126%	126 %	126%	135%	132 %	133 %	135 %	217 %	133 %	227 %	137 %	217 %	134 %	137 %	219 %
ELOY	141%	141 %	141%	151 %	141%	165%	157 %	152 %	153 %	221 %	152 %	221 %	164 %	224 %	151 %	153 %	221 %
ENTR	103%	103 %	105%	114 %	105%	114%	149 %	110 %	110 %	174 %	116 %	174 %	116 %	227 %	110 %	110 %	174 %
ESPR	134%	143 %	134%	134 %	143%	181%	134 %	151 %	159 %	180 %	151 %	209 %	181 %	180 %	151 %	159 %	180 %

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Health Centres	CD123	CD12	CD13	CD23	CD1	CD2	CD3	A123	A12	A13	A23	A1	A2	A3	B123	B12	B13
ESTR	127%	127 %	127%	139 %	127%	144%	165 %	137 %	137 %	202 %	142 %	202 %	146 %	239 %	137 %	137 %	202 %
FRON	114%	114 %	114%	126 %	114%	133%	150 %	121 %	121 %	166 %	127 %	166 %	135 %	202 %	121 %	121 %	166 %

LALS	126%	126	126%	144	126%	189%	144	154	154	168	157	168	182	178	153	153	166
		%		%			%	%	%	%	%	%	%	%	%	%	%
LANG	102%	102	109%	102	109%	112%	118	103	103	153	103	153	112	155	103	103	153
		%		%			%	%	%	%	%	%	%	%	%	%	%
LCAS	112%	116	118%	112	123%	120%	118	117	122	179	117	204	126	179	115	119	177
		%		%			%	%	%	%	%	%	%	%	%	%	%
LROS	122%	122	122%	131	122%	180%	131	146	146	164	146	164	180	167	146	146	164
		%		%			%	%	%	%	%	%	%	%	%	%	%
LYEB	102%	107	108%	102	113%	117%	108	103	107	139	103	155	117	139	103	107	139
		%		%			%	%	%	%	%	%	%	%	%	%	%
LUCE	106%	106	107%	111	107%	122%	127	110	110	136	114	136	128	155	109	109	136
		%		%			%	%	%	%	%	%	%	%	%	%	%
MANG	103%	103	108%	104	108%	105%	120	105	105	191	105	191	106	192	105	106	191
		%		%			%	%	%	%	%	%	%	%	%	%	%
MAQU	104%	104	107%	108	107%	116%	121	109	110	174	109	174	116	179	109	110	174
		%		%			%	%	%	%	%	%	%	%	%	%	%

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Health Centres	CD123	CD12	CD13	CD23	CD1	CD2	CD3	A123	A12	A13	A23	A1	A2	A3	B123	B12	B13
MARB	100%	100%	100%	100%	100%	129%	100%	100%	100%	100%	100%	100%	128%	100%	100%	100%	100%
MARJ	108%	111%	108%	114%	111%	135%	114%	124%	127%	149%	124%	161%	135%	149%	123%	125%	147%
MIGS	122%	122%	122%	124%	122%	134%	132%	127%	129%	192%	127%	195%	134%	192%	124%	125%	186%
MIRS	100%	152%	100%	100%	152%	225%	100%	120%	191%	120%	120%	200%	226%	120%	117%	190%	117%
MONR	119%	134%	119%	120%	134%	265%	120%	141%	172%	141%	141%	172%	260%	141%	139%	171%	139%
MONS	141%	142%	148%	141%	148%	148%	150%	154%	159%	265%	154%	285%	160%	265%	154%	159%	265%
NAVA	100%	100%	100%	100%	100%	119%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
NUFA	101%	103%	111%	101%	112%	114%	113%	102%	104%	126%	102%	129%	116%	126%	101%	103%	124%
PACI	128%	134%	128%	128%	134%	152%	128%	132%	136%	173%	132%	204%	141%	173%	133%	139%	175%
PASE	126%	126%	126%	127%	126%	158%	129%	127%	127%	142%	127%	142%	158%	142%	127%	127%	142%
PAVO	107%	107%	107%	115%	107%	124%	133%	112%	112%	141%	116%	141%	125%	166%	111%	111%	141%
POTO	100%	138%	100%	100%	145%	138%	100%	136%	143%	186%	136%	284%	143%	186%	136%	144%	186%
POZU	117%	146%	117%	117%	146%	198%	117%	160%	180%	168%	160%	232%	196%	168%	158%	179%	164%
PRES	115%	115%	115%	136%	115%	138%	170%	134%	134%	197%	141%	197%	142%	266%	133%	133%	196%

RAMO	100%	100%	100%	100%	100%	105%	100%	110%	113%	191%	110%	211%	113%	191%	110%	113%	190%
REIN	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
SAND	105%	105%	105%	120%	105%	128%	132%	118%	118%	158%	122%	158%	132%	183%	117%	117%	157%
SCAR	119%	119%	119%	130%	119%	159%	131%	128%	128%	138%	131%	138%	162%	148%	128%	128%	138%
SJUA	139%	142%	139%	139%	142%	164%	139%	155%	159%	229%	155%	257%	163%	229%	153%	158%	225%
SANM	100%	100%	100%	100%	100%	100%	100%	102%	102%	203%	102%	203%	102%	207%	105%	105%	204%
SISA	106%	106%	106%	110%	107%	120%	114%	110%	111%	146%	110%	154%	117%	146%	110%	111%	146%
SECT	127%	127%	127%	135%	127%	147%	136%	140%	142%	204%	140%	213%	146%	204%	136%	138%	197%
SEGR	130%	160%	130%	130%	160%	169%	130%	169%	178%	238%	169%	326%	179%	238%	167%	176%	234%
SILV	127%	127%	127%	137%	127%	189%	137%	158%	163%	182%	158%	192%	176%	182%	158%	163%	181%
TORI	100%	100%	100%	100%	100%	111%	100%	100%	105%	140%	100%	154%	108%	140%	100%	105%	140%
VIVA	100%	100%	105%	100%	105%	100%	115%	100%	100%	182%	100%	182%	100%	190%	100%	100%	181%
VILC	129%	129%	129%	131%	129%	221%	131%	133%	133%	133%	134%	133%	221%	134%	133%	133%	133%
VILO	142%	149%	145%	142%	158%	151%	146%	155%	160%	247%	155%	292%	160%	247%	150%	155%	238%

Health Centres	B23	B1	B2	B3	C123	C12	C13	C23	C1	C2	C3	D123	D12	D13	D23	D1	D2	D3
ADEL	136 %	259 %	139 %	230 %	138 %	381 %	230 %	138 %	259 %	141 %	230 %	134 %	136 %	141 %	134 %	141 %	143 %	142 %
ALAO	165 %	236 %	190 %	191 %	165 %	558 %	190 %	165 %	235 %	192 %	190 %	123 %	135 %	123 %	123 %	135 %	198 %	123 %
ALGE	131 %	116 %	161 %	138 %	116 %	301 %	116 %	132 %	116 %	163 %	138 %	107 %	107 %	107 %	131 %	107 %	171 %	131 %
ANDR	149 %	327 %	150 %	287 %	153 %	644 %	287 %	153 %	327 %	156 %	287 %	133 %	135 %	147 %	133 %	154 %	136 %	147 %
ARAN	114 %	145 %	129 %	149 %	114 %	442 %	145 %	114 %	145 %	129 %	149 %	114 %	114 %	118 %	114 %	118 %	131 %	127 %
ARAV	157 %	256 %	186 %	167 %	157 %	559 %	168 %	157 %	257 %	190 %	168 %	116 %	158 %	116 %	116 %	158 %	202 %	116 %
ARRM	102 %	168 %	109 %	134 %	100 %	204 %	129 %	100 %	167 %	108 %	129 %	107 %	114 %	109 %	107 %	121 %	123 %	109 %
BARC	107 %	230 %	107 %	243 %	107 %	314 %	229 %	107 %	229 %	107 %	240 %	106 %	106 %	123 %	106 %	123 %	106 %	144 %
BARP	103 %	128 %	115 %	120 %	103 %	245 %	120 %	103 %	128 %	116 %	120 %	105 %	105 %	105 %	106 %	105 %	128 %	108 %
BENI	120 %	269 %	120 %	248 %	120 %	564 %	248 %	120 %	269 %	120 %	248 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %
CANA	125 %	205 %	130 %	201 %	124 %	346 %	196 %	124 %	203 %	128 %	196 %	122 %	122 %	123 %	126 %	123 %	138 %	135 %
CANI	125 %	154 %	136 %	160 %	126 %	402 %	155 %	127 %	155 %	142 %	164 %	112 %	112 %	112 %	127 %	112 %	148 %	128 %
CEAB	142 %	272 %	142 %	291 %	148 %	398 %	274 %	148 %	274 %	148 %	297 %	137 %	137 %	140 %	143 %	140 %	145 %	172 %
CERR	118 %	217 %	118 %	239 %	119 %	320 %	217 %	119 %	217 %	119 %	236 %	119 %	119 %	127 %	124 %	127 %	125 %	157 %
CERA	137 %	161 %	187 %	137 %	135 %	270 %	135 %	135 %	160 %	189 %	135 %	121 %	128 %	121 %	121 %	128 %	212 %	121 %

LANG	103	153	112	155	103	586	153	103			155	102	102	109	102	109	112	118
	%	%	%	%	%	%	%	%	153%	112%	%	%	%	%	%	%	%	%
LCAS	115	203	121	177	115	385	176	115			176	113	117	118	113	123	127	118
	%	%	%	%	%	%	%	%	203%	121%	%	%	%	%	%	%	%	%
LROS	146	164	180	167	146	654	164	146			167	122	122	122	131	122	180	131
	%	%	%	%	%	%	%	%	164%	180%	%	%	%	%	%	%	%	%
LYEB	103	155	117	139	103	741	139	103			139	102	107	108	102	113	117	108
	%	%	%	%	%	%	%	%	155%	117%	%	%	%	%	%	%	%	%
LUCE	112	136	122	153	109	351	135	112			152	107	107	107	114	107	128	128
	%	%	%	%	%	%	%	%	135%	122%	%	%	%	%	%	%	%	%
MANG	105	191	106	192	106	232	189	106			189	110	110	114	113	114	118	133
	%	%	%	%	%	%	%	%	190%	107%	%	%	%	%	%	%	%	%
MAQU	109	174	116	179	109	765	174	109			179	104	104	107	108	107	116	121
	%	%	%	%	%	%	%	%	174%	116%	%	%	%	%	%	%	%	%

(continued)

Health Centres	B23	B1	B2	B3	C123	C12	C13	C23	C1	C2	C3	D123	D12	D13	D23	D1	D2	D3
MARB	100%	100%	129%	100%	100%	281%	100%	100%	100%	129%	100%	100%	100%	100%	100%	100%	133%	100%
MARJ	123%	160%	134%	147%	122%	270%	145%	122%	160%	135%	145%	118%	118%	118%	122%	118%	152%	122%
MIGS	124%	193%	129%	186%	127%	427%	190%	127%	194%	134%	190%	123%	123%	123%	127%	123%	141%	134%
MIRS	117%	199%	222%	117%	116%	381%	116%	116%	199%	225%	116%	102%	158%	102%	102%	158%	249%	102%
MONR	139%	171%	256%	139%	141%	407%	141%	141%	172%	265%	141%	121%	137%	121%	121%	137%	283%	121%
MONS	154%	285%	160%	265%	154%	1018%	265%	154%	285%	160%	265%	141%	142%	148%	141%	148%	148%	150%
NAVA	100%	100%	103%	100%	100%	146%	100%	100%	100%	119%	100%	103%	103%	104%	106%	104%	136%	112%
NUFA	101%	128%	115%	124%	101%	303%	122%	101%	128%	114%	122%	103%	104%	114%	103%	114%	122%	114%
PACI	133%	205%	144%	175%	136%	555%	181%	136%	207%	152%	181%	128%	134%	128%	128%	134%	155%	128%
PASE	127%	142%	158%	142%	127%	499%	142%	127%	142%	158%	142%	126%	126%	126%	127%	126%	158%	129%
PAVO	115%	141%	124%	164%	111%	363%	140%	115%	140%	124%	163%	108%	108%	108%	117%	108%	130%	134%
POTO	136%	284%	144%	186%	134%	311%	181%	134%	282%	144%	181%	114%	145%	114%	114%	152%	149%	114%
POZU	158%	230%	191%	164%	160%	602%	168%	160%	232%	198%	168%	118%	147%	118%	118%	147%	208%	118%
PRES	138%	196%	139%	263%	133%	443%	195%	138%	195%	139%	261%	115%	115%	115%	140%	115%	143%	170%

RAMO	110%	211%	113%	190%	108%	297%	184%	108%	209%	110%	184%	100%	100%	100%	100%	100%	105%	100%
REIN	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	136%	136%	136%	164%	136%	181%	173%
SAND	119%	157%	124%	179%	117%	438%	158%	120%	158%	128%	183%	105%	105%	105%	120%	105%	132%	132%
SCAR	131%	138%	158%	148%	128%	422%	138%	131%	138%	159%	148%	119%	119%	119%	130%	119%	162%	131%
SJUA	153%	256%	161%	225%	156%	573%	233%	156%	259%	168%	233%	139%	142%	139%	139%	142%	164%	139%
SANM	105%	204%	105%	210%	104%	197%	202%	104%	202%	104%	203%	104%	104%	107%	107%	107%	109%	127%
SISA	110%	154%	117%	146%	111%	293%	146%	111%	154%	120%	146%	111%	111%	111%	115%	111%	133%	119%
SECT	136%	211%	142%	197%	140%	399%	202%	140%	212%	148%	202%	131%	131%	131%	140%	131%	161%	141%
SEGR	167%	324%	176%	234%	166%	477%	231%	166%	323%	177%	231%	130%	161%	130%	130%	161%	171%	130%
SILV	158%	192%	177%	181%	162%	506%	190%	162%	195%	189%	190%	129%	129%	129%	138%	129%	198%	138%
TORI	100%	154%	109%	140%	101%	378%	141%	101%	155%	111%	141%	100%	100%	100%	100%	100%	114%	100%
VIVA	100%	181%	100%	188%	100%	160%	158%	100%	158%	100%	161%	111%	111%	120%	114%	120%	116%	145%
VILC	134%	133%	221%	134%	133%	593%	133%	134%	133%	221%	134%	129%	129%	129%	131%	129%	221%	131%
VILO	150%	289%	155%	238%	150%	418%	236%	150%	287%	155%	236%	146%	152%	149%	146%	160%	159%	149%

Appendix A.3: Rotated Component Matrix: Factor loadings

	PC1	PC2	PC3	PC4	PC5	PC6	PC7
ABCD123	0.391	0.743					
ABCD12	0.391	0.743					
ABCD13		0.748					
ABCD23	0.355	0.874					
ABCD1	0.672		0.353	0.601			
ABCD2	0.974						
ABCD3		0.933					
ABC123	0.695	0.410	0.366		0.418		
ABC12	0.895						
ABC13			0.938				
ABC23	0.692	0.453			0.423		
ABC1			0.902				
ABC2	0.981						
ABC3		0.438	0.890				
ABD123	0.386	0.745					
ABD12	0.756			0.504			
ABD13		0.748					
ABD23		0.880					
ABD1	0.671		0.351	0.604			
ABD2	0.974						
ABD3	0.050	0.933					
ACD123	0.413	0.711				0.357	
ACD12	0.759			0.489			
ACD13		0.717	0.369			0.356	
ACD23	0.368	0.851					
ACD1	0.674		0.366	0.593			
ACD2	0.974						
ACD3	0.056	0.930					
BCD123	0.390	0.742					
BCD12	0.757			0.502			
BCD13		0.746					
BCD23	0.354	0.874					
BCD1	0.671		0.354	0.602			
BCD2	0.974						
BCD3		0.932					
AB123	0.695	0.400	0.370		0.422		
AB12	0.695	0.400	0.370		0.422		
AB13			0.942				
AB23	0.692	0.445			0.426		
AB1			0.904				
AB2	0.981						
AB3		0.421	0.897				
AC123	0.695	0.407	0.373		0.413		
AC12	0.890						
AC13			0.938				
AC23	0.692	0.451			0.420		
AC1			0.902				
AC2	0.982						
AC3		0.438	0.891				
AD123	0.410	0.705				0.360	
AD12	0.760			0.497			
AD13		0.707	0.367			0.364	
AD23	0.361	0.855					
AD1	0.674		0.362	0.602			
AD2	0.974						
AD3		0.927					
BC123	0.694	0.409	0.371		0.416		
BC12	0.894						

BC13			0.937	
BC23	0.691	0.452		0.421
BC1			0.902	
BC2	0.981			
BC3		0.439	0.890	
BD123	0.385	0.744		
BD12	0.755			0.506
BD13		0.747		
BD23		0.879		
BD1	0.670		0.352	0.605
BD2	0.975			
BD3		0.932		
A123	0.700	0.390	0.377	0.413
A12	0.887			
A13			0.943	
A23	0.696	0.439		0.420
A1			0.903	
A2	0.982			
A3		0.417	0.900	
B123	0.694	0.399	0.377	0.419
B12	0.893			
B13			0.942	
B23	0.690	0.444		0.424
B1			0.905	
B2	0.981			
B3		0.420	0.898	
C123	0.692	0.400	0.384	0.412
C12		0.379		0.708
C13			0.937	
C23	0.690	0.444	0.355	0.422
C1	0.268		0.902	
C2	0.980			
C3		0.437	0.891	
D123	0.382	0.610		0.432
D12	0.729			0.535
D13		0.601	0.361	0.369
D23		0.742		-0.415
D1	0.642		0.625	
D2	0.934			
D3		0.790		-0.485

Figures lower than 0.4 in absolute value have been removed.

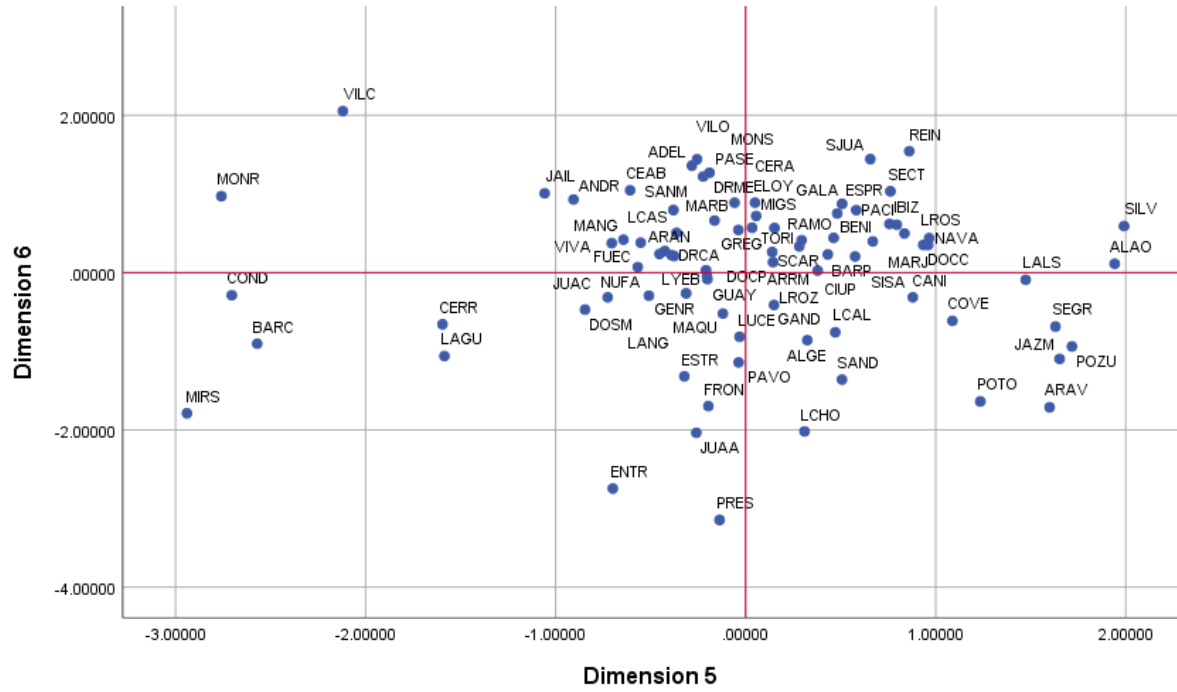
Appendix A.4: Rotated Component Matrix: Coordinates

	PC1	PC2	PC3	PC4	PC5	PC6	PC7
ADEL			1.138	0.945		1.360	-0.857
ALAO	1.717	-0.613	0.618	-0.980	1.942		0.692
ALGE			-1.366	-1.518		-0.860	-0.578
ANDR		0.893	2.452	1.208	-0.906	0.929	0.789
ARAN	-0.647		-0.894	0.743			0.613
ARAV	1.670	-1.366		1.967	1.599	-1.713	
ARRM	-0.978	-1.304	-0.639	0.950	0.144	0.132	
BARC	-1.081		1.517		-2.570	-0.904	
BARP	-0.787	-0.983	-1.056				
BENI		-2.108	2.619	-2.947	0.669		1.477
CANA	-0.467					0.662	
CANI			-0.568	-0.791	0.880		
CEAB		0.976	2.197	-0.604	-0.608	1.046	-1.891
CERR	-0.806	0.789	0.979	0.558	-1.595	-0.657	-0.961
CERA	1.467	-0.633	-0.709	-0.843		0.567	-0.856
CIUP		-0.977		0.602			0.766
COVE		0.989	-1.174	-0.679	1.088	-0.614	-1.131
COND	2.942	-1.255	-0.598		-2.704		
DARO	-0.742		-1.456	0.609			
DOCC	-0.579			-0.517	0.935		
DOCP			0.988	-0.559			0.652
DOSM	-0.940			0.651	-0.845	-0.471	0.524
DRCA	-0.761		-0.920				1.231
DRME			0.780			0.888	
ELOY		2.149		0.911		0.889	
ENTR	-0.750	0.580		-0.890		-2.746	
ESPR	0.845	0.844		1.096		0.874	1.561
ESTR		1.980				-1.319	
FRON		1.112				-1.699	
FUEC	-0.507		1.036		-0.552		
GALA	0.977	1.731	-0.682			0.752	
GAND		0.694	-0.469			-0.412	0.521
GENR			-1.405				1.229
GOYA			-1.568	0.917			1.617
GREG	-0.394		0.283			0.542	
GUAY	-0.654		-0.855				1.291
IBIZ	0.492				0.756	0.619	0.842
INFA	0.774	2.039			0.795	0.608	
JAIL	-0.863	-1.723	2.080	-1.813	-1.058	1.008	-0.690
JAZM	1.307	-0.766	1.728	2.267	1.652	-1.097	
JUAA	-0.506	0.912		-0.476		-2.037	
JUAC	-0.705	0.540		0.505	-0.726		
LCHO		1.486		-0.894		-2.020	
LAGU	-1.260		0.524		-1.585	-1.062	
LCAL		1.451	0.576	-0.797		-0.759	
LROZ	1.727	-0.700	-0.672				

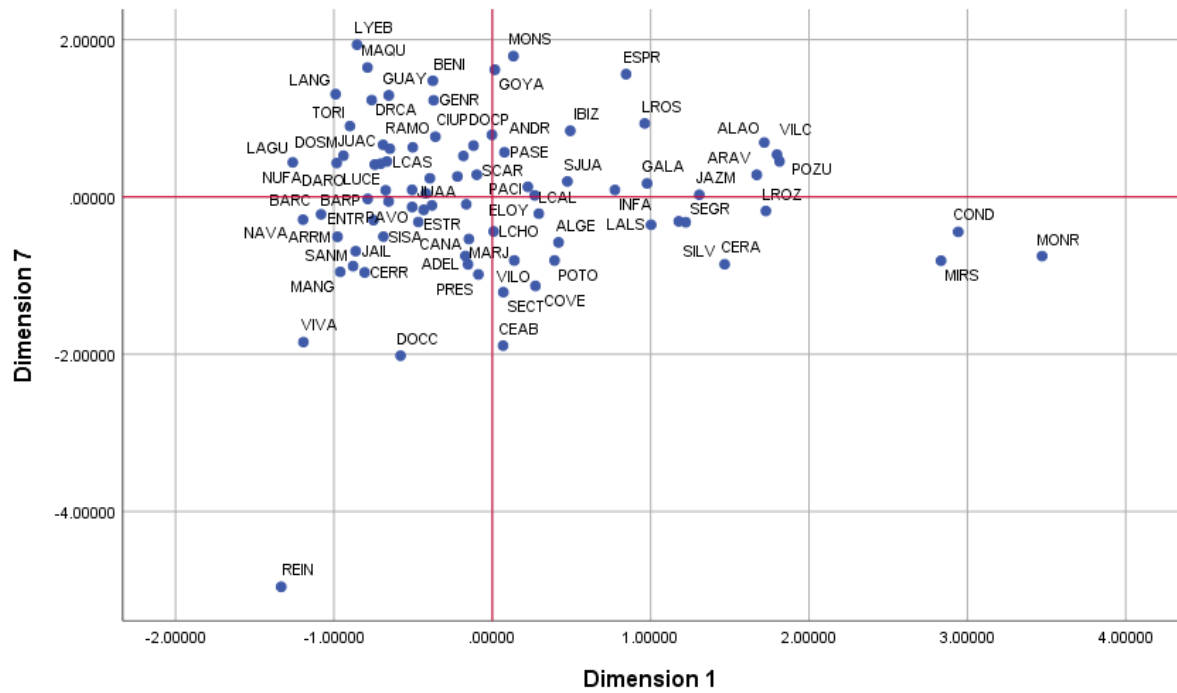
LALS	1.003	1.098	-0.558	-1.176	1.473		
LANG	-0.989	-0.508			-0.509	1.307	
LCAS	-0.666			0.795		0.507	0.451
LROS	0.963	0.586		-1.243	0.835		0.934
LYEB	-0.854	-0.851	-0.656				1.935
LUCE	-0.673		-0.843			-0.816	
MANG	-0.960	-0.805	0.621		-0.643		-0.953
MAQU	-0.788			-0.647			1.646
MARB		-1.065	-1.535	-0.620		0.570	0.630
MARJ		-0.569	-0.575		0.960		-0.750
MIGS	-0.433	0.359				0.720	
MIRS	2.833	-2.114		1.743	-2.940	-1.789	-0.811
MONR	3.472			-1.997	-2.759	0.971	-0.752
MONS		1.473	1.554	1.010		1.270	1.790
NAVA	-1.195	-0.942	-1.658		0.965		
NUFA	-0.982		-1.148	0.862	-0.568		
PACI				1.091	0.582	0.795	
PASE		0.827	-1.256	0.682		1.221	0.568
PAVO	-0.655		-0.747				-1.142
POTO		-2.140	0.981	2.116	1.235	-1.638	-0.807
POZU	1.798	-1.085		0.579	1.717	-0.939	
PRES		1.770	0.684	-1.110		-3.145	-0.985
RAMO	-0.690	-1.697	0.954	-1.595			0.662
REIN	-1.333		-1.898	1.282	0.861	1.544	-4.957
SAND				-1.193	0.507	-1.360	
SCAR		0.768	-1.161				
SJUA		0.823	0.896	0.545	0.656	1.443	
SANM	-0.879	-1.491	1.207	-1.470		0.796	-0.879
SISA	-0.688	-0.774	-0.511		0.576		-0.504
SECT				-0.140	0.762	1.034	-1.212
SEGR	1.222	-0.731	1.669	1.715	1.630	-0.687	
SILV	1.177			-1.502	1.991	0.592	
TORI	-0.899	-1.324		-0.673			0.901
VIVA	-1.193	-0.740			-0.705		-1.846
VILC	1.814	0.931	-1.357	-0.914	-2.120	2.054	
VILO		1.219	1.037	2.431		1.441	-0.808

Figures lower than 0.6 in absolute value have been removed (except for few cases with low values overall)

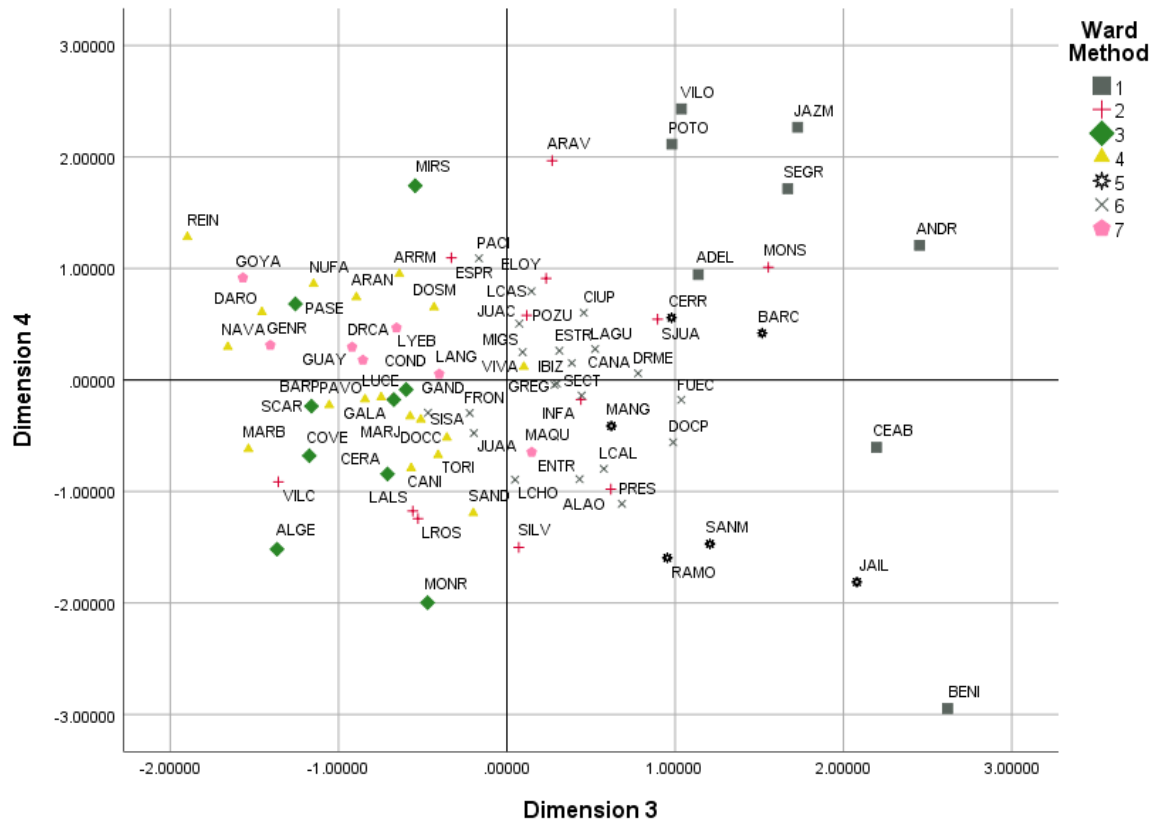
Appendix A.5:



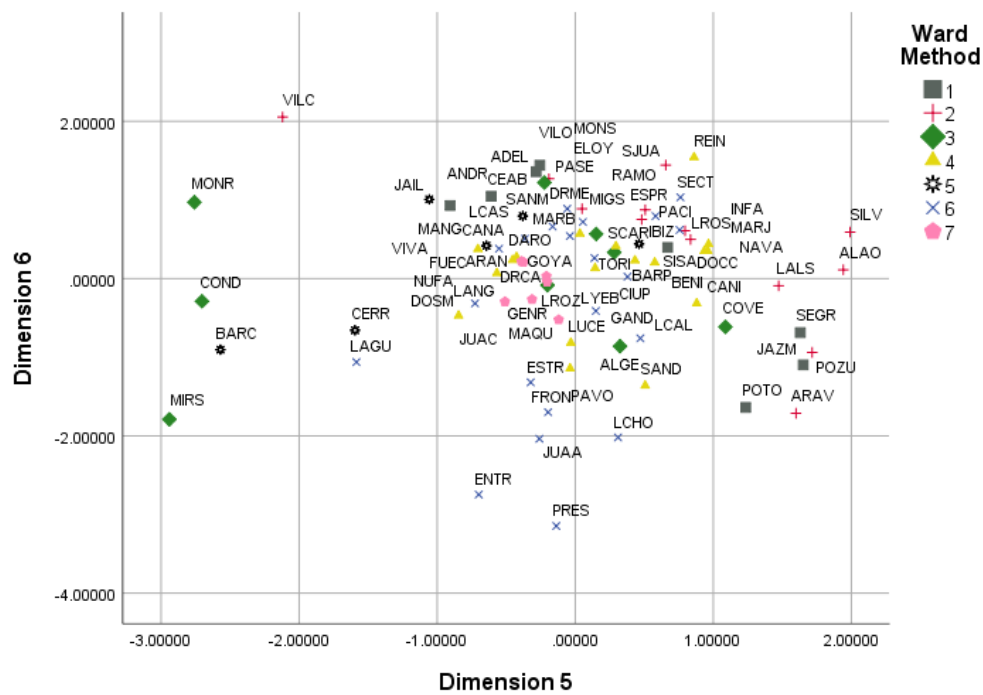
Appendix A.6:



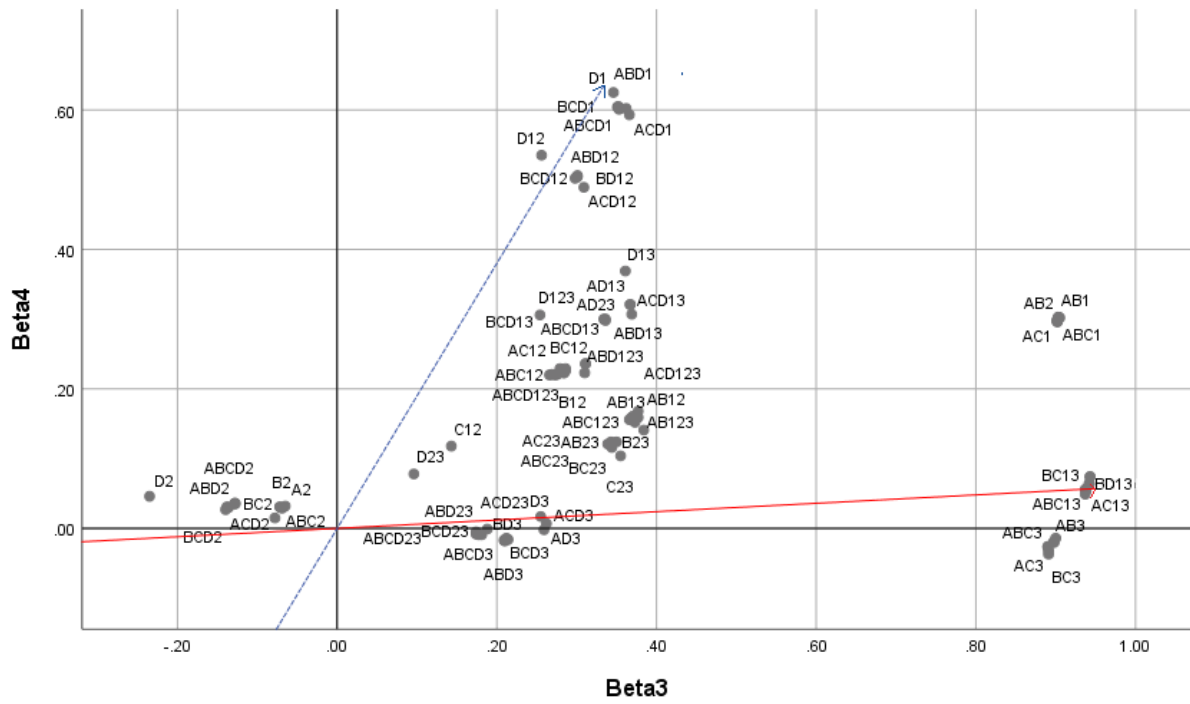
Appendix A.7: Common Map. Cluster Analysis (Factors 3 and 4)



Appendix A.8: Common Map. Cluster Analysis (Factors 5 and 6)



Appendix A.9: ProFit for Dimensions 3 and 4.



Appendix A.10: ProFit for Dimensions 5 and 6.

