JOURNAL OF DESIGN FOR RESILIENCE
IN ARCHITECTURE & PLANNING

Research Article
Online: www.drarch.org
Volume 2, Special Issue, (89-114), 2021
DOI: 10.47818/DRArch.2021.v2si037

Linking space syntax and cluster analysis to design and plan temporary housing neighborhoods: A taxonomy of sites in Norcia

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Abstract

Building Back Better in disaster recovery and reconstruction requires the adoption of integrated and context-sensitive approaches to the design and planning of Temporary Housing (TH) sites. However, there is a lack of methods for enabling successful outcomes in housing assistance provision, e.g. via a quantitative evaluation of the social-spatial qualities of the sites, and supporting the negotiation of urban design changes and the development of a coherent end-of-life plan. The paper aims to uncover formal analogies between different TH sites' layouts by linking Space Syntax and Clustering analysis within an unsupervised machine-learning pipeline, which can consider a virtually unlimited number of configurational qualities and how they vary across different scales. The potential benefits of the proposal are illustrated through its application to the study of 20 TH sites built in Norcia after the 2016-2017 Central Italy earthquakes. The results indicate the proposal enables distinguishing different types of spatial arrangements according to local strategic priorities and suggest the opportunity to extend the study in the future to set up rules of thumb for the design of site layout options. The paper ultimately aims to equip local administrations and contracted professionals with a much-needed tool to develop and rapidly audit proposals for temporary neighbourhoods oriented at enhancing the resilience of disaster-affected towns both in the medium and in the long term.

Keywords: temporary housing, space syntax, cluster analysis, neighbourhood design, disaster recovery

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Article history: Received 08 December 2021, Accepted 21 December 2021, Published 31 December 2021
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1. Introduction

During the last decades, the incidence of disasters that stem from natural hazards has increased considerably (EM-DAT [no date]), threatening the housing security of the many people currently living in areas suffering from inherent socioeconomic and spatial vulnerabilities. Following disasters, damage to housing accounts for 40% to 90% of all damage to private properties, showing an increase at a global level from 1990 onwards (Wahba et al. 2018). Experts therefore advocate a closer integration of urban contingencies in urban planning (Borsekova and Nijkamp 2019) and agree on the need to advance Disaster Risk Reduction (DRR) policies and practices, including via Building Back Better (BBB) in disaster recovery and reconstruction (Kennedy et al. 2008).

A growing awareness of the scale of the problem and increasing concern about "humanitarian aftershocks" increasing pre-existing vulnerabilities (Alexander 1989; Davis and Alexander 2015; Contreras et al. 2017) have recently pushed forward research in the area of post-disaster housing assistance, whose volume of publications is rapidly expanding in multiple directions (Yi and Yang 2014). In particular, operational research studies have focused on developing Decision Support Systems for selecting the location of the TH sites (El-Anwar and Chen 2013; Hosseini et al. 2018) or the design of the TH units (Hosseini et al. 2016), often relying on multi-criteria optimisation methods (El-Anwar et al. 2010; El-Anwar and Chen 2014; Rakes et al. 2014; Perrucci and Baroud 2018). However, research on analytical methods supporting the spatial design of socially adequate temporary housing (TH) neighborhoods which add to the resilience of disaster-affected settlements, and enabling the assessment of different site layouts, is still in its infancy.

In practice, the problem of designing temporary neighborhoods is addressed mainly in qualitative terms. Within the Italian context, which represents the background of the empirical research presented in this paper, spatial layouts of TH are broadly distinguished among three archetypical arrangements, namely detached houses, courtyard or terraced housing arrangements (Figure 1), including possible hybrid solutions, with no clear indication of social and spatial performance requirements (CONSIP & NDCP 2014). Strategic and managerial guidelines for the design and planning of TH, published after the 2016-2017 Central Italy earthquakes (i.e., the lastest major earthquake disaster in Italy to date), contain only generic inputs for designing their spatial layouts. In a nutshell, they recommend that TH sites are built as close as possible to the disaster-affected areas, compact and equipped with all the necessary services and infrastructure, including connections to the permanent road network (NDCP 2016; Presidenza del Consiglio dei Ministri 2017). However these requirements (as well as the permanent nature of the reinforced concrete foundations used in Central Italy) imply a change of land use which contradicts the character of impermanence of TH plans. Furthermore, the lack of clarity and guidance regarding the design of temporary neighborhoods has in the recent past fuelled conflicts between local stakeholders and external decision-makers, e.g., over the implementation of detached TH arrangement (Oggioni et al. 2019).

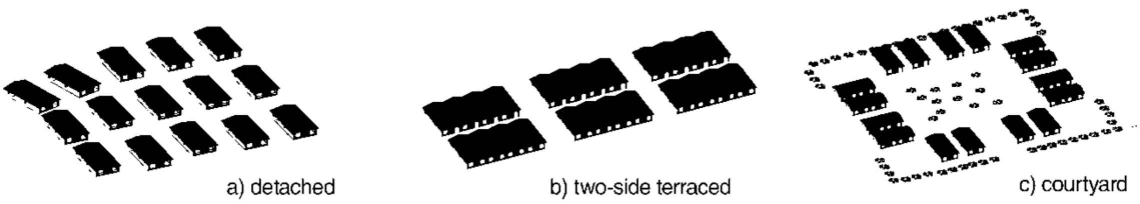

Figure 1 TH sites' typologies. Image adapted from (CONSIP & NDCP 2014).

Albeit overlooked in current technical specifications, TH layouts are important determinant of the success of TH assistance interventions. On the one hand, they influence the street network patters, contributing to the accessibility of TH sites. On the other hand, they determine different opportunities for human-to-human face-to-face interaction (or avoidance). Additionally, since TH neighborhoods can hardly be considered temporary, they should be designed and planned in a way that is consistent with the configurational qualities of local social-spatial patterns to ensure their long-term social, cultural, economic and environmental (in terms of resources' consumption) sustainability. This appears crucial when intervening on "inner" mountainous, and thus fragile, territories subjected to shrinking (Rotondo et al. 2020).

This paper seeks to move steps towards the evidence-based management of disaster-stricken cities by contributing to the construction of a broader Computation Planning Support System (CPSS), which adopts an integrated and context-sensitive approach to the design and planning of Temporary Housing (TH) sites. To this end it proposes a method designed to find natural groupings among hybrid layout arrangements - which defy the typological description of the three pure archetypical TH sites' arrangements (i.e., detached, terraced, courtyard) - without a priori expectations regarding the result. In this sense its application is exploratory in nature and exploits the explanatory power of different unsupervised machine learning methods to yield useful insights. The objective is to visualise relationships in multidimensional datasets, besides creating opportunities to create higher-level attributes from existing ones, to be used to establish urban design targets and inform design moves.

This paper links Space Syntax and Cluster analysis to enable the statistical learning of configurational patterns relevant to the design and planning of TH neighbourhoods. Both official and open data are used to feed different configurational analysis models, whose outputs are then aggregated and further analysed via machine learning using three different algorithms. The proposal and its potential benefits are illustrated through its application to the study of 20 TH sites built in Norcia after the 2016-2017 Central Italy earthquakes. The paper is organised as follows. The theoretical background is presented in Section 2. Section 3 explains the methodology and results are then illustrated in Section 4. The discussion and conclusions can be found in Sections 5 and 6, respectively.

2. Exploring Spatial Patterns of TH Layouts

Following a visual tradition inaugurated by the 1748 map of Rome by Giambattista Nolli, morphological differences in patterns of urbanisation can be qualitatively observed using figure-ground maps, see for instance the TH sites of Norcia in Figure 2. The image shows that most of the neighbourhood designs for Norcia's TH sites are variations of simple terraced arrangements, sometimes interrupted by small pockets. The maps enable making some simple observations based on the coarseness, griddedness, and permeability of their spatial layouts and can help convey complicated spatial concepts (e.g., about the different spatial order of planned and organically grown settlements) to different publics (Boeing 2019a). However, these representations cannot offer a quantitative indication of how spatial qualities vary within TH neighbourhoods and how these are related at a broader scale, determining hierarchies in movement and accessibility patterns in cities. To grasp more complex and subtle functional relationships, we need robust spatial analysis methods grounded in theory and the support of machine learning to deal with multidimensionality.

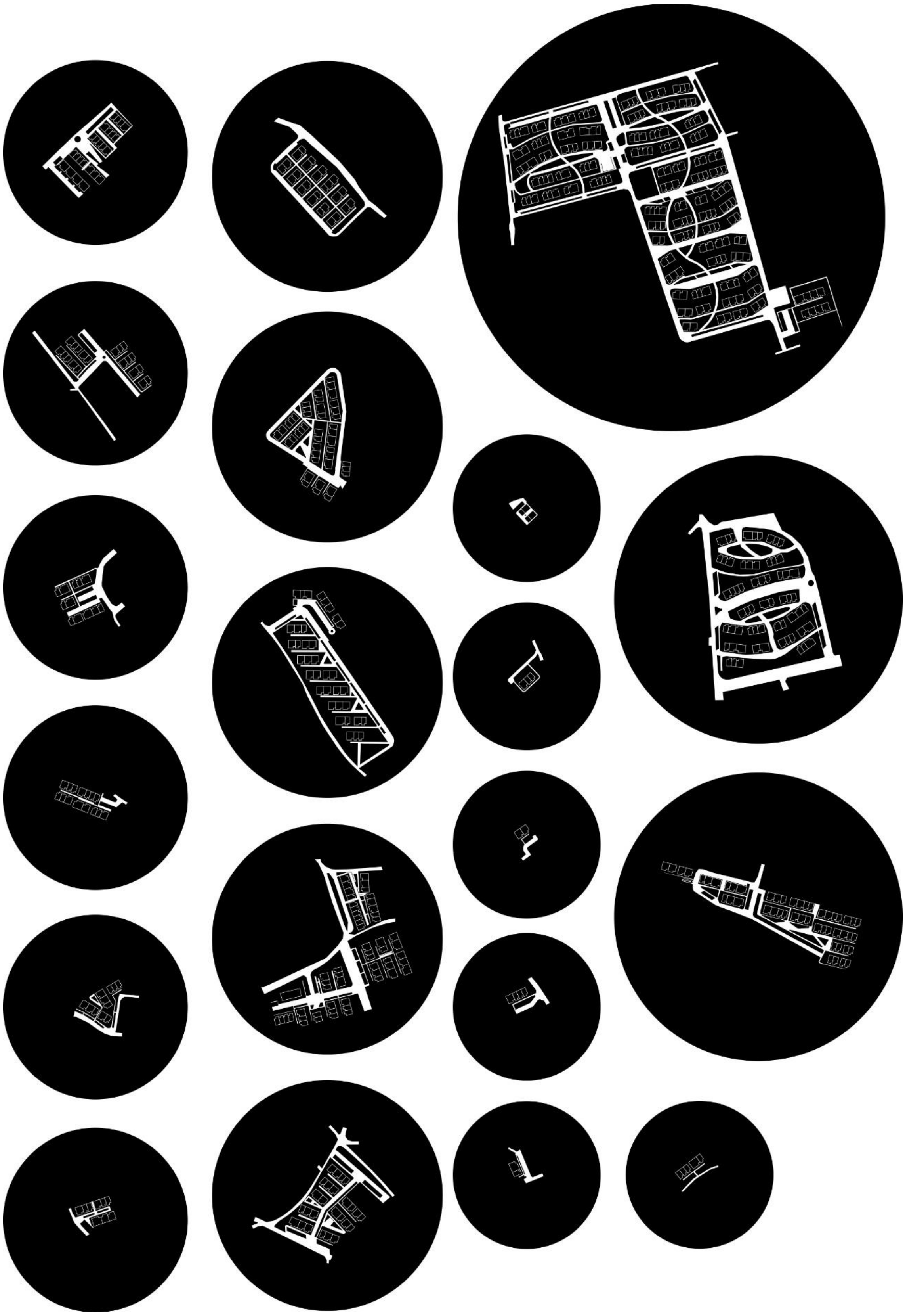

Figure 2 Norcia 20 TH sites layouts. The space considered in the spatial permeability analysis is represented in white.

This research adopts the configurational analysis approach (Hillier and Hanson 1984) and statistical learning (Hastie et al. 2009) to study the spatial permeability patterns of built examples of TH sites layouts. This approach is essentially grounded in two main conceptual pillars. On one hand, the assumption of a configurational point of view involves focusing on the relationships of the spatial elements rather than on their intrinsic geometric or morphologic features: "human space is not just about the properties of individual spaces, but about the inter-relations between the many spaces that make up the spatial layout of a building or a city" (Hillier, 2005, p. 98). On the other hand, the assumption of a city as a socio-spatial system, in which the blocks and buildings shape the space of interaction between activities and individual behaviour, and the intrinsic integration and complementarity of spatial properties and social aspects are what makes the configurational parameters resulting from the analysis of an urban settlement suitable for reproducing its potential to match both the expected positional values of the places and the behavioural patterns of the located community. As Hillier put it, we should think of space "not as the background to human activity, but as an intrinsic aspect of everything humans do" (Hillier 2005, p.98).

When referred, as in this case, to temporary housing, two fundamental issues are therefore concretely to be explored: the first, more obvious and usually considered, concerns the spatial relationships of the TH settlement with respect to the pre-existing city, so as to reproduce the positional values of the settlement and the hierarchical relationships in terms of connection, integration and segregation; the second is subtler and less explored, as it refers to the intrinsic configurational properties of the TH settlement, to the spatial organization of its internal geography and to the behavioural pattern it prefigures. Precisely, to this end, the Space Syntax approach combines multiple configurational indicators suitable to statistically appreciate the degree of similarity of different TH layouts, considering how well these reproduce the original qualities of the disaster-affected town. In other words, the proposal focuses on the multidimensional learning of configurational qualities that contribute to define the spatial identity of different temporary neighbourhoods built after disasters.

The rationale behind this proposal is that statistical algorithms using weak clues can effectively inform TH-related decisions because most post-disaster decision-making situations tend to be noisy, if not wicked (i.e. teaching experts the wrong lessons), (Hogarth et al. 2015). This means that experts' intuitions are likely to be unreliable in this context since the environment is not regular enough to be predictable and regularities cannot be learned through prolonged practice (Kahneman 2011).

3. Materials and Methods

This research is the natural continuation of a set of previous investigations (Pezzica et al. 2020; Chioni et al. 2021; Pezzica et al. 2021), which illustrated the potential of adopting Space Syntax analysis to generate scenarios useful to assess the socio-spatial impact of TH sites. At a methodological level, this research is connected to the latter of these, focused on the urban scale, in which Space Syntax and Cluster analysis were used to analyse hidden trade-offs between properties of street network resilience and efficiency following to the construction of TH sites (Pezzica et al. 2021). Moving the focus to the neighbourhood scale, this research illustrates how a similar method can be used to classify in an unsupervised way different TH layouts based on a given set of configurational qualities, which contribute to determine their socio-spatial performance at different scales.

The 20 TH sites built in Norcia after the 2016-2017 Central Italy earthquakes were chosen as the testbed for the analysis because they present a suitable variety of sizes, morphologies and locations in the municipal street network, and Norcia hosts the highest number of TH units (639, as of 2019) as well as more TH sites than most municipalities in the Central Italy seismic crater. This study considers the spatial permeability of TH sites as well as their relationship with the "destroyed" city (Ruggiero 2018), whose transition post-disaster is affected by the construction of the TH sites. Although a specific selection of configurational indices is used to this end in this study, the method supports the choice of a virtually unlimited number of different combinations as required by different practical applications.

As shown in Figure 3, this study is performed in three steps:

- Space syntax analysis (ASA + VGA) as described in Section 3.1.
- Calculation of summative configurational metrics, where required.
- Cluster analysis (HC, K-means and FCM) as described in Section 3.2.

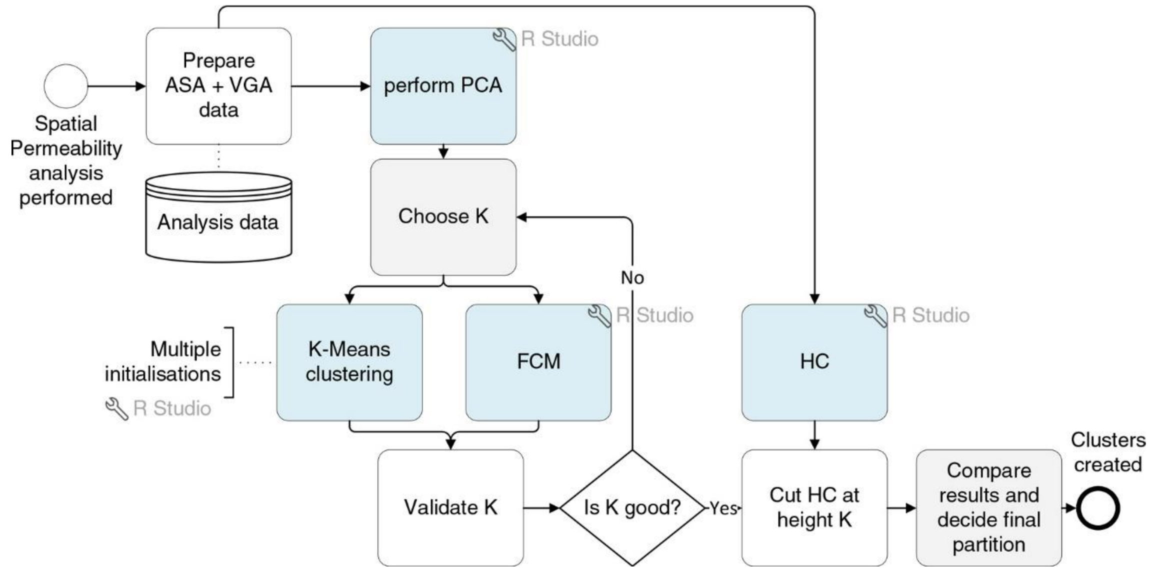

Figure 3 Cluster analysis methodology, including HC, K-Means and FCM.

3.1. Space Syntax analysis

To prepare the data for the Cluster analysis, first, a Space Syntax Visual Graph Analysis (VGA), (Turner et al. 2001), and an Angular Segment Analysis (ASA), (Turner 2007), are performed to extract the configurational indices which describe the levels of global and local accessibility of the TH sites as well as the morphologic characteristics of the TH sites' layouts, including their visual complexity, convexity, control, connectivity etc. In the end a 28-dimensional description of each TH site layout (Annex A) is obtained by calculating the median (i.e., the middle value of the value distribution taken in sorted order) and the Gini coefficients (Gini 1910), of all chosen configurational indices. This enriches their description as shown in the Principal Component Analysis (PCA) plot in Figure 4, which helps exploring data visually through a low-dimensional representation which captures the directions in which it has maximal variance (James et al. 2013). After joining all summative metric in one table, these were then scaled (using a data standardisation method known as Z-score normalisation) and used as inputs to the Cluster analysis.

In this paper, the ASA outputs were extracted from Norcia's street network analysis by clipping the map with the boundary polygons of all the TH sites in a GIS environment. Next, each segment within the boundary was assigned an attribute with the name of the corresponding TH neighbourhood. This allowed grouping the data by site (in R Studio, RStudio Team 2015) and calculating for each settlement the corresponding summative metrics. When a mean value should normally be considered (e.g., street segment length, connectivity), for consistency, the median of the distribution was calculated instead.

The VGA was performed separately for each layout (using a 1m grid), so results could be compressed immediately for each site and then joined with those from the ASA within R studio. Coherently with a view of TH sites as integral parts of a recovering town, this exploration focuses on the experience of a generic visitor moving around a TH settlement. Therefore, in addition to the footprints of the TH units, their immediate premises (which in Central Italy have been often protected by a fence by their inhabitants), the green areas, and the parking lots, were excluded from the VGA analysis. These features create an urban design interface at the neighbourhood scale, which effectively defines user groups and generates patterns of encounter or avoidance among residents, and between them and external visitors. Hence, albeit their consideration could represent an interesting starting point for future studies, this analysis falls out of the scope of this investigation.

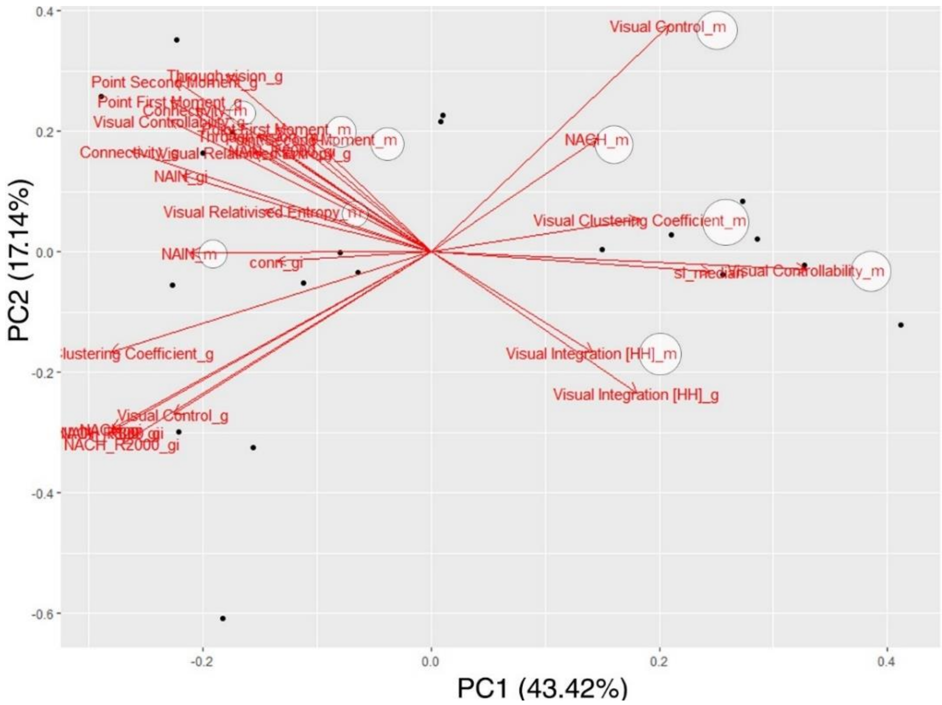

Figure 4 PCA (before K-means analysis), Median (suffix _m) and Gini coefficient (suffix_g).

3.2. Cluster analysis

Cluster analysis has been studied since the 1960s and clustering algorithms are numerous. They can be either hierarchical, which divide the pattern in an iterative way, or based on partitioning, which assign data to a number (K) of clusters using an optimisation function (Saxena et al. 2017). As illustrated in Figure 3, this study adopts and cross-compares results from three clustering algorithms: (i) Hierarchical Clustering (HC); (ii) K-means clustering; and the more sophisticated Fuzzy C-Means (FCM) clustering method (also known as soft K-means).

HC is an agglomerative clustering method which creates a hierarchical structure that can be cut at a certain height after the analysis, following a bottom-up process which starts from assigning a cluster to each datapoint. Starting from the bottom and moving up in the hierarchy, these are recursively paired at each level, by selecting the smallest intergroup dissimilarity. Starting from n elements, the algorithm will always define $n-1$ levels, each representing a specific grouping of the datapoints into disjoint clusters of observations (Hastie et al. 2009). HC plots show these groupings in an ordered sequence, but their interpretation is left to the urban analyst, who must decide which level (if any) represents an ideal cut of the output rooted binary tree, also known as dendrogram. This algorithm has been used in urban analysis research studies (Crucitti et al. 2006; Louf and Barthelemy 2014; Boeing 2019b) to synchronously compare different urban street networks. Here, the HC dendrogram is used to visualise the taxonomic relationships between different layouts of TH sites in Norcia.

Differently from HC, K-means (Pakhira 2014) and FCM are partitioning methods, which provide different outputs according to the choice made for (K). First described by (MacQueen 1967), K-means clustering is a simple and widely known iterative descent algorithm, which assigns each datapoint to one unique cluster. It works with quantitative data and uses the squared Euclidean distance as a dissimilarity measure for the grouping. The process converges to a solution rapidly, without the need of sophisticated termination criteria (Kubat 2017). The fuzzy K-means clustering version first developed by (Dunn 1973), assigns to each data point a membership coefficient (

Table1), which indicates the level of fit of each datapoint with each cluster. Therefore, FCM makes probabilistic rather than deterministic assignment of TH layouts to cluster centres and coincides with K-Means if membership coefficients become 0 and 1. In fuzzy methods, if a preferential assignment cannot be made, the same datapoint can have membership in more than one cluster; what makes FCM less prone to create uninteresting locally optimal data partitions. As in the case of HC, K-means and FCM require an appropriate attribute scaling as part of the data preparation to prevent distorting the measured distances between attribute vectors. Moreover, when deploying K-means and FCM methods, attention should be paid to the initialisation of the partition.

Importantly, in both K-Means and FCM, K (i.e., the number of clusters) needs to be inputted. Since in this application the goal of the Cluster analysis goal is to provide a descriptive statistic for gauging to which extent the analysed TH sites fall into natural distinct groupings, K is initially unknown and needs to be estimated from the data. Therefore, a statistical validation step is added to both (not to the HC as this does not affect the clustering result). This is essentially an assessment of how good a partition is based on the calculation of one or more internal validity indices among the many proposed in the scientific literature. The evaluation involves assessing the quality of clusters as well as their optimal number. To this end, for the K-means it is used the NbClust package for R (Charrad et al. 2014), which makes readily available and directly comparable several indices by using a single function call. Specifically, this study used the silhouette (Kaufman and Rousseeuw 1990) and gap statistic (Tibshirani et al. 2001) methods. Additionally, since most of these indices work with hard memberships and cannot be used for fuzzy clustering applications within R, the results of FCM are evaluated using an additional four internal validity indices, which are available in the "fclust" package for R by (Ferraro and Giordani 2015). These are the: Fuzzy Silhouette Index (F.Sil., the higher the better); Modified Partition Coefficient (MPC, the higher the better in a scale from 0 to 1); Partition Coefficient (PC, the higher the better); and Partition Entropy (PE, the lower the better).

After running the K-means and FCM algorithms for K= 2, 3, 4, 5, 6 and 7 it was clear that the best partition from a statistical standpoint could be found for K=2 (as shown in the Silhouette plot in the bottom-right corner of Figure 5). However, the results for K=3 are presented in this paper as these are more interesting to discuss, obtained acceptable clustering validation results and, in all cases, are consistent with the K=2 partition although, in general, when the cluster membership changes, K-means and FCM groupings can change in arbitrary ways (Hastie et al. 2009). This behaviour differs from that of HC, which naturally retains all the information about higher- and lower- level associations. Finally, once the value of K was decided, the HC, K-means and FCM clustering methods were used on the same dataset to identify a final clustering result, robust to algorithm and metrics' variations. In case of ambiguity a layout was assigned to the cluster receiving more "votes" and considering the membership values suggested by the FCM.

In this paper, the level of inter-cluster separation is measured using the complete linkage method, which determines the similarity of two groups by calculating the maximum (Euclidean) distance between any element of one cluster to any element of the other. The use of the Euclidean distance for this calculation, is what requires performing the data rescaling step before the analysis, to re-centre the values of the summative metrics (mean 0) to prevent metrics with higher weights from skewing the Cluster analysis results.

4. Results

This section is divided in two parts: the first (Section 4.1) presents the results of the analysis considering the TH sites layouts in isolation from the rest; the second (Section 4.2) links the results of the analysis to the planning regulations of Norcia and to the morphology of the destroyed city.

4.1. Taxonomy of TH sites in Norcia

As shown in Figures 5-7, which illustrate the results obtained from the K-means, FCM and HC analysis respectively, the three clustering algorithms assigned 18/20 TH sites unanimously to either Clusters 1, 2 or 3. Only in two cases, namely the TH sites of Montedoro and Valcaldara, one of the three methods assigned the layout to Cluster 1 instead of 3, or vice versa. The indecision regarding the assignments of these two TH sites to one or the other cluster is reflected in the FCM probabilistic values since their relative memberships to clusters 1 and 3 appear somehow comparable (Table 1). This could have been expected if we consider that Clusters 1 and 3 are close one to another whereas Cluster 2 appears more clearly separated from them. Indeed, as mirrored in Figure 7, for K=2 the analysis groups together Clusters 3 and 1. Hence, instead of than “clustering”, we could use the term “segmentation” to describe more accurately the intra-cluster division obtained for K=3, albeit the former is used in the text for matters of simplicity. As described in Section 3.2, in the end, the assignment of these two TH sites was decided based on the clustering result obtained from two out of three algorithms. The final grouping rsults are shown in Figures 8 and 9.

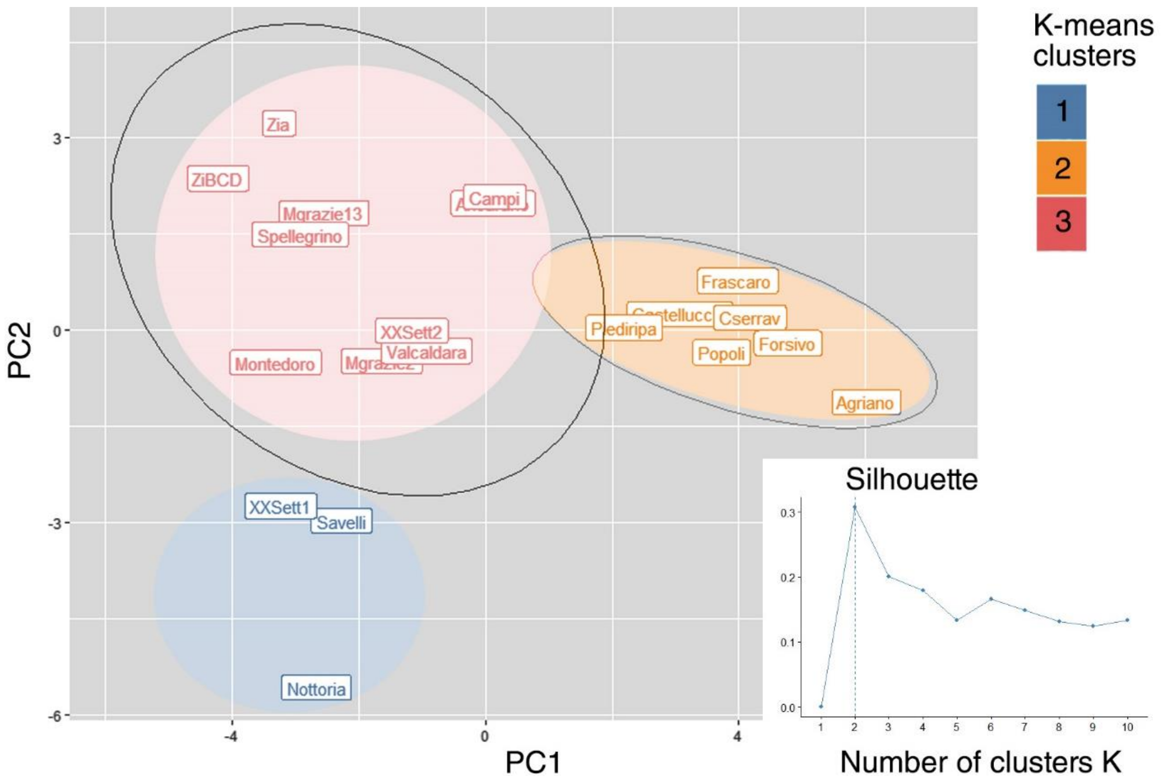

Figure 5 K-means analysis (K=3). In the corner the plot used to evaluate the choice of K

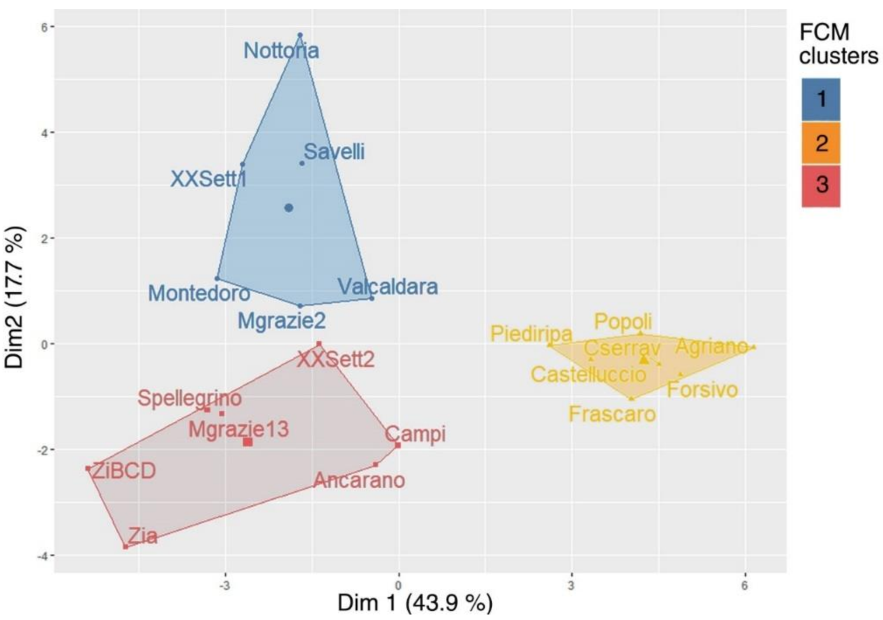

Figure 6 FCM (K=3)

Table 1 FCM membership coefficients.

	Cluster 1	Cluster 2	Cluster 3
Agriano	0.218573678319838	0.55314515823891	0.228281163441252
Ancarano	0.290312974173666	0.250939380359542	0.458747645466792
Campi	0.267222331532113	0.234272813177824	0.498504855290064
Castelluccio	0.214812140020607	0.543453960753009	0.241733899226384
Cserrav	0.102787683096174	0.783658313816487	0.113554003087338
Forsivo	0.206411131219699	0.570784809862456	0.222804058917845
Frascaro	0.193035013107517	0.59484784626083	0.212117140631653
Mgrazie13	0.339549669205141	0.121906827244888	0.538543503549971
Mgrazie2	0.480577868235047	0.110119566044045	0.409302565720907
Montedoro	**0.590493257268913**	0.0620264623751992	**0.347480280355888**
Nottoria	0.519033887686083	0.182414841433934	0.298551270879983
Piediripa	0.20125276942297	0.570414702915743	0.228332527661287
Popoli	0.144371026392816	0.702315273864646	0.153313699742538
Savelli	0.616280742367203	0.113795539817464	0.269923717815333
Spellegrino	0.334875457103565	0.0807471287339077	0.584377414162527
Valcaldara	**0.42823958287465**	0.144243916442863	**0.427516500682486**
XXSett1	0.621475308185735	0.0992853821318792	0.279239309682386
XXSett2	0.424598063725587	0.0667541268707096	0.508647809403703
Zia	0.340328977324271	0.154777096175658	0.504893926500072
ZiBCD	0.366799454594893	0.110467810280798	0.522732735124309

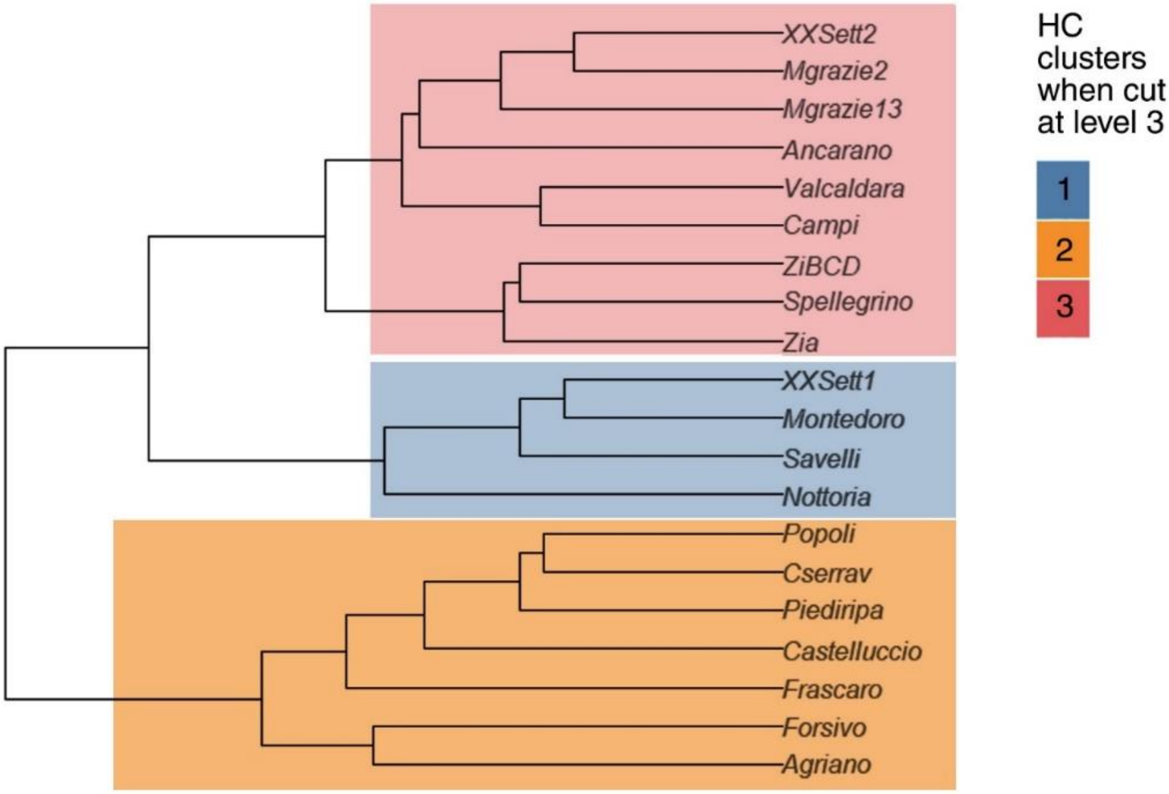

Figure 7 HC-derived dendrogram. The colours show the result when the tree is cut at K=3.

At a first glance at Figure 9, it may appear that TH layouts have been grouped according to the relative dimension of the sites. However, through a more careful observation, it is possible to notice that this correspondence is not always there. For instance, Frascaro is assigned to Cluster 2 although it is medium-sized. Nottoria is assigned to Cluster 1, and Valcaldara is assigned to Cluster 3, albeit both are small. Thus, although the size certainly constrains the spatial arrangement possibilities, the outcome indicates that the division is based on more subtle characteristics. To facilitate the interpretation of these results, the clusters were also represented using the same three colours within a ®Tableau sharable and interactive dashboard, of which Figure 8 is a print screen. In Figure 8, the dimension of the circles representing the clusters is set to be directly proportional to the number of TH units in each settlement. Moreover, geolocating the clusters enables displaying their relative distance to Norcia city centre, as well as the topography of the area in which they are built. The image shows that neither distance nor dimensions can fully explain the logic of the partition, which seems a good indication of the goodness of the approach and of the potential usefulness of the proposed method for the multidimensional analysis of complex spatial patterns.

Thus, an alternative reading of results is proposed, which, coherently with the analysed data, is more focused on the morphology of the temporary neighbourhoods. Figure 9 shows that the TH sites in Cluster 3 have more complex layouts, with gradual angular changes, loops, varying TH units' orientations, and hierarchical width of paths, including some outstanding larger open spaces. Although the TH units are arranged in rows, they have some hybrid qualities which resemble those of courtyard arrangements and seem to offer a more sophisticated spatial permeability interface. Albeit qualitatively close to those in Cluster 3, the sites belonging to Cluster 1 present harsh 90 degrees turns and lack variations in the way their TH units are arranged. When present, open spaces are concentrated at the centre and present a compact boundary. Finally, Cluster 2 includes quite simple layout arrangements, which can be reduced a few convex elements with an elongated shape.

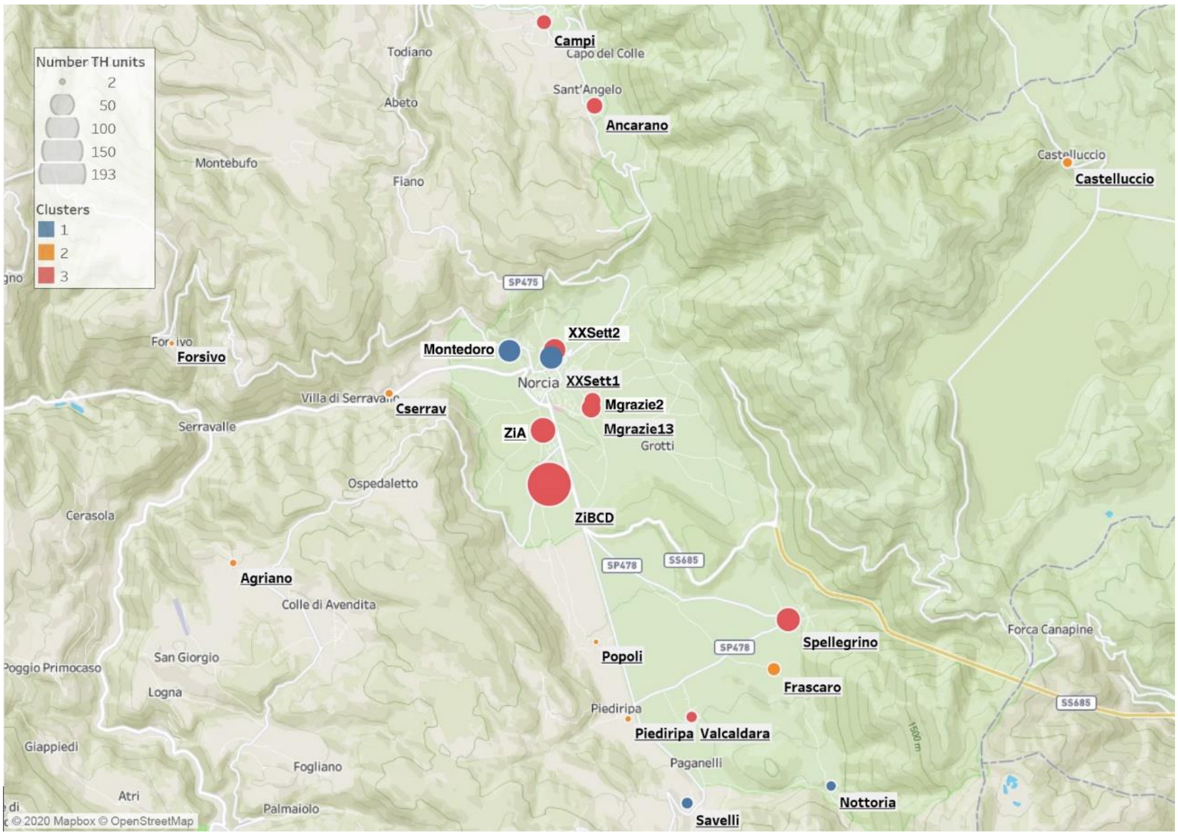

Figure 8 Final clustering result of Norcia TH sites transferred on a ®Tableau dashboard.

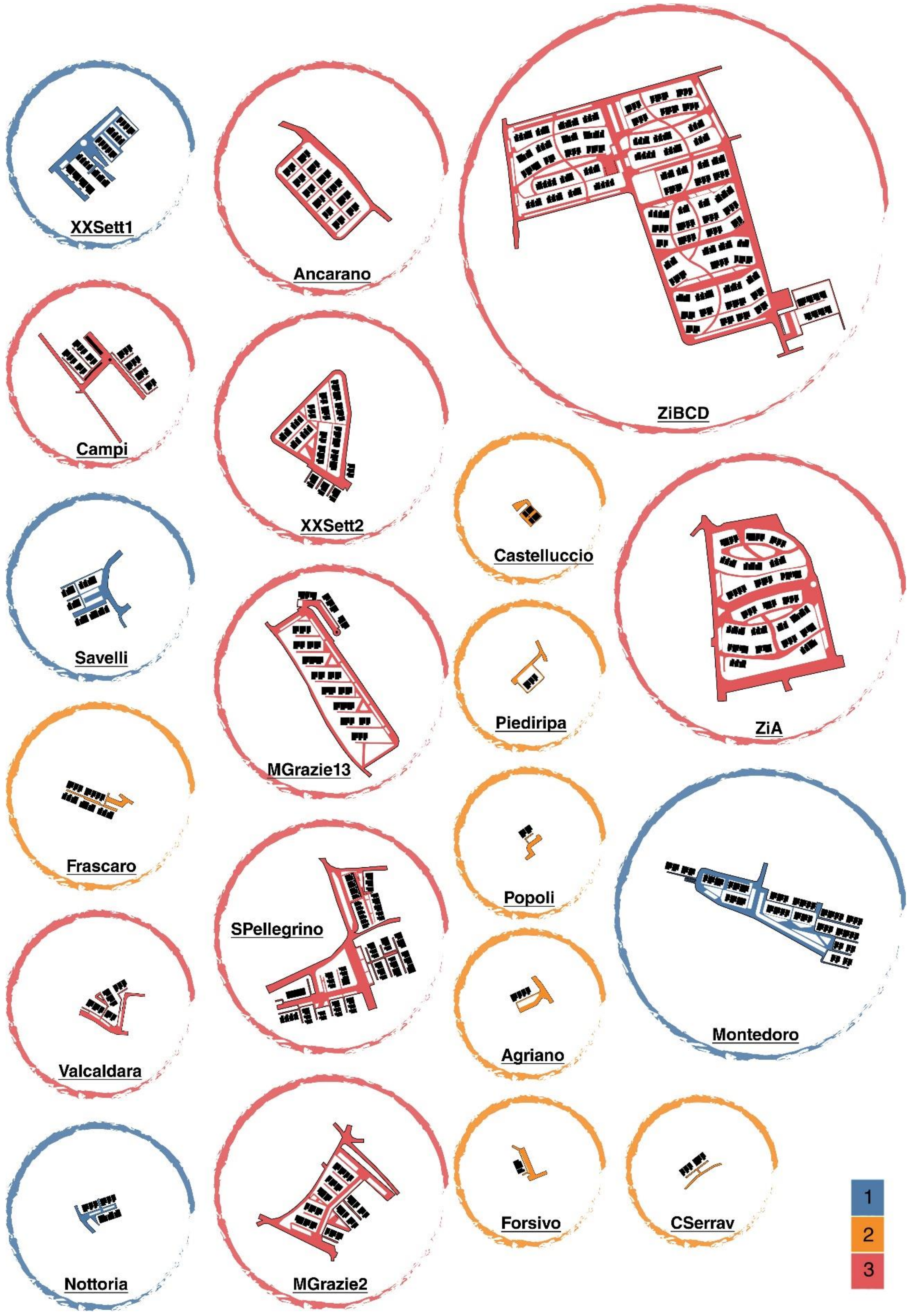

Figure 9 Norcia TH sites layouts summative clustering result K=3.

Finer grain differences, such as those between Castelluccio, Piediripa and Agriano (which present one looping spatial element) and the remaining sites of Cluster 2, can be appreciated only for bigger values of K (see for instance Figure 10, in the right corner). At this level of segmentation, it is possible to observe a difference between Montedoro and the other TH sites in Cluster 1. In fact, the FCM groups it together with TH sites belonging to cluster 3 at K=3, which here is further divided in three subgroups. However, the clustering validation indices indicate that these intra-cluster differences are less relevant than at level 3, and thus possibly not worth considering. In fact, F.Sil. at K=7 evaluates at 0.20 (down from 0.42 at K=3), PE results 1.37 (up from 0.94), PC 0.39 (down from 0.44) and MPC 0.28 (up from 0.15). Furthermore, limiting their number allows making considerations relevant to the evaluation of real-world planning outputs and layout design guidance drafting. Additionally, referring to a smaller number of clusters is more practical if the objective is to expand the analysis to a larger number of examples. This seems a path worth pursuing in future research for achieving a more comprehensive taxonomy of TH sites' layouts in Italy, considering that Norcia's layouts are mostly hybrid row housing arrangements.

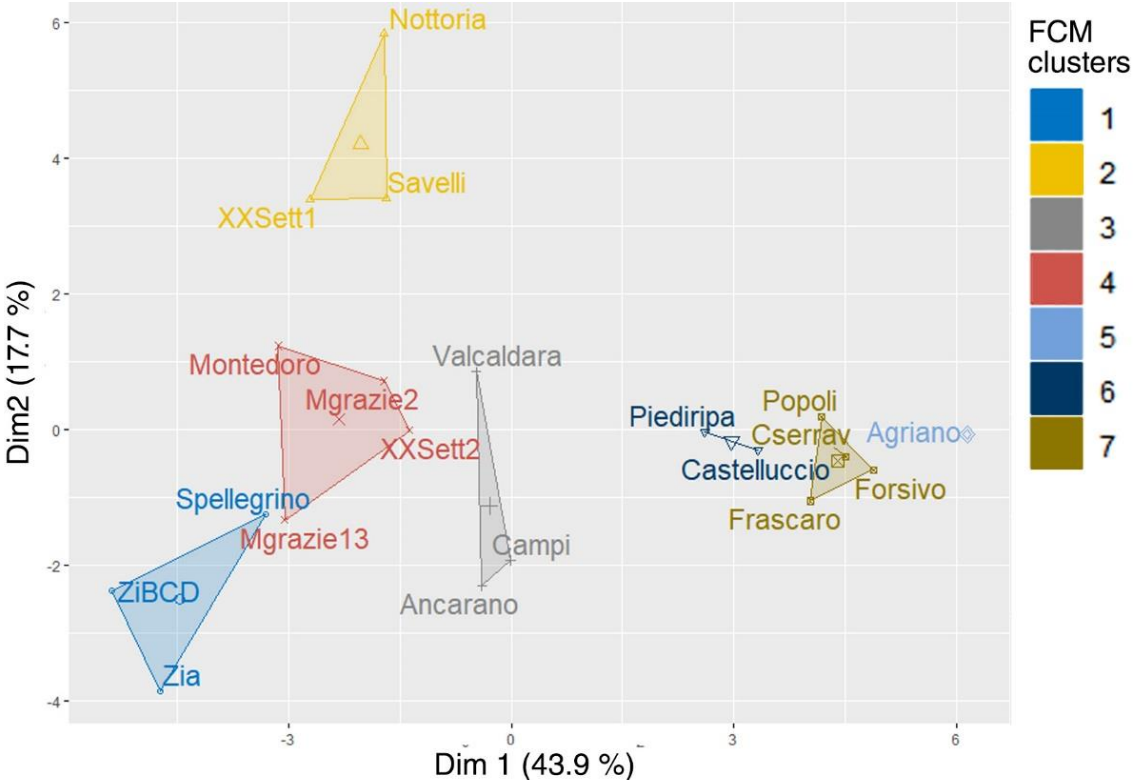

Figure 10 FCM (K=7)

4.2. The form of Temporary Neighbourhoods and The City

To understand how these results connect to the city of Norcia and its planning, the three clusters of temporary neighbourhoods represented in Figure 9 are here further analysed in terms of how well they relate to the new land use destinations assigned to the TH sites by the new general plan of Norcia, known as Piano Regolatore Generale (PRG). The latter was deposited in May 2019 (Norcia Municipality 2019) and approved by the major of the city on the 7th of October 2020, after receiving a positive result from the Environmental Impact Assessment (i.e., the VIA). The PRG will drive the reconstruction of the city in the years to come, while determining the future of the TH sites, to which the plan assigns one or more of the following functions, if any:

A. Area equipped or to be equipped for recreational-tourist-sport uses.
B. Public endowments.
C. Civil Protection use.
D. Mainly residential area.
E. Site for activities and services - tourism, sport, leisure, hospitality.
F. Reuse of facilities for hospitality-tourism.

G. Site for activities and services.
H. Relocation area.

In Table 2 these planned land uses are assigned to the relevant TH site (and cluster) using a Boolean index: Y for Yes and an N for No. In two cases, namely Piediripa and Popoli, no indication of future use was found in the PRG and therefore all possible functions are marked with an N in the table. To allow an easier visualisation of patterns, the clusters in column 3 are coloured using the same colour coding adopted in the plots presented in Section 4.1. The letters corresponding to the different uses are assigned different colour gradients, according to the corresponding functional themes (i.e., green for recreational, tourism etc., blue for residential including relocation, yellow for services both public and not).

By looking at Table 2 it is possible to observe the neat prevalence of the generic civil protection use (in violet), although in TH sites with more than 15 TH units this is coupled with other uses (except from Mgrazie2). Cluster 3 is assigned the vast majority of residential and hospitality uses. Interestingly, Ancarano, Campi and San Pellegrino (Figure 11), which are all located "far" from the city centre (see Figure 8) but belonging to Cluster 3 and having a medium size, have all been planned to have a continued residential use. Conversely the largest TH sites, i.e., Zia and ZiBCD have been assigned a hospitality role, somehow continuing their original vocation for temporary urbanism. Additionally, the TH sites belonging to Cluster 2, which are all modest in size (except for Frascaro which presents 15 TH units), seem to lack a clear functional future role. Considering that smaller sites have also a higher cost (CONSIP & NDCP 2014), the picture indicates the controversial role of this group/cluster of TH settlements, which opens doors to a discussion about the possibility to implement different technical solutions for this spatial typology of TH site.

Table 2 Future uses of Norcia TH sites, PRG 2019.

TH site	TH units	clusters	A	B	C	D	E	F	G	H
Montedoro	49	1	N	N	N	Y	N	N	N	N
Nottoria	9	1	N	Y	N	N	N	N	N	N
Savelli	12	1	N	N	Y	N	N	N	N	N
XXSett1	53	1	N	Y	Y	N	N	Y	N	N
Agriano	4	2	N	N	Y	N	N	N	N	N
Castelluccio	8	2	N	Y	N	N	N	N	N	N
Cserrav	5	2	N	Y	Y	N	N	N	N	N
Forsivo	2	2	N	N	Y	N	N	Y	N	N
Frascaro	15	2	N	N	Y	Y	N	N	N	N
Piediripa	3	2	N	N	N	N	N	N	N	N
Popoli	2	2	N	N	N	N	N	N	N	N
Ancarano	25	3	N	Y	Y	N	N	N	N	Y
Campi	20	3	N	N	N	Y	N	N	N	N
Mgrazie13	36	3	Y	N	Y	N	N	N	N	N
Mgrazie2	26	3	N	N	Y	N	N	N	N	N
Spellegrino	55	3	N	Y	Y	Y	N	N	N	N
Valcaldara	11	3	N	N	Y	N	N	N	N	N
XXSett2	48	3	N	N	N	Y	N	N	N	N
Zia	63	3	N	N	Y	N	Y	N	N	N
ZiBCD	193	3	N	N	Y	N	Y	Y	Y	N

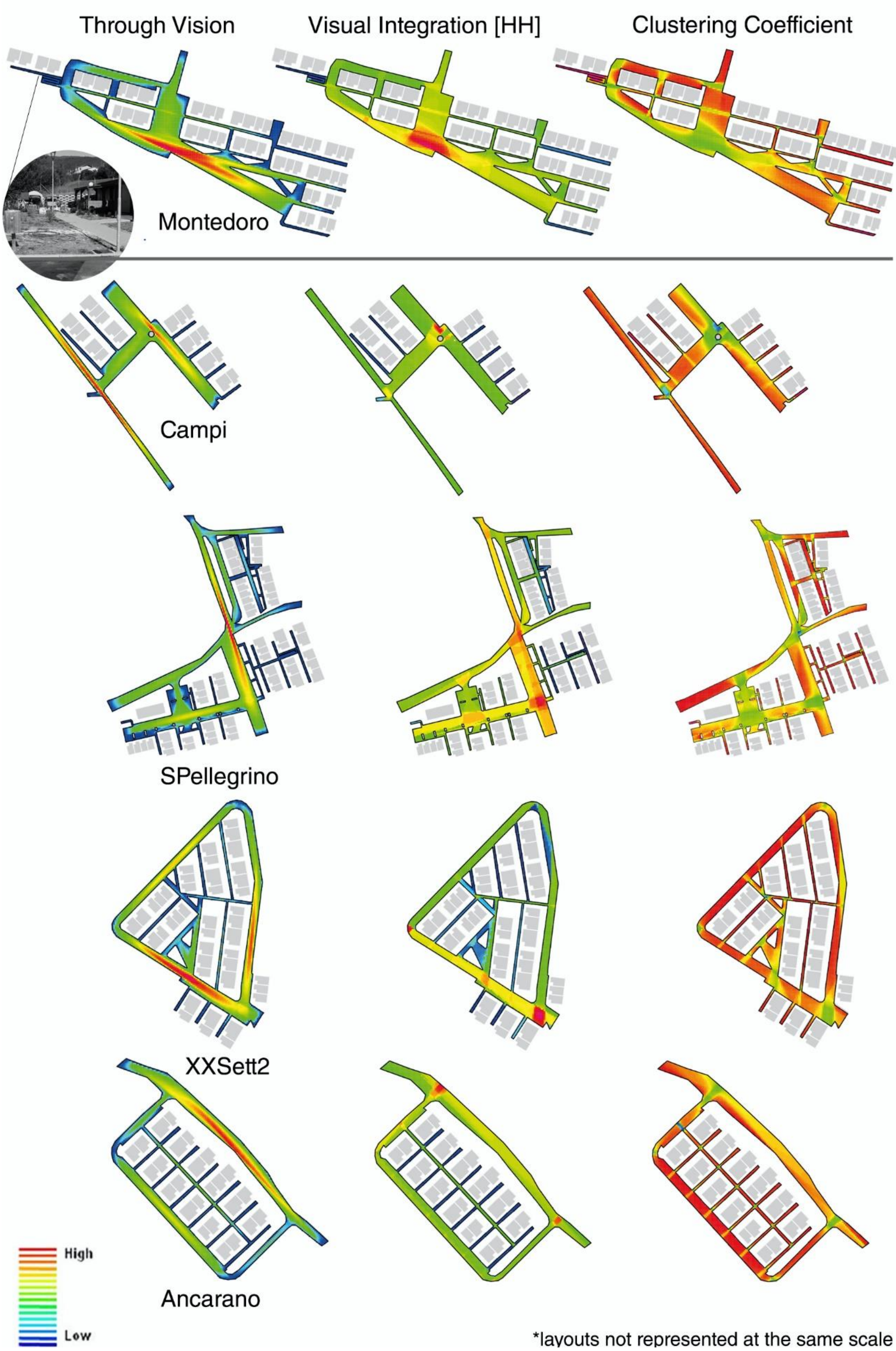

Figure 11 VGA Through Vision, Visual Integration, Clustering Coefficient of the TH sites in Clusters 1 and 3, which have been assigned a future residential use.

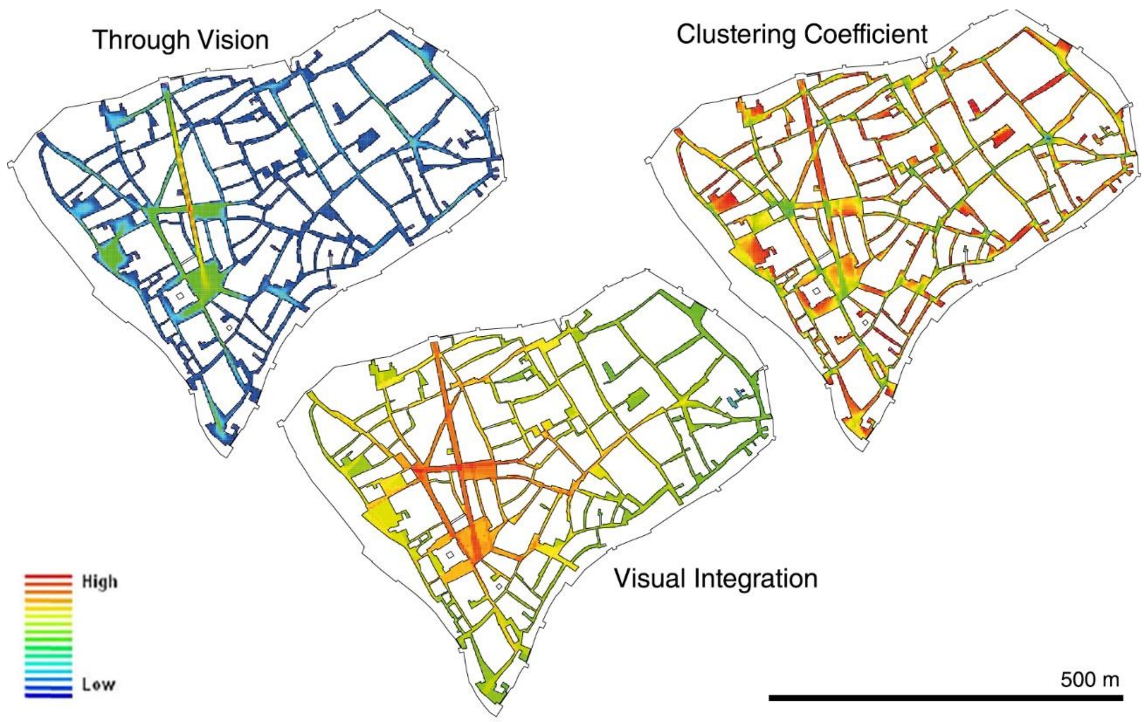

Figure 12 VGA Norcia city centre. Through Vision, Visual Integration, Clustering Coefficient

Providing good spatial qualities is particularly important for those sites which will be prevalently residential in the future. Figures 11 and 12, show the distribution of three of the key VGA indices, namely Visual Integration (to-movement), Clustering Coefficient (see and being seen) and Through Vision (through movement), in the future residential sites belonging to Clusters 1 and 3, and in Norcia's city centre. By looking at them, it is possible to observe the different spatial permeability patterns originated by planned and self-organised historic neighbourhoods, in order. Within the site layouts, we can find small green areas which clutter the permeability of the TH sites, fragmenting spaces that could have a gathering function. Sometimes, the remaining permeable space is also occupied with bike racks, benches, and other elements of urban furniture, while some green areas are used by the residents for private "temporary" installations such as inflatable pools, urban gardening lots etc. By contrast, the city centre (shown in Figure 12) presents a neater organisation of the public open space, with large and permeable public meeting places and smaller, less accessible, and yet still compact, semi-private ones.

But how spatially (diss)similar is the city centre to the TH sites? To respond to this question, the clustering analysis was repeated, this time considering only 18 VGA dimensions and adding the VGA data of Norcia's city centre, i.e., the area enclosed by the historic walls of the town. In this case, the results of the analysis (the comparison is done at K=3) show only a few variations with respect to the former one. Specifically, Campi, MGrazie2, XXSett2 and Valcaldara now belong to Cluster 1 rather than to Cluster 3 (these assignations were determined following the same democratic voting principle as before, based on the results shown in Figures 13-15). However, as previously mentioned, Clusters 1 and 3 are not as distant from each other as they are from Cluster 2. As it could have been expected, Norcia city centre was assigned to Cluster 3, albeit in the plots it always appears somehow distant from the other TH sites belonging to the same group. Furthermore, when incrementing the number of partitions (K) in the FCM, Norcia's city centre is assigned to a separate sub-cluster together with the two TH sites built in the industrial area, and destined to a hospitality and services' use, namely ZiA and ZiBCD. Although the FCM plot is not shown to avoid confusion, the HC dendrogram in Figure 15 shows a closer proximity of the city centre configuration with that of ZiA, than with those of all the other TH site layouts. This confirms the initial hypothesis that its spatial qualities are not fully replicated in the temporary housing settlements. When it comes to this, it seems worth noting that an interview conducted by Chioni (2019) in the TH site of Borgo1 TH in Arquata del Tronto, which was built following similar principles, shows that residents can perceive this as a gap in the design of the temporary neighbourhoods as they aspired to a closer resemblance of these and the two.

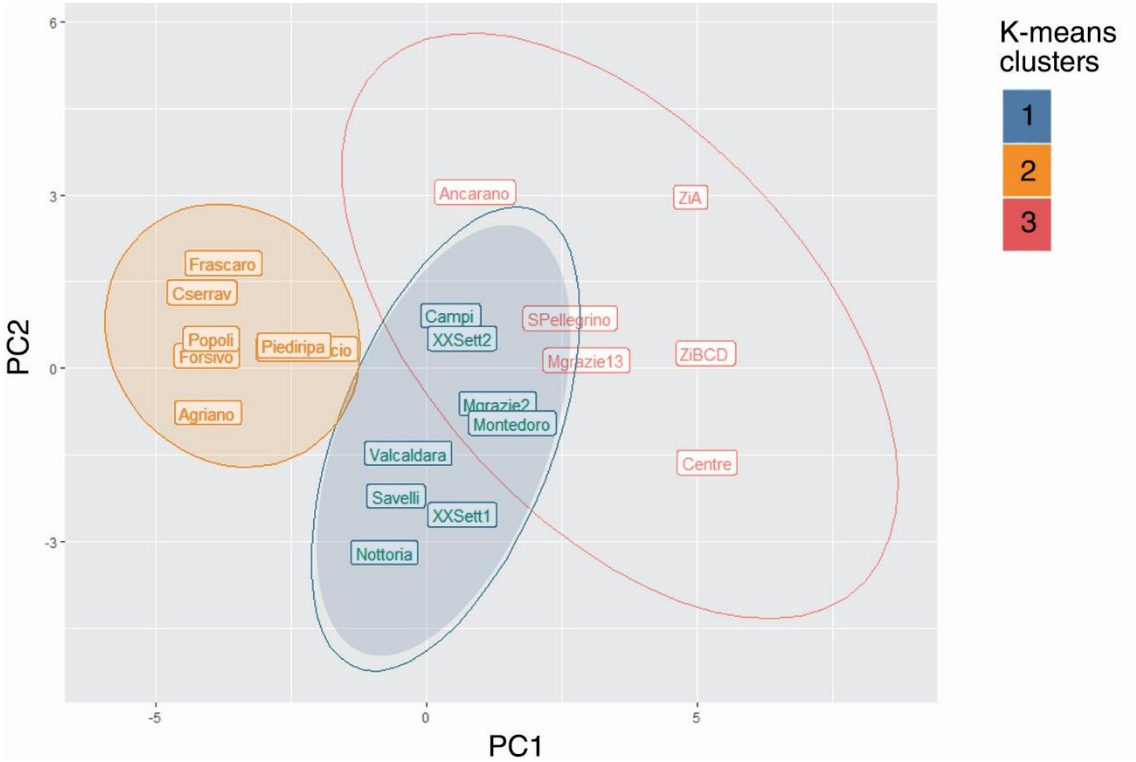

Figure 13 K-means analysis (K=3), VGA indices and city centre.

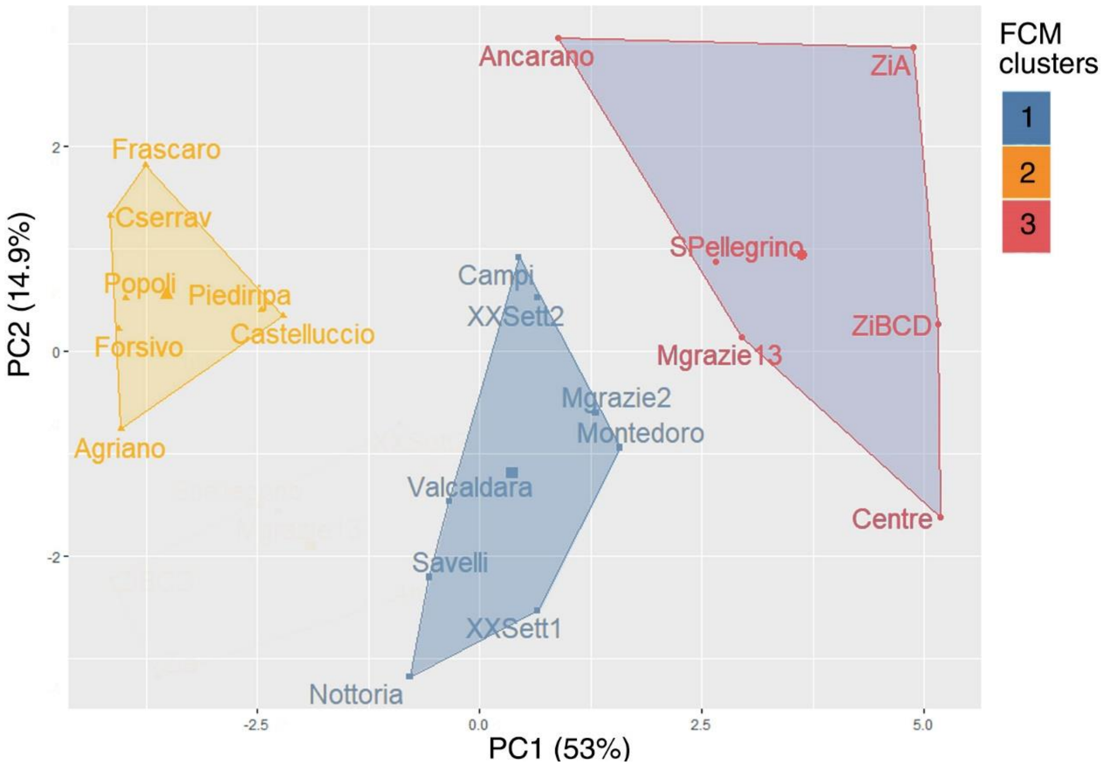

Figure 14 FCM VGA with city centre (K=3).

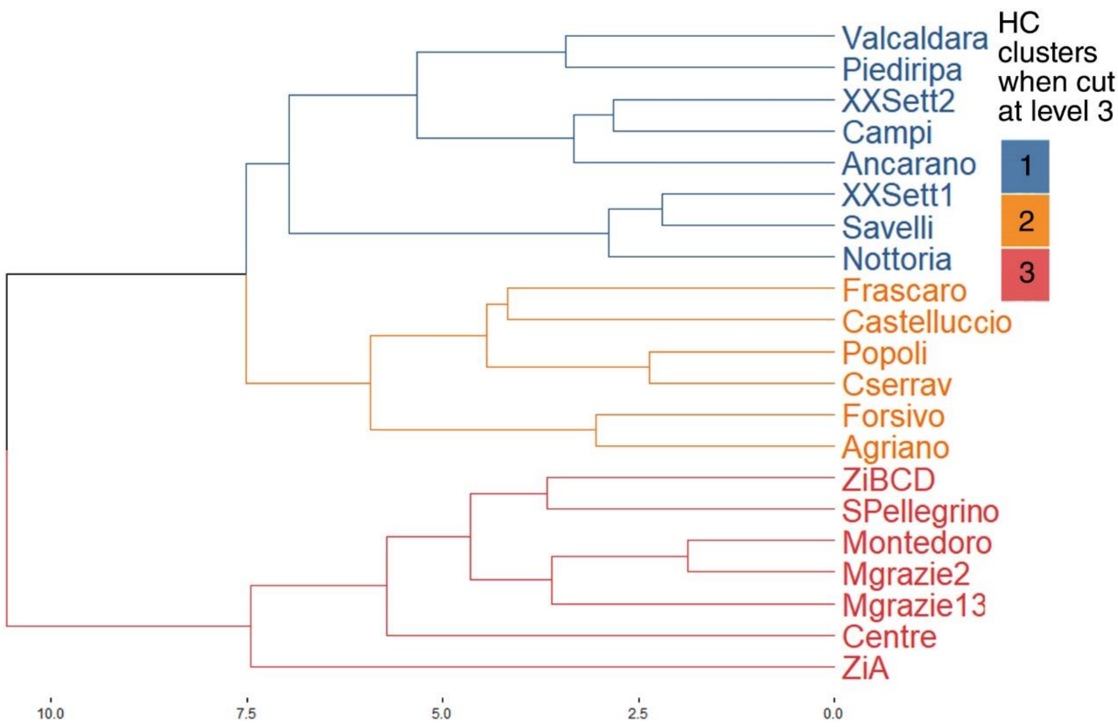

Figure 15 HC-derived VGA dendrogram with the tree is cut at K=3.

5. Discussion

TH assistance programmes require a more effective coordination through time and space, which can be achieved through the systematic assessment of candidate TH planning and layout design proposals. This paper moved another step towards the development of a Computation Planning Support System (CPSS) for the evidence-based design and planning of TH assistance after rapid-onset urban disasters. If we consider Space Syntax the language of space, then configurational and cluster analysis visualisations become the object of an interpretative effort to translate the mapped spatial relationships into planning propositions. Statistical learning methods and related visualisations can be seen as tools which support a process of critical reflection about built TH plans/designs as discussed in this paper.

Although the empirical basis of this study should be further expanded to yield generalisable results, the analysis presented in this paper identifies a mismatch between the designed form and the functional program of Norcia's TH sites. One explanation for this outcome is the lack of sufficient and clear guidance in relation to the arrangement of TH units within their sites in the context of a temporary neighbourhood. In fact, if not curious, it is at least atypical that the temporary neighbourhoods which present the highest configurational quality for residential use in their spatial design are those located in the industrial area of the town and assigned a future hospitality use. By contrast, those which according to the PRG will continue having a residential function, will need a regenerative urban design intervention to enhance their current qualities.

The approach adopted in the analysis of Norcia's TH sites offered the opportunity to conduct a nuanced multidimensional exploration of different TH layout arrangements, which could have been simply labelled as a form of "row housing" in a single terraced disposition. The proposed method enabled distinguishing TH sites with a more pronounced element of hybridity with courtyard layouts, while clarifying how opportunities for richer social interactions are weakened by a fragmented urban design that favours social separation and privacy. From an operational standpoint, the flexibility of the method proved important to synchronously consider the ASA and VGA data, although the former did not have, in the analysed case, a major impact on the final clustering results. While this may have been expected considering that the layout of Norcia appeared the most stable in the diachronic urban scale analysis presented in (Pezzica et al., 2020), this indicates also that the method is sufficiently robust to input variations.

The proposed machine learning pipeline supported a nuanced interpretation of urban planning outcomes and design processes from a critical realism perspective (researcher as a critical thinker, inventor and discoverer), which could feed forward TH planning and design theory and practice. The critical realism approach enables studying causal relationships between spatial configuration and social phenomena, including individuals' actions (of experts and of lay people), however it requires interdisciplinary integration to arrive at valid knowledge as it assumes that both physical structures (e.g., space or buildings) and agency have independent causal powers (Næss 2015). This means that to generate actionable results we would need access to post-occupancy studies, besides scaling up the number of examples to create a reference benchmark. This would indeed increase the cluster analysis explanatory power, empirical support, and interpretation precision in describing the functioning of transitional settlements from a socio-spatial perspective.

The proposed approach can effectively support different tasks. In a previous study it was shown that one is to enable the analysis of spatial trade-offs and pattern discovery in diachronic spatial configurations to grasp the influence of street network configuration on physical urban resilience and how TH plans (actual or predicted) can add or detract from this. This paper demonstrated how the proposal can help exploring multidimensional relationships between components of urban form and visual/spatial permeability levels, considering how these relate to the present and future functions of temporary neighbourhoods. In addition to this, the combined use of Space Syntax and Cluster analysis can enable a wider range of explorations (Kubat 2017). For instance, knowledge of clusters can be exploited to: (i) estimate missing attribute values; (ii) optimize (e.g., Bayesian) classification tasks by using the centroids of the clusters; (iii) serve as input in supervised learning pipelines.

6. Conclusions

This contribution offers a new instrument to reflect on the design and spatial quality of existing and future temporary neighbourhoods built after disasters, bringing a different flavour and depth to the configurational analysis through the use of statistical learning for pattern discovery. The paper demonstrated that linking Space Syntax and Machine Learning enhances possibilities for analysis automation, replicability, and flexibility, and can assist understanding of how local people perceive and interact with the spaces of the transitional city, and in particular its TH sites. The application of the proposal to the case of Norcia illustrates how multidimensional configurational assessments could make human-centred spatial performance targets quantifiable and explicit towards increasing experts' accountability and facilitating collaboration with key stakeholders, as well as communication with the public. The results obtained in this case seem highly promising, in that they prove that the proposed combination of Space Syntax and unsupervised Cluster analysis can effectively support the design and planning of TH sites, by augmenting decision-makers' capacity to:

- Comparatively evaluate alternative spatial arrangements for TH sites in terms of how they influence the socio-spatial performance of temporary neighbourhoods and predict their impact on urban systems and their parts.
- Represent, understand, and then resolve, in an informed way, potential contradictions amid the form and function of TH sites to enable the achievement of local planning priorities in disaster recovery and reconstruction.

This research suggests the need to carefully negotiate in the disaster preparedness phase the relative weighting of technical components according to strategic and policy priorities, so this can be reflected in future strategic framework agreements for the supply and delivery of TH. These should recognise the importance of spatial configuration for the achievement of social and cultural sustainability targets. Although 28 configurational indices of urban street network centrality and layout spatial permeability were selected in the analysis of Norcia's TH sites, the proposal enables the selection of a virtually unlimited number of indices of different nature relevant to inform planning and design actions. Working with Big(er) Data may require making some changes in the selection of the specific clustering algorithms to reduce time complexity; however, the overall analysis pipeline should not change substantially.

By expanding the study of natural groupings in TH layout data to a higher number of cases the defining qualities of the clusters are likely to become clearer and more meaningful to urban and architectural design, seen as a process of interpretation and reflexive synthesis. If clusters of temporary neighbourhoods could be clearly associated to levels of socio-spatial performance (e.g., assessed via a post-occupancy study), the results obtained from the application of the proposed analysis method may become particularly useful to feed forward future practices in the design and planning of TH sites. In this case, the analysis could in fact generate opportunities to set minimum urban design spatial permeability targets, which consider multiple interdependent dimensions, thus boosting DRR-oriented innovation in policymaking. This in turn open possibilities to the development of quick to deploy rules of thumb for the design of site layout options for temporary neighbourhoods built after disasters.

While increasing the range of applications, integrating the configurational, the social and the environmental perspectives seems a highly interesting direction for future studies exploring the dynamic interplay between efficiency, resilience, and urban form. Future research could consider exploring the spatial qualities of the sites at the neighbourhood scale together with their environmental performance, thus bridging the urban and the architectural design levels. This may allow to better separate clusters with TH units oriented in multiple directions, as it requires considering the third dimension and how it adds to the resilience of the temporary neighbourhoods, thus enabling a clear-cut differentiation between (and comparative assessment of) one- and multiple-storey layouts. Moreover, future studies should clarify how social habits and behavioural patterns interact with urban form at the scale of temporary neighbourhoods.

Acknowledgments

This paper is based on results from a PhD dissertation titled "Temporary Housing and Transitional Urbanism: planning for sustainable post-disaster recovery under uncertainty", financially supported by the Department of Energy, Systems Territory and Construction Engineering (DESTEC), University of Pisa.

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Resume

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Annex A

ASA normalised values Norcia TH sites

TH site	N.CH_g	N.IN_g	N.CH_m	N.IN_m	N.CH2000_g	N.IN2000_g	N.CH800_g	N.IN800_g	conn_g
Montedoro	1.3721	1.0367	-0.7958	0.4000	0.9747	0.8133	1.0021	1.0021	0.0910
Nottoria	2.3444	-0.9531	-1.5218	0.2792	2.5259	-0.8493	2.1832	2.1832	0.2831
Savelli	1.0145	0.8761	-0.8287	0.2527	1.2436	0.1767	1.4034	1.4034	1.9550
XXSett1	1.3891	1.0484	-0.9268	0.7181	1.3762	0.6566	1.5636	1.5636	-0.4489
Agriano	-1.2775	-1.9899	2.6681	-1.6802	-1.5319	-2.1391	-1.5974	-1.5974	0.7912
Castelluccio	-0.9280	-1.4617	-0.4323	-2.0560	-0.9028	-1.0533	-0.8640	-0.8640	-2.1189
Cserrav	-0.9332	-0.2982	-0.3175	0.6700	-1.0741	-0.4275	-1.0814	-1.0814	-0.3582
Forsivo	-0.9497	-0.7701	0.6717	-2.2965	-0.8644	1.7736	-1.2206	-1.2206	-0.5072
Frascaro	-1.0045	0.2964	1.3478	0.3698	-0.6600	-0.1073	-0.7651	-0.7651	0.8189
Piediripa	-0.8523	-0.6134	-0.9953	0.7691	-0.7470	-0.6800	-0.5203	-0.5203	-0.9284
Popoli	-0.9916	-0.3401	-0.4214	-0.0421	-0.9449	-0.2751	-0.9406	-0.9406	-2.1189
Ancarano	-0.2008	-0.6877	-1.1572	-0.8573	-0.3010	-0.6506	-0.1750	-0.1750	0.9251
Campi	-0.7295	0.7063	0.7361	-0.9321	-0.6094	1.1097	-0.4767	-0.4767	-0.8717
Mgrazie13	0.4185	-0.5148	1.0222	0.7762	0.3449	-0.6443	0.3131	0.3131	0.0203
Mgrazie2	0.5254	-1.0544	-0.0981	0.8909	0.4938	-1.1911	0.5033	0.5033	0.0874
Spellegrino	0.2029	1.7288	0.4321	0.3801	0.3794	0.4965	0.5250	0.5250	0.1566
Valcaldara	-0.2177	0.6951	0.3938	0.3707	0.0030	0.5932	0.1145	0.1145	0.3025
XXSett2	0.6902	0.4243	0.3630	0.5024	0.5099	-0.2286	0.3809	0.3809	0.1283
Zia	-0.1367	1.0783	0.2795	0.8883	-0.2269	1.2716	-0.2537	-0.2537	0.8782
ZiBCD	0.2645	0.7930	-0.4195	0.5968	0.0111	1.3549	-0.0945	-0.0945	0.9146

Geometry-based normalised values Norcia TH sites

TH site	x	y	TH units	sl_m
Montedoro	13.086771	42.798535	49	-0.7078
Nottoria	13.155918	42.729921	9	-0.1651
Savelli	13.124981	42.72721	12	-0.9295
XXSett1	13.095772	42.797497	53	-0.1358
Agriano	13.027397	42.765085	4	3.2881
Castelluccio	13.206744	42.828198	8	-0.4042
Cserrav	13.060902	42.791823	5	0.9809
Forsivo	13.014165	42.799722	2	1.1524
Frascaro	13.143627	42.748345	15	1.2305
Piediripa	13.112281	42.740495	3	0.1165
Popoli	13.105384	42.752637	2	-0.8594
Ancarano	13.105076	42.837134	25	0.0956
Campi	13.0942	42.8503	20	-0.0357
Mgrazie13	13.104355	42.789506	36	-0.5469
Mgrazie2	13.104632	42.79064	26	-0.3667
Spellegrino	13.146716	42.756153	55	-0.5631
Valcaldara	13.125947	42.740805	11	-0.8295
XXSett2	13.096489	42.798681	48	-0.3495
Zia	13.094	42.786	63	-0.5724
ZiBCD	13.095339	42.777482	193	-0.3984

VGA normalised values Norcia TH sites

TH site	Conn_g	T.V_g	Clust.C_g	V.Ctrl_g	V.Int._g	V.Ctrllab_g	V.Rel.Entr_g	P.1stM_g	P.2ndM_g
Montedoro	0.2511	0.3326	0.9078	0.4622	-0.8104	0.2880	-0.0797	0.5660	0.7823
Nottoria	-0.7373	-1.3637	1.3036	1.5929	0.6235	-0.1730	-0.3151	-1.1171	-1.1407
Savelli	-0.1460	-0.8041	0.5650	1.0577	0.6753	-0.4605	-0.6768	-0.5788	-0.8937
XXSett1	0.0571	-0.7147	1.9393	1.7542	0.1616	-0.5679	0.4936	-0.3513	-0.2492
Agriano	-1.4434	-1.6166	-0.4464	-0.1749	1.7424	-1.0073	-1.6456	-1.6975	-1.8860
Castelluccio	-0.8336	-0.6429	-0.1744	-1.0297	-1.0218	0.2778	-0.6156	-1.0618	-1.2519
Cserrav	-1.2870	-1.0678	-1.2873	-0.5753	0.4777	-1.7413	0.6032	-1.2497	-1.4562
Forsivo	-1.0286	-0.8269	-1.3011	0.2173	2.3105	-0.4071	-1.4548	-0.9074	-0.8745
Frascaro	-1.9788	-0.9716	-1.4194	-1.7056	-0.6971	-1.9588	-2.1248	-1.1935	-0.2829
Piediripa	-0.3501	-0.3586	-1.1190	-0.8612	1.3389	-0.7112	-0.0430	-0.1230	0.0069
Popoli	-1.2407	-0.8563	-0.6152	-1.1889	1.5819	-1.9408	0.6490	-1.1293	-1.1897
Ancarano	0.2130	0.0602	-1.4485	-0.8768	-1.2009	1.4810	0.5427	-0.1147	-0.2889
Campi	-0.4295	0.2900	-0.2599	-0.5911	-0.4529	0.6011	1.5754	0.1659	0.4811
Mgrazie13	1.1964	1.3083	0.7424	-0.0698	-0.3906	1.7382	0.2687	1.3332	1.2837
Mgrazie2	0.2658	0.0371	0.4031	0.7409	-1.1514	0.7581	-1.1612	0.0178	-0.0200
Spellegrino	0.7948	0.4596	0.6631	-0.0135	0.2373	0.8077	1.6313	0.4754	0.5922
Valcaldara	0.3699	-0.0677	0.2135	0.9924	0.6819	0.1012	1.4177	0.0451	-0.0760
XXSett2	-0.0323	-0.3705	-0.0865	0.6020	-0.3254	-0.3040	0.0238	-0.1630	-0.1527
Zia	0.3035	0.1878	0.9119	0.0849	-0.8380	0.5435	0.4474	0.4201	0.5813
ZiBCD	1.5524	1.4369	0.7710	1.1374	-0.5732	0.7158	0.0530	1.4540	1.3865

VGA normalised values Norcia TH sites

TH site	Conn_m	T.V_m	Clust.C_m	V.Ctrl_m	V.Int._m	V.Ctrllab_m	V.Rel.Entr_m	P.1stM_m	P.2ndM_m
Montedoro	-0.1372	-0.4099	-0.4973	-0.7456	-0.7199	-0.5572	-0.0845	-0.3555	-0.3630
Nottoria	-0.1505	-0.2617	-0.4231	-2.7165	1.0543	-0.2585	-0.1885	-0.5659	-0.5161
Savelli	-0.5227	-0.4957	-0.8496	-1.2009	0.3466	-0.6855	-0.2227	-0.5673	-0.4801
XXSett1	-0.2581	-0.3508	-0.9957	-0.9750	0.1864	-0.6796	-0.2153	-0.4073	-0.4065
Agriano	-0.6449	-0.6295	-0.1077	-0.0923	1.9509	0.9115	-0.8263	-0.6759	-0.5472
Castelluccio	-1.1580	-0.8136	1.3203	0.1610	-0.6074	0.7221	-0.0979	-0.8290	-0.5954
Cserrav	-1.1793	-0.7958	1.1296	1.6271	-0.1950	1.9026	-0.9124	-0.8149	-0.5847
Forsivo	-0.6157	-0.6644	0.8659	0.9979	3.3406	1.8769	-0.9519	-0.6837	-0.5530
Frascaro	-1.0038	-0.7461	-0.1480	1.8007	-0.6631	1.7320	-0.5215	-0.7779	-0.5809
Piediripa	-0.9905	-0.7600	1.6458	-0.1374	-0.1280	0.4065	-1.2915	-0.7857	-0.5776
Popoli	-1.0650	-0.7984	-0.0285	0.7504	0.6304	1.4562	-1.4337	-0.8219	-0.5937
Ancarano	0.7295	0.0492	0.7113	0.9266	-0.0265	0.5341	-0.2836	0.5353	0.4825
Campi	-0.0601	-0.2636	0.7266	-0.2795	-0.0763	0.0762	-0.3986	-0.1958	-0.1800
Mgrazie13	-0.1585	-0.2046	0.1555	0.6466	-0.2052	-1.0753	0.7711	-0.2539	-0.2236
Mgrazie2	-0.0840	-0.2449	-0.4976	-0.3384	-0.4947	-0.4486	0.2821	-0.1921	-0.1975
Spellegrino	0.8863	0.3948	-0.6647	-0.1034	-0.2055	-0.6476	-0.6059	0.4720	0.3539
Valcaldara	-0.8390	-0.6986	0.6612	-1.1833	-0.0946	0.0293	-0.7872	-0.7077	-0.5446
XXSett2	0.3573	0.0224	0.5621	0.2203	0.1449	-0.3890	0.2346	0.1734	0.1143
Zia	2.7233	2.1033	-1.4352	0.5773	0.0836	-0.8317	0.0764	1.6833	1.4923
ZiBCD	0.9342	1.0563	-0.9031	-0.5420	-0.2560	-1.4688	0.8944	0.6754	0.7201