CAN SEVERITY PROFILES OFFER AN ALTERNATIVE TO PERSONS-IN-NEED ESTIMATES?

An experiment with data from Syria

September 2017

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A note for ACAPS

Can severity profiles offer an alternative to persons-in-need estimates?

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All errors, factual and of interpretation, are mine.

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summary

Estimates of persons-in-need are a key result expected of humanitarian needs assessments. However, they are challenging. Some are not informative, because of the methods chosen, missing and unreliable data or the way the humanitarian partners collaborate. In the absence of satisfactory PiN figures, substitutes are needed to inform prioritization and response planning. Other types of information may still be available in adequate scope, coverage and reliability. If the analyst manages to build a process model and a measurement model that delivers some measure of severity and of the associated populations, the needs assessment succeeds even in the absence of ordinary PiN estimates.

This note proposes a method in situations where sectors, clusters and perhaps other actors contribute two types of information: sectoral severity rankings (which are ordinal variables) as well as demographic and situational indicators (which may come as categorical or as continuous variables). The method combines the severity rankings and the indicators in a simultaneous model. The model is estimated through a statistical procedure known as Latent Profile Analysis. It delivers two things:

- A set of profiles – groups of communities that share configurations of severity in several dimensions.
- A "causal signature" of indicator levels associated with each profile.

The populations living in the communities under the various profiles can be estimated.

We use a dataset from the Syria 2017 Humanitarian Needs Overview (HNO) preparations for a demonstration. This set is particularly helpful for its high resolution. It holds data from a deeper level than the sub-districts, i.e. from over 5,000 localities (the so-called Admin-4 level). The sectors and partners supplied severity ratings for most of these, plus information on war exposure, population and IDPs.

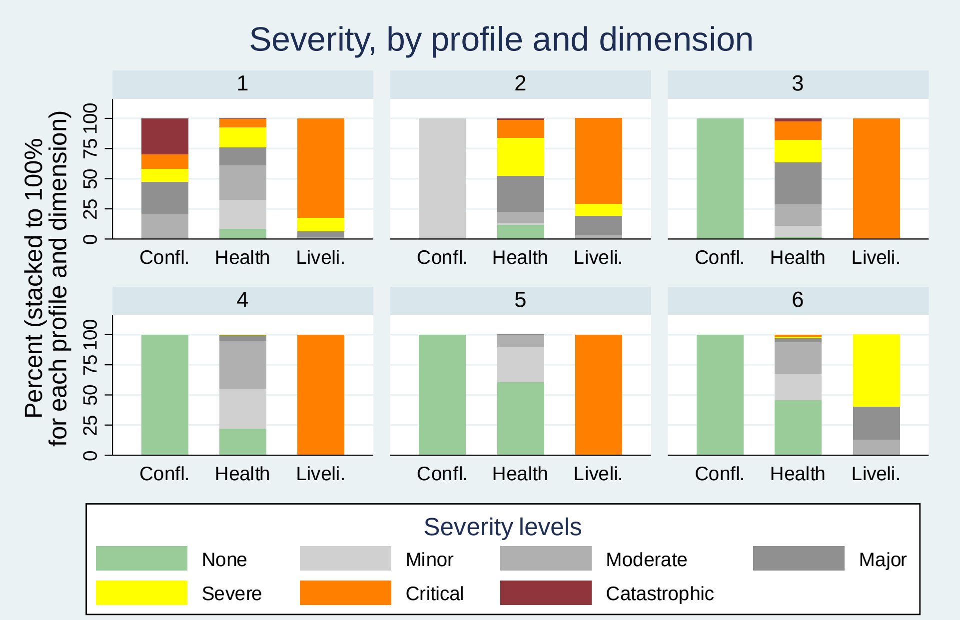
Using data on 4,904 localities with population information, we formulated and estimated a number of models. This strictly is a first experiment; in order to cope with its complexities, we limited the severity picture to three sectors / dimensions:

- Directly conflict-related severity
- Health-care related
- Livelihoods-related

(we give a rationale in the main body of this note). We limited the causal signatures to four indicators.

The model that we retained for its best informational properties divides the localities into six profiles. This graph gives a first taste of their diversity. The severity scales used by the sectors follow the model proposed by ACAPS, with seven levels.

Figure 1: Six latent profiles - severity ratings in three dimensions



Note: Syria 2017 HNO. 4,904 localities (Admin-4). 6 latent profiles. Re-weighted by locality population.
Number of localities in profiles 1 to 6: 545 / 942 / 1,490 / 347 / 901 / 679.

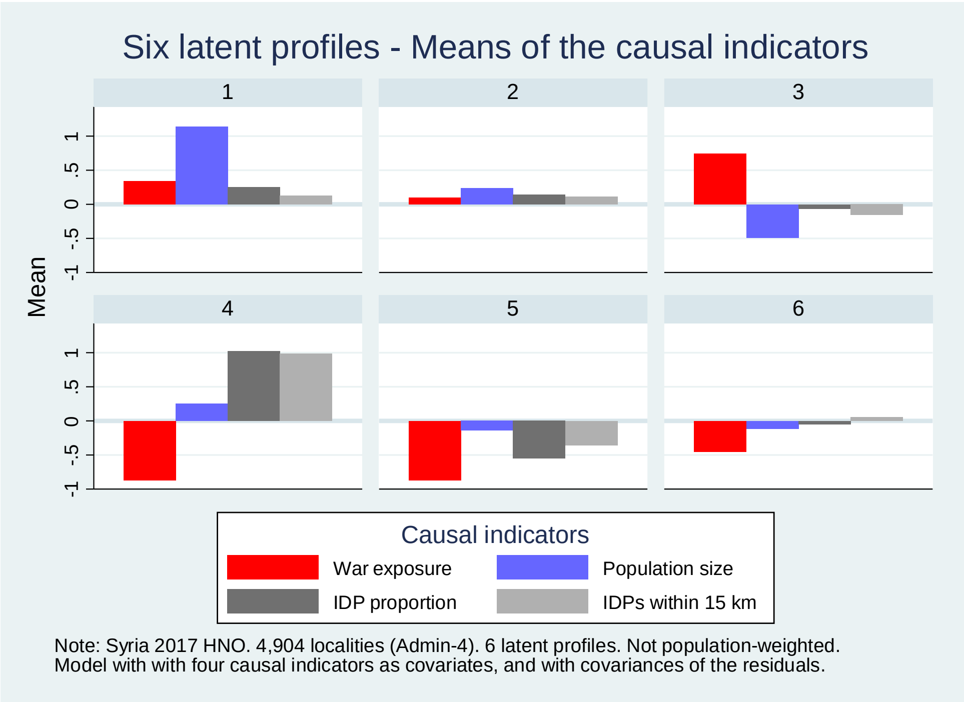
What makes these six profiles distinct?

- Profiles 1 and 2 gather localities exposed to direct conflict impacts; in # 1 the localities are rated between moderate and catastrophic on that dimension of severity. In # 2, the level is uniformly minor.
- Profiles 3 – 6 have localities with conflict-related severity at 0-None level. They are distinguished by the levels of livelihoods severity. It is critical for localities in profiles 3 -5. Localities in profile 6 suffer livelihoods severity at various levels lower than “critical”.
- The distinctions among profiles 3 to 5 are not crisp. The differences are gradual in the composition of the health care severity, with #3 overall showing more severe conditions than #4, and #4 more so than #5.

It must be noted that it is the profiling algorithm, not the analyst, that worked out the profiles. The algorithm works with criteria of optimal distinction. Similarly, the algorithm identified the communities associated with each profile.

The profiles show distinct causal signatures. Without going into the metric in this summary, the reader can easily grasp that the profiles are characterized by large differences in indicator levels.

Figure 2: Causal signatures of the six profiles



The populations associated with the profiles can then be estimated.

Figure 3: Total population, by profiles

Profile	Localities	Population 2017				
		Sum	Minimum	Median	Mean	Maximum
1	545	12,121,579	10	4,500	22,241	1,584,000
2	942	2,556,720	10	1,000	2,714	150,000
3	1,490	1,200,850	10	400	806	35,000
4	347	665,678	20	1,000	1,918	14,560
5	901	932,164	10	620	1,035	12,000
6	679	1,132,073	10	620	1,667	190,000
Total	4,904	18,609,064	10	730	3,795	1,584,000

The profiles give a rich picture. The method combines information in ways that previous approaches seldom or never achieved. This demonstration does not prove that this is the way to an alternative to persons-in-needs estimates, but it deserves to be investigated as a possible tool to offer viable substitutes when informative PiN figures are wanting.

introduction

Persons in need

Persons-in-need (PiN) estimates are part and parcel of humanitarian assessments. The mere distinction between PiN and those not in need of humanitarian assistance is necessarily imprecise and of limited practical value. There is a case for graded categories. Benini (2015) presented evidence from the Syria Multi-Sectoral Needs Assessment (MSNA) (Humanitarian Liaison Group 2014) to show that the distinction between PiN in moderate needs and those in acute needs had informational value. Such estimates can inform response planners more accurately of groups needing aid with high priority.

In practice, this has proven difficult. Sector analysts do rate communities by levels of severity using their sector definitions. But not all sectors are at ease making or sharing estimates of persons-in-need, let alone graded estimates. For a given community, the maximum PiN estimate across sectors is a reasonable estimator of the inter-sectoral PiN. However, when analysts provide uniform proportions of PiN in populations or proportions that, for policy reasons, are higher than those by other sectors, the intersectoral PiN estimates become uninformative. For example, in the 2017 Humanitarian Needs Overview (HNO) for Syria, intersectoral PiN numbers were estimated for 4,904 geo-referenced local communities ("localities"), a large dataset of high geographic resolution[1]. In 4,074 cases, the estimated proportions of PiN were within ± 2 percent of the overall mean of 71.2 percent. This is an institutional artefact. The Health Cluster uniformly fixed its sectoral proportions at 69.3 percent in most (256 out of 266) sub-districts that have health sector PiN figures; the Protection Cluster used the same figures in 198 sub-districts and higher ones in 54. The resulting intersectoral PiN distribution is, for these reasons, uninformative.

Severity ratings

What can be done, given the inability or unwillingness to supply detailed and differentiated PiN estimates? The Health Cluster did provide valuable information. We have severity estimates of the level of access to health care for 1,573 localities and for all 270 sub-districts, using the HNO severity scale (see below). This information, together with the severity ratings supplied by the other sectors and clusters as well as with background variables of interest, can be exploited. The objective is to find a meaningful, parsimonious description of how the affected communities are distributed along one or very few measures of severity, and how many people live in distinct sets of more severely vs. less severely affected communities.

Before we propose a strategy and demonstrate an experiment, one more reminder is in point. Severity ratings are ordinal data. Aggregating ordinal variables has more challenges than interval or ratio-level variables present. The ACAPS note "Severity measures in humanitarian needs assessments" discusses pitfalls and work-arounds,

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[1] The 4,904 localities form the effective sample for this study, i.e. those with complete values in the variables of interest.

such as the little known ridit and other data transformations (Benini 2016:22-45). The analytic benefits of such transformations will loom large in what follows.

Objective and assumptions

Objective

Our objective is to demonstrate a method to statistically partition the communities and populations on which needs assessments return detailed data. Each group displays a distinct profile of attributes that are of interest to humanitarian monitors and planners. Such a method, we believe, is particularly needed when PiN estimates are absent, uninformative or unreliable. It may be attractive also where PiN estimates are good, ready to be combined with other information in new and meaningful ways.

Different names are in use for such groups – "groups", "clusters", "classes", "groups with certain profiles", or simply "profiles". The idea is to identify groups of people and communities that differ significantly on key attributes – such as the severity ratings that the sectors gave them. Unlike PiN that are graded unidimensionally (not in need / moderate / acute), profiles need not be distinguished on attributes that all show either an ascending or descending order.

To illustrate, the attributes of interest are mean monthly household income (I) and mean child malnutrition rates (M), and we seek to divide the population into three optimally distinct groups A, B and C. It may not be possible to form groups such that $I_A > I_B > I_C$ as well as $M_A < M_B < M_C$ – unless we accept extreme individual overlap across groups and/or some group that is so small as to be of no policy interest. We may wind up assigning individuals to groups A, B, C such that, for example, $I_A > I_B > I_C$, $M_A < M_B$, and $M_B > M_C$. This would be the case, conceivably, when group A is relatively well-to-do, B and C are both poor, although B slightly less so, and the nutrition part of the assessment finds that child malnutrition in B is more prevalent than in both A and C. The question why that is so – what is it that makes M_B unexpectedly high, or I_C unexpectedly low - would likely be relevant to the users of the needs assessment.

Our objective is to find a method that allows such inconsistently ordered multi-attribute profiles – provided the groups are sufficiently distinct. They can be distinct on statistical or policy grounds or, ideally, on both.

This approach is different from index methods well familiar to humanitarian analysts in which attributes (indicators) are aggregated into one index that provides a complete ordering of the assessed units. A lower value on one indicator is compensated for by a higher on another, at rates defined by the weights. It differs also from non-compensatory methods in which some attributes dominate others for policy considerations. ACAPS has published guidance on both of those. This note addresses something new.

Assumptions

Face validity

A coordinating unit receives measures of humanitarian interest from affiliated organizations such as cluster and sector coordination units. Some of the measures express the concept of severity, in various dimensions. Others relate to affected groups and the social, political and other ecology of the crisis area. They are either antecedent (factors causing severity) or contemporary (e.g., geographic coordinates) or outcome measures (e.g., excess mortality). All measures have errors the extent and direction of which are only partially known. Uncertainty is considerable also about the relationships among causal factors, severity measures and outcomes; some are empirically known and confirmed; others are intuitively plausible or speculatively extrapolated from other knowledge. All measures have been selected because of good face validity and the sector analysts' competence.

Severity as magnitude and intensity

The observed severity – the measures – reflect magnitudes and intensities of the underlying suffering, which is not directly observed. The relationship between observed and latent may vary by type of measure and subject. To exemplify for continuous measures, the proportion of IDPs in the local population varies theoretically from 0 to 1 (0 to 100 percent). The underlying pressure on survival resources may be thought of, but not observed, as a non-linear function of the proportion p. It is reasonable to model it as the odds of p, i.e., $p/(1 - p)$, or even better, with a correction factor $1 > c >> 0$, $(pc) / (1\text{-}pc)$, to avoid the singularity as p approaches 1 (communities where everybody is IDP).

Such relationships are particularly critical to the treatment of ordinal variables. Obviously, severity scales are the prime instance of interest here. The scale that ACAPS recommends, and which has been followed in several assessments, has seven levels, numbered 0 - 6:

```
0 None
1 Minor
2 Moderate
3 Major
4 Severe
5 Critical
6 Catastrophic
```

We assume that in the minds (and algorithms where they exist) of the sector analysts who form ratings on this scale, the suffering of the individuals or communities rated 1-None, 2-Minor, etc., is "somewhat" proportionate to an exponential function. Examples are: 1, 2, 4, 8 .., or 1, 10, 100, 1000, .., or any exponential sequence using a meaningful base. These bases are unknown (at least to outsiders), and so are the cut-off points between the levels (the category boundaries). Apart from rare situations[2], analysts will allow the cut-off points to be data-driven. In particular, they will give out "catastrophic" ratings sparingly, i.e. define a cut-off point between "critical" and "catastrophic" such that the category is not overused. At the same time, the analysts form their rating judgments in response to the observed causal indicators. The response is either intuitively holistic or built on an aggregation formula.

We assume that *for given values of the observed causes* the latent (not directly measured) suffering S arrives from a lognormal distribution, and a particular severity rating $s = k$, k= 0, 1, .. 6, is given if log(S) falls between the cut-points c_k and c_{k+1}, k = 0, .., 6. If i denotes the individual person or community to be rated, j the sector, and k the rating option, formally we set:

$$\log(S_{ij}) \mid \text{observed conditions} \sim N(\mu_j, \sigma_j^2)$$
$$s_{ij} = k \text{ if } c_{jk} < \log(S_{ij}) \leq c_{jk+1}, \text{ with the extremes } c_{j0} = -\infty \text{ and } c_{j7} = +\infty$$

As noted the cut-points c_{j1} to c_{j6} are a function of the joint distribution of the observed indicators and may be (and likely are) specific to each sector.

The profiles are probabilistic

Different combinations of the causes of severity place individuals and communities in different severity types. How many distinct types there are, and how clearly distinct they are from each other, is not known in advance. The types are not directly observed; they are inferred from the distinct distributions of the indicators that the analyst considers relevant for their definition. Thus Type I, for an arbitrary example, may include communities exposed to low levels of conflict, but high economic stress. How low, and how high, is not known beforehand either – does it mean no conflict, no more than minor conflict, or moderate conflict at most?

Statisticians call such types – regardless of whether they concern severity or some other topic of interest – "latent classes" or "latent profiles". Technically, "latent profiles" is used when some of the indicators are continuous, rather than all of them categorical. We prefer "profiles" because of the closeness to the "profiling" concept in humanitarian assessments. But what really matters is the idea that each observed unit – e.g. each community – has probabilities of belonging to each of the profiles finally adopted.

[2] Conceivable as: complete data on relevant variables such as those defined by humanitarian standards; valid model to combine those variables; no ordinal variables until the categorization into the final scale.

Suppose four profiles emerge, as the combinations of low/high conflict exposure and low/high economic distress. The concerned sector analysts have rated community Example-Ville as exposed to minor conflict and going through major economic stress. Example-Ville could be a member of these profiles with probabilities such as:

Table 1: Example of probabilistic profile membership

Profile	Conflict exposure	Economic distress	Membership probability
1	Low	Low	0.40
2	Low	High	0.56
3	High	Low	0.01
4	High	High	0.03
		Total:	1.00

Probabilistic profiling has consequences:

- The individual unit will be pragmatically treated as belonging to the profile with the highest probability. Example-Ville is a profile-2 community.
- Collectively, the number of units in a given profile is the sum of probabilities over all units. This estimate has a confidence interval, i.e. a bounded uncertainty.
- The statistics of variables of interest – such as the total population belonging to a profile – are probabilistic too.
- The optimal number of profiles to retain depends not only on policy interests (informing humanitarian response plans), but also on statistical criteria of information value. These criteria are intransparent to all but statisticians.

These consequences require some re-thinking and may seem unnatural in the opinions of some. Thus, if Example-Ville has a population of 10,000, it contributes 4,000 to the estimated total population living in profile-1 communities, 5,600 to those under profile 2, etc. This fuzziness may seem disturbing.

It can be reduced when we add another radical idea. This is the belief that

1. The causes, some of which are observed, determine the hidden types (the profiles).
2. The hidden types determine the observed indicators.

In the application that interests us,

1. A coordinating body like UNOCHA assembles data on variables some of which can be considered causal to severity.
2. The causes generate distinct severity profiles that are initially unknown.
3. The profiles *cause* sector analysts to form severity ratings (sic!).
4. The profiles are revealed by: Distinct combinations of sectoral ratings as well as distinct levels on the causal indicators.
5. The humanitarian community decides which severity typologies – if several suggest themselves – have value for policy.

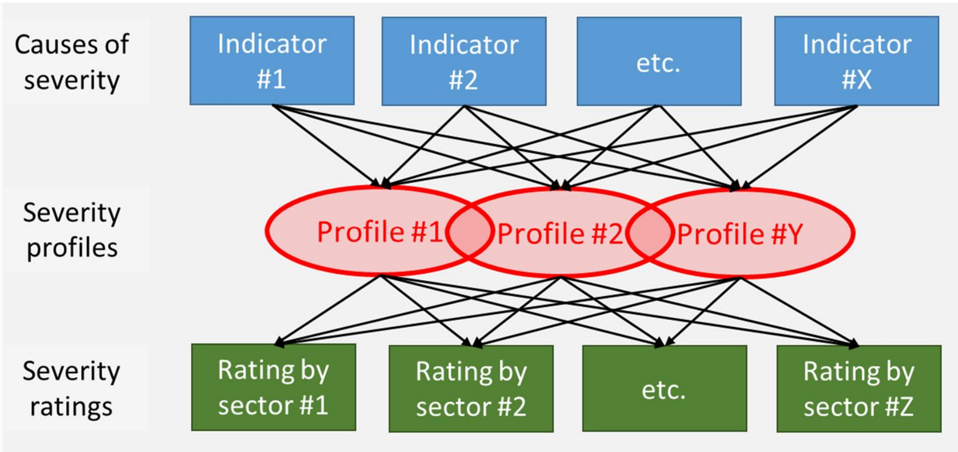
Point #3 makes strong metaphysical assumptions. Statisticians will be more comfortable saying that the severity types *predict* the analysts' ratings, and causal indicators predict the communities' membership in particular profiles. Next we will execute those concepts in a process and a measurement model, followed by a demonstration with real data.

The model

Process

The essentials are captured in this diagram. The causal arrows run from causes to profiles to severity ratings.

Figure 4: Causal flow through severity profiles



Profiles overlap because an observed unit – e.g. a community – has probabilities to belong to each of the distinguished profiles.

This scheme is different from the way humanitarian analysts commonly think, analyze and report. Traditionally, profiles are the result of the sector ratings (and possibly other measures such as PiN numbers or proportions)[3]. As such, they are an analysis product. Each unit – community, person, as may be the case – strictly belongs to one and only one profile.

Here we go the other way. Profiles exist in reality. But they cannot be observed directly. They *cause* the analyst's severity ratings[4]. They can be inferred, from those ratings and from the observed causes. They remain uncertain. The units' membership in the profiles remains uncertain. Even the number of profiles remains uncertain and eventually, for practical reasons, is fixed by choice. The choice responds to statistical, policy and didactic – what can be meaningfully communicated – concerns.

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[3] This is the *formative* measurement tradition, in which measures (the sector ratings) are treated as causes of the constructs (profiles).

[4] In this approach – *reflective* measurement -, the ratings are effects of the constructs. For a technical discussion why the reflective approach is preferable in situations with latent variables, see Edwards (2010). For a non-technical discussion, with examples of both types, see Benini (2016:47-49)

Measurement

Causal indicators

Substantive content

In principle, any indicators that have a plausible effect on suffering or on its reduction or avoidance may be considered for inclusion. Indicators that, by definition or observed correlation, are highly redundant with others should not be added or should be combined with them through an index procedure that removes redundancy[5].

It is not necessary that the causal indicators represent humanitarian sectors. If any of the indicators is commonly associated with a sector, it may be included on its broader merits. It does not require that other sectors be similarly represented. Thus, the proportion of bakeries still functioning (in terms of their pre-war numbers) at first sight appears to speak to food security. If we include it, it does not follow that we need to find a health-sector companion, such as the proportion of functioning pharmacies. Such companions are desirable, but the profile analysis can succeed without them, although less powerfully so. The bakery proportion is an indicator of the wider institutional functioning and, in the absence of appropriate health-sector data, is assumed to be correlated also with health care capacities.

In most situations, valid, reliable and complete indicators are not abundant. Analysts have to make work with what they find and make the best from among limited options, yet still with the aim of capturing severity in as much substantive breadth and depth as possible.

Formal considerations

The causal indicators are to be suitably transformed. "Suitably" depends on

- beliefs of how the variable contributes to severity, as well as on
- measurement scales.

For example, the population size of communities may proxy for institutional diversity; greater diversity may help reduce suffering of various kinds. However, the number of institutions, e.g. hospitals, will not likely grow in proportion to absolute numbers, but to the magnitude. On the other hand, more populous places may attract more displaced persons because they make it easier to organize relief. Also they may be the scenes of more heavy fighting, killing civilian or driving them away. Not knowing the scope and scale of the various effects, one may be well advised to safeguard against excessive

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[5] The Betti-Verma weighting schema (Betti, Cheli et al. 2005) achieves this in many situations. For a an explanation and demonstration in Excel, see Benini and Chataigner (2014:72-75).

influence of outliers in the estimation of any model. The logarithmic transformation lowers the misspecification risk.

Ordinal indicators will have to be transformed for similar substantive and formal considerations. The options include mapping onto an interval or ratio-level scale, dichotomization (high / low), or the creation of $k - 1$ dummy variables for k levels ($k - 1$ in order to avoid linear dependency). The first option makes (potentially misleading) assumptions about an underlying variable, but may be necessary in statistical procedures that perform poorly as the number of parameters increases.

The analyst may want to look for causal effects from places beyond the individual or community itself. Context variables may be taken from datasets of the next higher administrative or institutional level, or from aggregates (mean, median) of the same indicator for all other individuals / communities within a certain radius. An example will be presented in the demo section. We expect some of these context variables to be highly correlated with their individual level pendant. In such cases, they should be orthogonalized (made statistically independent) (Wikipedia 2014).

Similarly, data gaps at the lower level may prompt imputation lest too many observations be lost. In the absence of a regression-based imputation procedure, often one has no choice but to plug in the values from the higher level or the average (mean, median, mode) among neighboring units of the same level.

The continuous and transformed-continuous indicators may be standardized with a mean = 0 and standard deviation = 1 for ease of interpretation of estimated coefficients. This is a convenience step and not really an integral part of measurement.

Sectoral severity measures

Substantive content

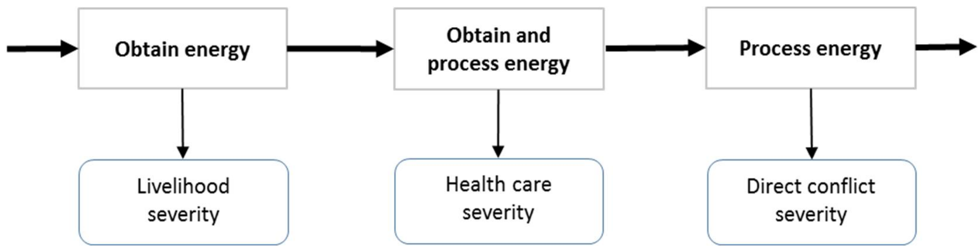
Severity measures are sector-specific until they are aggregated into some intersectoral construct. Which sectors produce usable measures may vary from crisis area to crisis area, and even from year to year.

In order to reveal important distinct types of severity, not all sectors are equally informative. From societal maintenance as well as human suffering perspectives, the choice of sectors should speak to two necessary capacities:

- *Obtaining* the energy necessary for physical and mental survival
- *Processing* the energy necessary for physical and mental survival

Measures of livelihood severity speak to the first. Measures of protection or otherwise conflict-related severity express the capacity to process the energy (because violence disrupts energy consumption even where people may have obtained it in the first place). Measures of health care severity address both capacities; for higher morbidity curtails both. Health care severity thus has a bridging function. We will find this confirmed in the correlation pattern of our demo data.

Figure 5: Energy flow in personal and societal maintenance



When we lengthen the time perspective, the cultural survival of persons and of the society takes greater urgency. Obviously measures of education severity become more important, but also those measuring severity in other sectors, notably protection, that address that aspect of societal pattern maintenance[6].

Formal considerations

In this note, we assume that all sectoral severity measures are ordinal rating scales, the ACAPS-recommended 7-level or some similar scale.

We transform the ratings into interval-level measures. This happens in three steps:

1. Taking the **ridit** of the raw values
2. Taking the **inverse cumulative normal** of the ridit
3. **Standardize** the inverse normal

The ridit (Brockett and Levine 1977) is a data-driven, meaning empirical distribution-dependent, mapping to the interval (0, 1). It ensures that all values are > 0 and < 1. For a detailed explanation, see Benini, op.cit.: 25-28, as well as the formulas in the sidebar below.

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[6] Sociologists may smell a whiff of the Parsonian AGIL model here, with its Adaptation, Goal Attainment, Integration and Latency functions for all living systems (Wikipedia 2017). If so, we have no intention to elaborate, believing that the two capacities of obtaining and processing energy, in their various sectoral expressions, suffice for our momentary purpose. But some minimal functional framework is clearly needed to evaluate variable selection and model building.

The inverse cumulative normal transformation, or short “inverse normal”, “stretches” the extremes further out, depending on the “rarity” of the extreme values (0 and 6 in the ACAPS rating scale). Some values become negative, which is ok since only the relative distances between the values matter. Severity scales do not have a natural zero point anyway.

Standardizing the values is a convenience step facilitating interpretation. It requires that the estimation procedure be indifferent to scale and location (but not to the shape) of the distribution. The profiling algorithm (see further below) meets this condition.

Following the worked example in the S, we will finally turn to a real dataset.

[Sidebar:] The ridit and subsequent transformations in Excel

You are a sector analyst in a crisis-shaken country in which your and several other sectors have conducted an assessment in 430 communities.

You produced severity ratings regarding your sector based on the part of the data that was of interest to you. The distribution of your ratings is in column 2 of the spreadsheet below. It is obvious that overall you judged the majority of the communities to be less than “2-moderately” impacted. Nonetheless, almost a fifth are in conditions that you consider majorly to catastrophically severe.

Table 2: Calculation of the ridit, inverse normal, and standardized severity score

	1	2	3	4	5	6	7	8	9	10
1	Severity rating	Communities	Frequency	Cumulative	Ridit	Inverse normal	Centered	Standardized	Exponential, scaled to 1 for severity = 0	Cut points
2	0	50	0.116	0.116	0.058	-1.571	-1.592	-1.748	1.000	
3	1	200	0.465	0.581	0.349	-0.388	-0.410	-0.450	3.662	1.914
4	2	100	0.233	0.814	0.698	0.518	0.496	0.545	9.905	6.023
5	3	50	0.116	0.930	0.872	1.136	1.115	1.224	19.538	13.911
6	4	20	0.047	0.977	0.953	1.680	1.658	1.821	35.479	26.328
7	5	8	0.019	0.995	0.986	2.199	2.177	2.391	62.725	47.174
8	6	2	0.005	1.000	0.998	2.830	2.809	3.084	125.506	88.726
9	Total	430	1.000							
10		Formulas (if two are given, the first is for the first numeric row, the second for all subsequent rows):								
11			=RC[-1]/R10C[-1]							
12				=R[-1]C[-1]						
13				=R[-1]C[-1]+R[-1]C						
14					=0.5*RC[-2]					
15					=RC[-1] + 0.5*RC[-2]					
16						=NORM.S.INV(RC[-1])				
17							=RC[-1]-R22C5			
18								=RC[-1]/R25C5		
19									= EXP(RC[-1]) / EXP(R2C8)	
20										=(R[-1]C[-1]*RC[-1])^0.5
21	Auxiliary calculations:									
22	Weighted mean of inverse normal:				0.021					
23					= SUMPRODUCT(R2C2:R8C2,R2C6:R8C6)/R9C2					
24										
25	Weighted sd of inverse normal:				0.911					
26					=(SUMPRODUCT(R2C2:R8C2,R2C7:R8C7,R2C7:R8C7) / (R9C2 - 1))^0.5					

You take pains to compute the transformations about which you read in this note. You get the results in the green columns by subsequently applying the formulas, moving through columns from C2 up to C8. Since your table is a summary, no longer a data table with 430 records, the standardization part in C8 requires weighting by the number of communities. You find formulas for these too.

The exponential scale

You are interested to see also an instance of the exponential function to which the level of the underlying causal force of the conditions that prompted your ratings may be proportional. You exponentiate the standardized ratings in C8 and scale them such that the value for your ordinal rating "0- None" becomes 1.

You wonder what this all means. You realize that your ratings correspond to intervals of the scaled exponential function. For example, "1-minor" goes with (1.914, 6.023]. "6-Catastrophic" goes with (88.73, +∞). Thus the ratio between the upper bound for minor and the lower bound for catastrophic is 88.73 / 6.023 ≈ 14.7. If you consistently rated community A's severity level "minor", and B's "catastrophic", you implied that the causes of severity in B were at least 14 times stronger than in A as far as your sector is concerned.

Consistent ratings

Assume now that the only information that you had to base your ratings on was the percentages of IDPs in the populations of those 430 communities. For example, from A a proportion of 5 percent was reported. However, B was struggling with 80 percent IDPs.

You agree that the suffering of communities in which fewer residents and more IDPs are trying to survive soar with the proportion of the latter. You find it convincing that this increases in proportion with the odds of being IDP. You calculate the odds for A as 0.05 / (1 – 0.05) = 0.0526 and for B as 0.8 / (1 – 0.8) = 4. The odds ratio B/A is 76. If A is minorly affected, B certainly deserves the predicate "catastrophic". Your ratings are consistent.

Realistically, you had data on several more variables that informed your ratings. The exponential mapping that resulted after the transformations is at best a belief model of how the strength of the causal forces and your judgments could be related.

From this point forward

From this point forward, you, your colleagues in other sectors and the intersectoral coordination unit have two basic choices of how to further develop the analysis:

1. **Intersectoral severity measure:** If the collective interest is chiefly in finding a measure of intersectoral severity, based solely on the sectoral ratings, then all the sector analysts could be asked to do this exercise with their ratings. This would produce sector-specific scales as in column 9 above. The coordination unit would assemble the sectoral scores (C9) and sectoral cutpoints (C10) in a table. The sectoral tables with the individual ratings of the 430 communities would also be joined. The sectoral scores and cutpoints would be imported from the combined transformation table (via VLOOKUP). The intersectoral exponential score could be computed by an appropriate formula (e.g., the geometric mean) and similarly the intersectoral cut points. These cut points define the intervals for the intersectoral ordinal ratings. Thus the intersectoral exponential scores can be mapped back into intersectoral ordinal ratings. In addition, various typological orderings may be attempted based on the sectoral exponential scores as policy interests and features of Excel, such as Pivot tables, empower the analyst community to perform.

2. **Incorporating severity ratings and causal indicators simultaneously:** If the analyst community wanted a typology that incorporates both severity ratings and causal indicators, a combined intersectoral data table, with adequate documentation of all variables, may be given to a statistician for a latent class or latent profile analysis. Its results may then be plugged in with the datasets of sectoral and coordinating unit, to pursue further work as needed.

The 2017 syria Humanitarian needs overview dataset

Locality and sub-district data

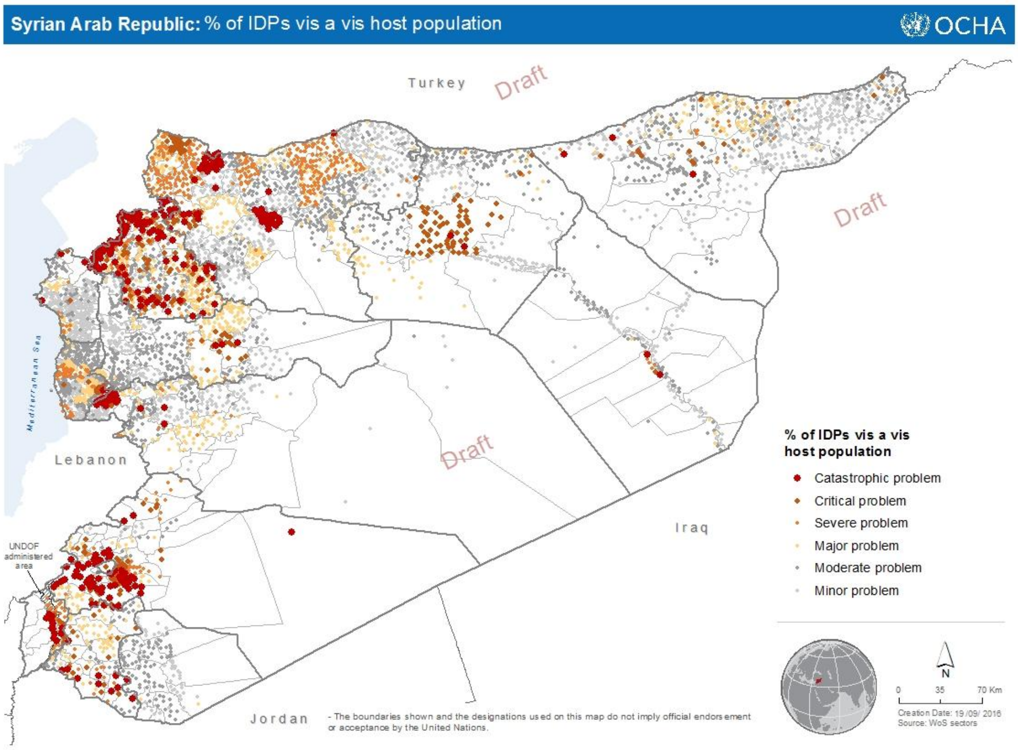
The 2017 HNO for Syria

The 2017 HNO for Syria report was published in December 2016 (UNOCHA and SSG 2016). Its key statistic is the estimate of 13.5 million people in need, those who require humanitarian assistance. Since we contend that the distribution of the intersectoral PiN estimates is not informative – see page 11–, we need to go back to the data.

Localities

In 2016, the humanitarian network, coordinated by UNOCHA, assembled data on conditions in communities at a lower level than the 270 sub-districts that had marked the highest level of resolution in previous HNO datasets. At this locality (Admin-4) level, the effort produced a table of 5,605 records and 107 variables. The localities are geo-referenced as points. There is little in the way of meta-data on coverage (there is no official Admin-4 gazetteer); the report states that 579 localities were not reached (op.cit., 27). A series of maps designed in September 2016 suggest that locality-level data were available on vast swathes of the country. Thus, for example, the locality IDP proportions have a positive variance in 259 of the 267 sub-districts that were covered. That implies that in the vast majority there were individually estimated values (as opposed to imputed to sub-district level estimates). Somebody went there, or called there or had other local sources. The blank spaces in the map are mostly uninhabited spaces.

Figure 6: Map of communities in Syria, by levels of IPPs in the population, 2016



701 records were missing population and/or IDP data. These were removed from our working dataset, leaving 4,904 localities with values.

Severity ratings

Severity ratings were given out in these sectors and in what one might call particular interest-domains, plus the combined intersectoral ones:

Figure 7: Distribution of severity ratings in 4,904 localities

Severity level	IDP proportion	Prices of commodities	Access to health care	Livelihoods coping	Conflict intensity	Intersectoral	Total ratings
0-None	1,473	900	440	0	3,417	0	6,230
	30.04	26.37	27.97	0	69.68	0	25.32
1-Minor	613	564	10	0	942	420	2,549
	12.5	16.53	0.64	0	19.21	8.56	10.36
2-Moderate	836	1,161	126	273	256	2,502	5,154
	17.05	34.02	8.01	5.57	5.22	51.02	20.95
3-Major	630	513	330	223	166	1,715	3,577
	12.85	15.03	20.98	4.55	3.38	34.97	14.54
4-Severe	587	124	445	496	58	256	1,966
	11.97	3.63	28.29	10.11	1.18	5.22	7.99
5-Critical	396	63	195	3,912	40	9	4,615
	8.08	1.85	12.4	79.77	0.82	0.18	18.76
6-Catastrophic	369	88	27	0	25	2	511
	7.52	2.58	1.72	0	0.51	0.04	2.08
Total	4,904	3,413	1,573	4,904	4,904	4,904	24,602
	100	100	100	100	100	100	100

Note: The second row at each severity level gives the column percentages.

Author's calculations

Notice the large number of missing in the commodity price and particularly in the health care access ratings. Our analysis does not use intersectoral severity ratings; the interested reader may find a description of the method on page 54 of the HNO report, op.cit.

Sub-districts

In addition, a sub-district level dataset was put together (270 sub-districts). Its 30 variables include severity ratings for the sectors. In the table they appear in this sequence: Intersectoral, CCCM, education, nutrition, protection, NFI, shelter, WASH, food security and early recovery sectors. They show no missing values.

Variables used in the analysis

Our model works with seven variables. Three of them are severity ratings, and three causal indicators, all at the locality level. The seventh was constructed from the IDP proportions, using also the geolocation variables. It will be described below.

Severity ratings

Selection

In keeping with our parsimonious model of energy acquisition and processing, we work with only three ratings: Livelihoods, health care, and conflict intensity. The 3,331 missing health care severity ratings were replaced with their sub-district level values, which were complete.

The ratings were thrice transformed, as described earlier.

Correlations

In the transformed ratings, health care severity is positively, though weakly correlated with livelihoods and directly conflict-related severity. We predicted this (see above) because of the bridging function that health care fills between obtaining and processing the energy for survival. Conflict-related and livelihoods severity are not correlated. The correlation table is for the transformed (i.e. continuous) values; below see an illustration of cross-tabulated raw (ordinal) values, with a considerably strong gamma = +0.50.

Table 3: Correlations among severity ratings

Pearson correlations among the transformed ratings (obs=4,904)

	Liveli.	Health c.	Direct conflict
Livelihoods	1.0000		
Health care	0.1720	1.0000	
Direct confl	-0.0177	0.3441	1.0000

[continued on the next page]

Association between the ordinal conflict and health care-related ratings

. tab conflict_sev health_sev_imp, gamma

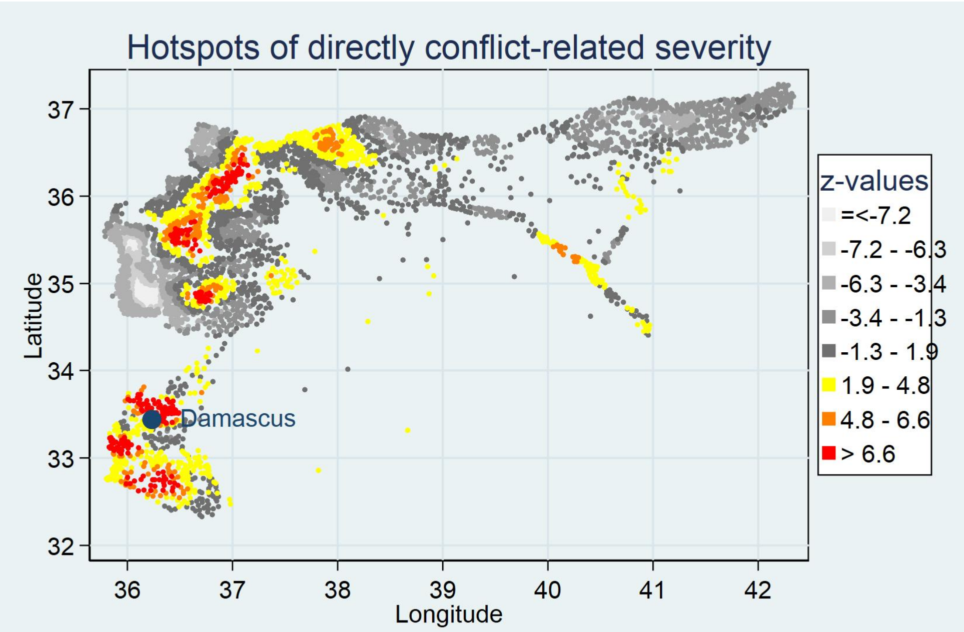
Conflict intensity	Health care severity (missing imputed) None	Minor	Moderate	Major	Severe	Critical	Catastrop	Total
None	1,004	744	725	398	300	221	25	3,417
Minor	110	16	90	240	324	144	18	942
Moderate	15	15	39	58	77	49	3	256
Major	8	10	40	39	44	19	6	166
Severe	1	8	12	18	14	4	1	58
Critical	1	5	14	8	7	5	0	40
Catastrophic	0	10	7	4	4	0	0	25
Total	1,139	808	927	765	770	442	53	4,904

gamma = 0.5021 ASE = 0.015

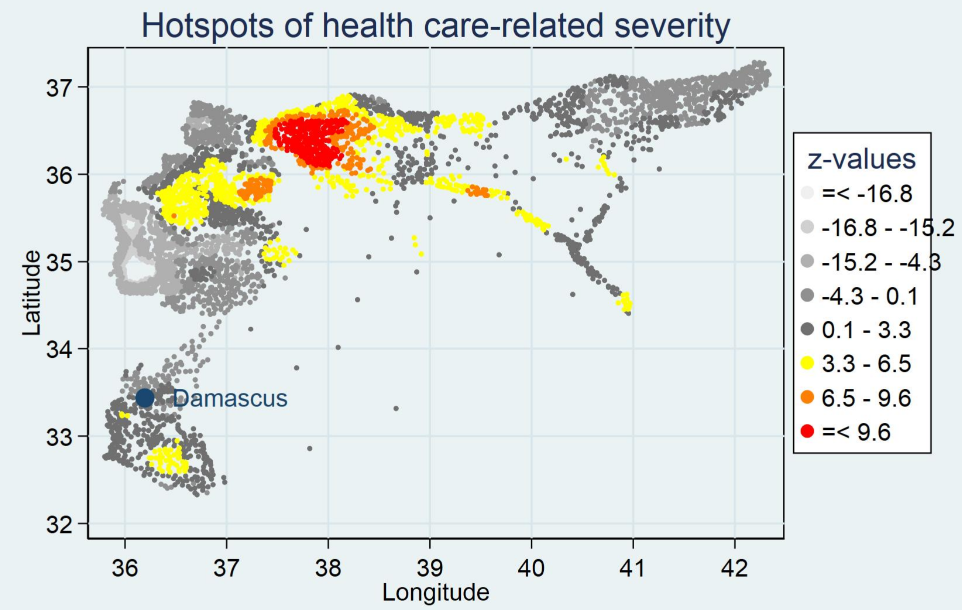
[Sidebar:] Hot spots of severity

Readers attuned to studying the distribution of humanitarian developments in space – making and reading maps – may find that they learn little of interest from correlational patterns without spatial dimensions. With this dataset, we can identify spatial patterns due to the fortuitous circumstance that all localities are geo-referenced. For quick orientation, hot spot maps of areas with clusters of localities showing high severity values may be helpful. In order to identify the hot spots, we use a spatial statistic known as Getis-Ord $G^*_i(d)$ (Ord and Getis 1995, Kondo 2016). It tests for every locality *i* whether it and its neighboring localities form a spatial cluster, given their above-average (hot spots) or below-average (cold spots) values on a variable of interest. We define as neighbors all localities within a radius from *i* of d = 15km. The variables of interest for the following maps are the transformed sectoral severity ratings. The maps are unprojected; the distances used to calculate the weight matrix are spherical. A Syria country outline was not available for this form.

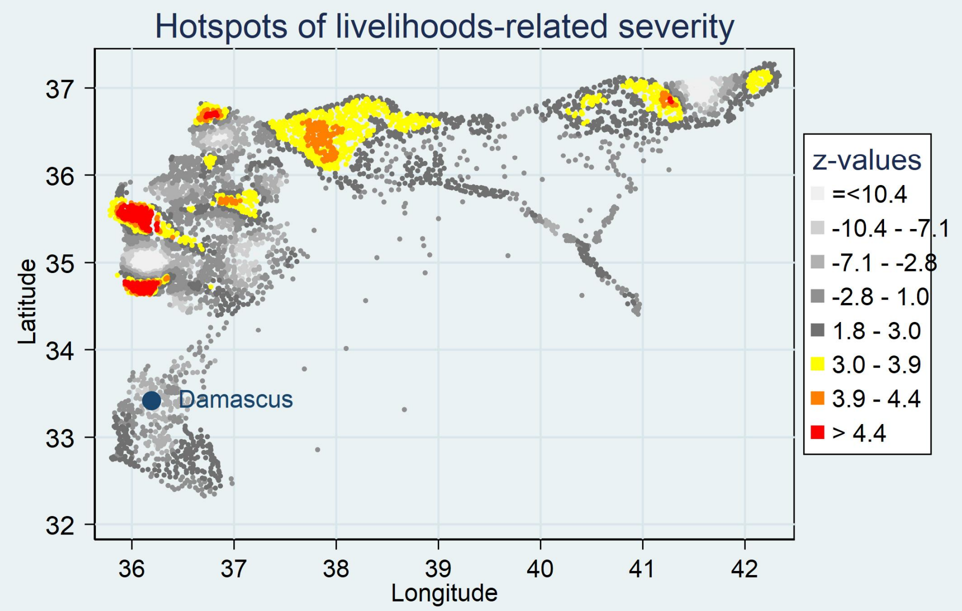
Figure 8: Hot-spot maps of three sectoral severity ratings



Note: Syria HNO 2017. z-value of the Getis-Ord G*i(d) statistic, binary weight matrix, radius of 15km.
Categories based on percentile breaks 5 10 25 50 75 90 95%. N = 4,904 localities.



Note: Syria HNO 2017. z-value of the Getis-Ord G*i(d) statistic, binary weight matrix, radius of 15km.
Categories based on percentile breaks 5 10 25 50 75 90 95%. N = 4,904 localities.



Note: Syria HNO 2017. z-value of the Getis-Ord G*i(d) statistic, binary weight matrix, radius of 15km.
Categories based on percentile breaks 5 10 25 50 75 90 95%. N = 4,904 localities.

Visibly, there is considerable overlap between the hot spots of directly conflict and health care-related severity. But at this “all localities within 15km, including the focal one”-level, all the correlations are stronger than at the focal-only locality level.

Table 4: Correlations among the Getis-Ord statistics

```
Pearson correlations (obs=4,904)

             |  Liveli.  Health c. Direct conflict
-------------+----------------------------------
Livelihoods  |   1.0000
Health care  |   0.3506   1.0000
Direct confl |   0.1132   0.6774   1.0000
```

While these hot spot representations may be helpful for those who seek primary orientation in maps, we need to forestall a misunderstanding. Our profiling model is not primarily a spatial model, but, at this experimental stage, a model including a single local context variable[7]. The variables – with the one exception – are observed for the individual locality, not for subsets of several localities. The exception is described below.

Causal indicators

War exposure

We use the humanitarian access ratings as a proxy for war exposure. This is an ordinal variable with four levels:

```
Access levels:
           1 Accessible
           2 Hard to reach
           3 Encircled
           4 Besieged
```

We transform it the same way as the ordinal severity ratings, through a 3-step process:

Table 5: Humanitarian access ratings and transformed values

Access status	Localities	Percent	Ordinal	Transformed
Accessible	2,633	53.7	1	-0.871
Hard to reach	2,135	43.5	2	0.884
Encircled	101	2.1	3	2.793
Besieged	35	0.7	4	3.573
Total	4,904	100.0		

Locality population

The theoretical status of locality population size is unclear. Larger settlements, as a general rule that seems to hold worldwide, tend to have greater institutional diversity, which may help to mitigate humanitarian problems. That this may be a wrong assumption was noted already above. Localities have larger populations because,

[7] Epidemiologists are developing spatial latent class models. See e.g., Wall et al. (2012).

among other reasons, they already include IDPs. This is one of the reasons why the IDP proportion is a critical variable.

We put the population to its logarithm, then standardize the variable. While the locality population and IDP estimates were produced during summer 2016, they were used in December as the basis for the 2017 planning, which is why we label them "2017".

Table 6: Descriptive statistics of the locality population

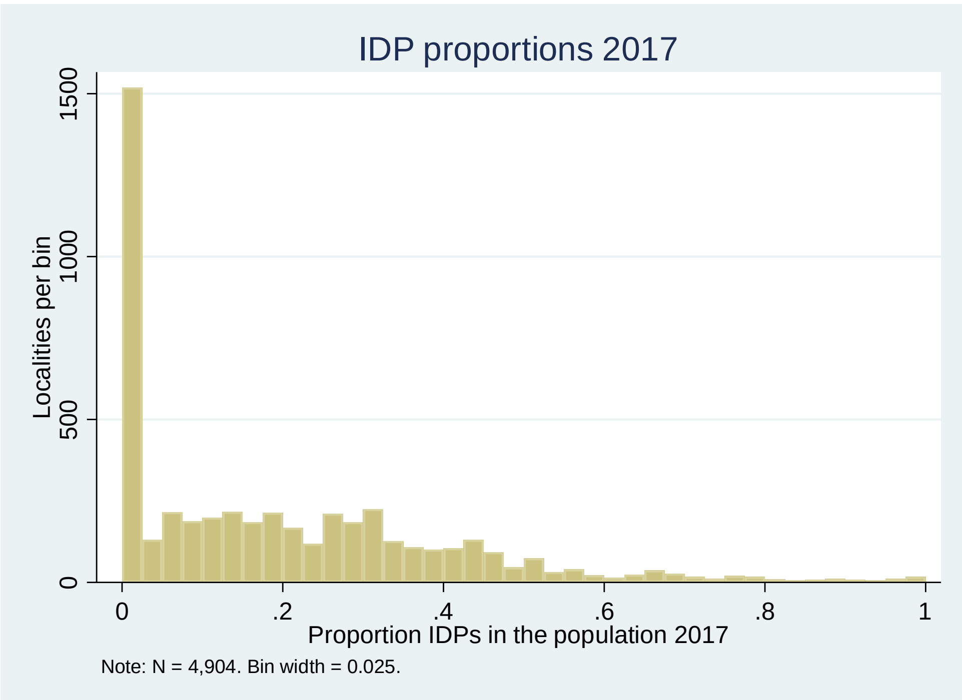
pop_est_2017	long	%10.0g	Estimated population 2017
log10_pop2017	float	%9.0g	Estimated population 2017 (log10)
c_popul	float	%9.0g	Population 2017 (log10, then standardized)

Variable	Obs	Mean	Std. Dev.	Min	Max
pop_est_2017	4,904	3,794.670	33425.727	10.000	1.58e+06
log10_p~2017	4,904	2.881	0.641	1.000	6.200
c_popul	4,904	0.000	1.000	-2.933	5.173

The proportion of IDPs

Among the 4,904 retained localities, 1,473 were reported to host zero IDPs. It is unknown how many of these claims are due to measurement or processing error.

Figure 9: IDP proportions in the localities



Among those reporting the presence of IDPs, the mean was 28.1 percent, the median 25.0 percent. The particular distribution advises against using the odds.

Re: standardization, see the next variable.

The immediate humanitarian context of the locality

The local context should be characterized by indicators that exclude the locality itself, but can be meaningfully attributed to the local environment of the war-torn country. We calculated the population-weighted IDP proportion among the nearest five localities within a radius of 15 km. These neighbor points were extracted using STATA's *geonear* procedure, which calculates geodetic distances (Picard 2012).

Table 7: Number of nearest-neighbor localities found within 15 km (max. 5)

No. found	Cases	Percent	Cum.
0	19	0.39	0.39
1	7	0.14	0.53
2	8	0.16	0.69
3	7	0.14	0.84
4	17	0.35	1.18
5	4,846	98.82	100.00
Total	4,904	100.00	

For the 19 localities without nearby neighbors, their own value was substituted.

In 596 cases, the locality and surrounding proportions are identical. In 551 of them, the proportions are zero. These must be areas without IDPs or with poor reporting. In surroundings with positive proportions, the mean is 23.4 percent and the median is 20 percent. These figures are population-weighted and thus are not strictly comparable with the focal locality statistics, which are not weighted.

The locality proportions and the 15 km surrounding proportions are strongly correlated (+0.68). To avoid collinearity problems, we orthogonalize them (Wikipedia 2014), with the locality variable going in first. This automatically standardizes them.

profiles

Descriptive profiles, based on the severity ratings

The ratings on each of the severity dimensions can be grouped, i.e., some levels can be combined. In Excel, Pivot tables and their grouping feature summarize data flexibly. A subset of localities defined by a particular combination of grouped ratings, together with statistics of variables of interest, may be considered a descriptive profile. For both cognitive and policy reasons, one may want to keep the number of profiles within reasonable limits. Here is an example of 2 * 2 * 2 = 8 profiles.

Table 8: An example of descriptive profiles

Severity dimensions			Distribution within effective sample				
Conflict	Livelihoods	Health care	Localities	Population		IDPs	
Any level above "none"	Is critical	Is severe or worse		Sum	Mean	Sum	Mean
No	No	No	658	1,111,283	1,689	326,993	497
No	No	Yes	27	31,250	1,157	3,595	133
No	Yes	No	2,213	2,350,853	1,062	549,203	248
No	Yes	Yes	519	437,379	843	87,524	169
Yes	No	No	209	2,420,020	11,579	1,050,285	5,025
Yes	No	Yes	98	460,420	4,698	184,578	1,883
Yes	Yes	No	559	8,149,377	14,578	2,957,349	5,290
Yes	Yes	Yes	621	3,648,482	5,875	1,155,551	1,861
		Total	4,904	18,609,064	41,482	6,315,078	15,107

Localities directly affected by the conflict tend to be much larger than those rated as “none” (9,871 vs. 1,150 in the mean). The opposite holds for health care severity; localities in severe or worse conditions tend to be smaller, although not by very much (3,619 vs. 3,986). Finally, overall, localities in critical livelihood situations tend to be smaller than those slightly or definitely better off, but again not by much (3.729 vs. 4,055).

Persons well familiar with the humanitarian situation inside Syria will no doubt be able to interpret these differences in terms of the greater sweep of the conflict. While such profile tableaux are easy to make and to rearrange, the purely descriptive analysis has its limitations:

1. The cutpoints are set by the analyst; they are not optimized by an algorithm that strives for informational discrimination. In directly conflict related severity, should the dividing line run between “0-None” and “1-Minor”, or should it be higher up? Or should there be more than two groupings? Similar questions can be asked about the other two dimensions.

2. With every dimension added, the number of profiles at least doubles. In this demo we have three dimensions and eight profiles. Two of them comprise relatively few localities, just 27 and 98 out of the 4,904. For a parsimonious presentation, it might be helpful to merge them with other, more populous profiles. But with which? How many profiles should there by finally? Description offers no guidance of its own.
3. Some basic causal analyses are quite feasible with the means of Pivot tables. The presentation can go in both directions. The means of causal indicators (e.g., the IDP proportion) can be computed for each of the eight profiles defined by the severity ratings. Conversely, the IDP proportions can be categorized, say into low/medium/high, and the distribution of the profiles over each of those categories can be called up. However, the analyst, limited to looking at multiple tables, will find it difficult to discern the relative influence of the causal indicators while they interact simultaneously.

We now turn to a statistical procedure - Latent Profile Analysis - that mitigates some of these issues.

Latent profiles

Background

Latent Profile Analysis is a subclass of a class of statistical models known as Latent Class Analysis, which in turn is a sub-class of mixture models. Mixture models seek to identify sub-populations of which membership cannot be directly observed, but can be inferred from observed attributes, although with uncertainty.

The sub-populations to be inferred are known by different terms such as “classes”, “clusters”, “types”. Latent Class Analysis historically was developed to deal with categorical indicators. It now is understood also to comprise models with continuous indicators, whose pioneers coined the term “Latent Profile Analysis”. Although severity ratings are categorical and as such can be handled by categorical mixture models, three sectoral scales at seven levels imply 21 possible combinations. This is likely to cause estimation problems particularly if some have few or zero members. This is one of the motivations to transform ratings to continuous variables.

Latent class and latent profile analysis can incorporate exogenous variables that predict class membership. In statistics, they are known as “covariates” or “exogenous variables”. We call them “causal indicators” but this interpretation makes demanding assumptions about causality. They may be warranted in the case of IDP proportions, but, as we have noted, are questionable for locality population.

Vermunt and Magidson (2002), who call the procedure “latent class cluster analysis”, provide a readable introduction in the sense that one can understand “what it is all about” while glossing over the few formulas[8]. In Stata (version 15), Latent Profile Analysis is part of Generalized Structural Equation Model estimation (*gsem*) (Stata Corporation 2017).

What the analysis produces

The Stata output – other statistical packages likely follow similar formats – essentially has three elements:

What makes the classes different

- A coefficient table informs for each inferred class how the various causal indicators differentiate it from other classes (one of the classes serves as the baseline)
- Another table presents for each class the estimated means of the endogenous (dependent) indicators (which in our case are the transformed severity ratings)
- the overall probabilities to belong to a given class

Table 9: Example: Estimated means of the transformed severity ratings

```
Latent class marginal means                     Number of obs     =      4,904

------------------------------------------------------------------------------
Class        |              Delta-method
      Sector |      Mean     Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
1            |
    s_liveli |  -1.963995     .022799   -86.14   0.000     -2.00868    -1.91931
    s_health |  -.6348349    .0301787   -21.04   0.000     -.693984   -.5756858
  s_conflict |  -.6166428    .0067153   -91.83   0.000    -.6298045    -.603481
-------------+----------------------------------------------------------------
2            |
    s_liveli |   .4771704    .0153732    31.04   0.000     .4470396    .5073013
    s_health |    .402529    .0280955    14.33   0.000     .3474627    .4575952
  s_conflict |  -.6166428     .004476  -137.77   0.000    -.6254156   -.6078699
-------------+----------------------------------------------------------------
Note: Results for classes 3 – 6 not shown here for space reasons.
Model with 6 classes, covariates (“causal factors”) and covariances.
-------------+----------------------------------------------------------------
```

What strikes the eye is that the members of both classes have the same means for conflict-related severity – far into the negative, so probably rated “0-none”. We will check asap; see below. But the differences in livelihoods and health care severity are major. Class 1 members are not affected; class 2 means are positive, meaning more severe.

[8] Available at https://pure.uvt.nl/portal/files/487979/hagenaars2002b.pdf .

Note the small standard errors and therefore the narrow confidence intervals; however, they are wider for health care severity. Thus we expect more variation in the health care severity ratings.

We translate this back into the language of ordinal severity ratings.

Table 10: Example of translating severity levels back to ordinal language

	Class 1: 679 localities			Class 2: 1,490 localities		
Severity	Livelihoods	Health care	Directly conflict	Livelihoods	Health care	Directly conflict
None	0	300	679	0	25	1,490
Minor	0	148	0	0	259	0
Moderate	224	168	0	0	361	0
Major	110	36	0	0	328	0
Severe	345	8	0	6	290	0
Critical	0	19	0	1,484	202	0
Catastrophic	0	0	0	0	25	0
Total	679	679	679	1,490	1,490	1,490

Note: Results for classes 3 – 6 not shown here for space reasons.

It is now obvious what defines these two classes:

- Class 1:
  - For all 679 member localities, livelihoods severity is less than critical.
  - For all, health care severity is less than catastrophic (most in low levels).
  - For all, directly conflict-related severity is “none”.

- Class 2:
  - For all 1,490 member localities, livelihoods severity is critical.
  - Wide variety in health-care severity, with members in both extremes.
  - For all, directly conflict-related severity is “none”.

Note again that it was not the analyst who pre-defined the classes. Class characteristics and class size result from the statistical algorithm. The analyst does decide the number of classes (see below).

Where the individual sample members belong

- For each sample member, Stata computes the probabilities of belonging to the various classes. This is the basis for calculating population and IDP estimates with confidence intervals.
- Assigning each sample member to the class in which it has the highest probability, as a pragmatic way to show how the classes relate to certain other

attributes of interest (chiefly where they are in terms of geography and administrative units).

Table 11: Example of class probabilities and class assignment

Four arbitrarily chosen locality records in a model with 6 classes

record_id	Probability to belong to class						Assigned to class
	1	2	3	4	5	6	
12	0.00	0.26	0.28	0.00	0.00	0.45	6
13	0.00	0.00	0.00	0.01	0.99	0.00	5
14	0.00	0.00	0.00	1.00	0.00	0.00	4
16	0.00	0.36	0.21	0.00	0.00	0.43	6

Which model with how many classes should be preferred

- Information measures are provided to let the analyst see whether models with more classes yield statistically better results, or are unbeneficial complications.
- The measures include the log-likelihood (ll), Akaike's information criterion (AIC) and the Bayesian information criterion (BIC)[9]. Models with clearly *larger* ll and *smaller* AIC and BIC are preferable. But the time computers take to work through the estimation of models with more and more classes increases rapidly, meeting limits of capacity or patience.

Table 12: Example of model comparisons on information criteria

```
     Classes |        Obs  ll(null)  ll(model)      df         AIC         BIC
-------------+-----------------------------------------------------------------
           2 |      4,904         .  -17876.51      17    35787.02    35897.48
           3 |      4,904         .  -17284.48      25    34618.95    34781.40
           4 |      4,904         .  -17204.27      33    34474.54    34688.96
           5 |      4,904         .  -14550.66      41    29183.31    29449.72
           6 |      4,904         .  -13527.91      49    27153.83    27472.22
-------------------------------------------------------------------------------
```

The gain from estimating a model with 5 classes over one with only 4 is dramatic. Moving on to 6 classes gives still better results, but the gain in information value is smaller.

[Sidebar:] Understanding mixture models while riding the Metro

An illustration from a totally different context may be helpful – the Metro, short for metropolitan subway. Suppose you want to know the composition of the ridership. Riders do not wear batches saying “I am a resident” or “I am a tourist”. You cannot interview a good enough sample of riders

[9] A Wikipedia search for “information criterion” returns articles about the AIC, BIC and other criteria.

while traveling yourself. Yet, by observing dress, families with children, queues in front of single-ticket machines, and the people who stand on the wrong side of the escalators, you can form a fairly good estimate of the current proportion of tourists, without ever approaching any fellow riders verbally. But you can never be totally sure about any one particular individual.

Mixture models in statistics do the same. They assign probabilities that a sample member, given its observed attributes in the context of the joint distribution for the full sample, belongs to particular groups. Moreover, if the analyst wishes to vary the number of groups, they provide informational measures about the preferable number, based on discrimination and model parsimony.

The analyst decides how many groups ultimately serve the purpose. She may override the informational criteria (documenting them, of course, in a little notebook happily while squeezed into a narrow Metro train seat!). She will do so in the interest of meaningful interpretation, perhaps going for fewer, perhaps for more groups. To remain with the subway for a moment, the algorithm may say that the distribution of the observed attributes suggests four distinct types of riders rather than three or five. The analyst easily interprets two of the four as tourists and as office commuters. But she is not sure what the other two are. Is one of them composed mostly of students? She does not know because the observers didn't note the finer age grades. Thus she settles for estimates of "tourists", "office workers" and "all others".

Some mixture models can be combined with causal analysis. For the subway analyst, it certainly helps to know when the observations were made, on which line, and in which direction the trains were running. Office workers travel during rush hours; tourists move later, around the time shops and museums open. In the minds of most people – yours probably, too - the hour in the day doesn't "make" somebody a tourist. Whatever your meta-physical persuasions, noting time improves the ability of the model to discern a group of people many of whom likely are tourists.

Estimated models

Including the same three transformed severity ratings in every models, we ran 20 models. They had between 2 and 6 classes. A 6-class model took some 10 minutes to finish, the limit of our patience. Also, models with more classes would be increasingly likely to produce some with few members. In general, this is not desirable. In Syria, this may be different, even desirable. Models with more classes might single out encircled and besieged communities, which are in the direst conditions, and are priorities for the humanitarian community. But such groups should be singled out right away on policy grounds (as the 2017 HNO has done), without relying on probabilistic statistics.

Two of the twenty models did not converge and had to be aborted. One of the six-class models did converge, but produced members only in five classes (actually a useful result, showing the power of probabilistic approaches to single out also low-probability states).

Apart from the number of classes, the models differed in these features:

- Whether they included covariates ("causal factors") or not

- Whether they permitted the residuals in the transformed ratings to be correlated (so-called models with covariances) or not – mostly a statistical technicality.

Models that differed in the second feature had very similar results when they were the same in the first and had the same number of classes. We will therefore not discuss them.

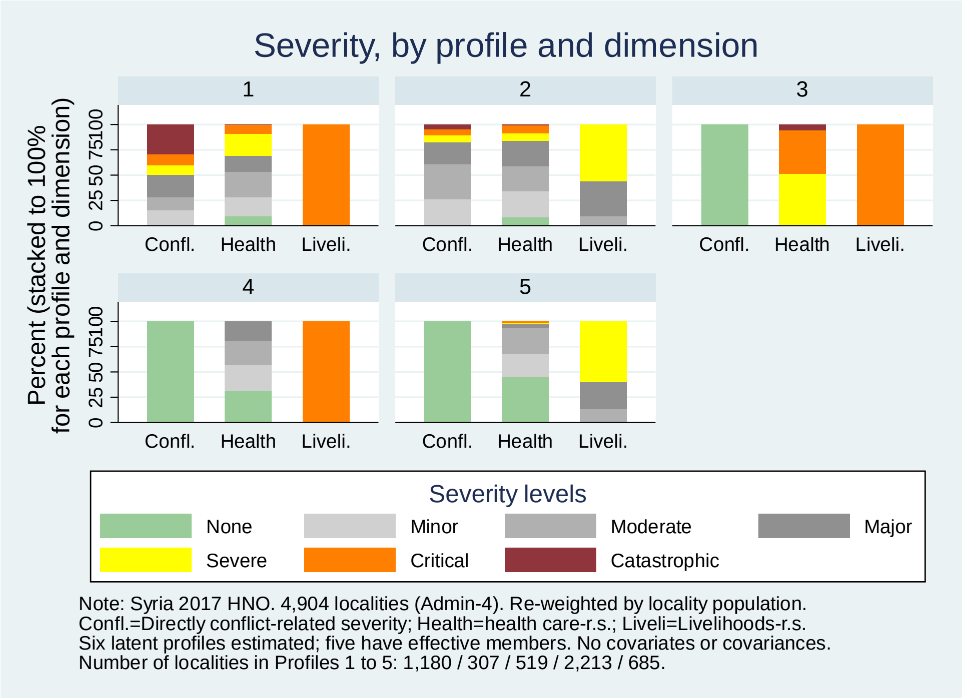
The models that differed in the first feature produced different and interesting results. We briefly compare two models, both with six classes. Then we present one of them in greater detail. We summarize the essence of its six classes. We discuss some select features such as the estimated populations associated with the classes and an illustration of probabilistic membership.

Models with and without covariates

What if we do not consider causal factors?

Models that exclude the causal factors do not make use of prior knowledge to predict analysts' severity rankings from the so-called objectively measured conditions such as the IDP rate. They only look at the rankings themselves to infer the latent classes. Our 6-class model produced five classes with members (the membership probabilities in the sixth class were too small to even produce a single member). These five effective classes were defined by the four combinations {livelihoods severity: critical / less than critical} X {directly conflict-related severity: none / minor or worse}. Health-care severity was a secondary defining attribute. Two classes were defined primarily by the combination "severe livelihood severity" and "zero-level conflict-related severity". They were distinguished such that one had all members with severe-to-catastrophic health-care conditions; the members of the other were all at less than severe levels.

Figure 10: Five profiles - model without covariates or residual covariances



What is noteworthy about those profiles? Chiefly where the algorithm set the cut-points:

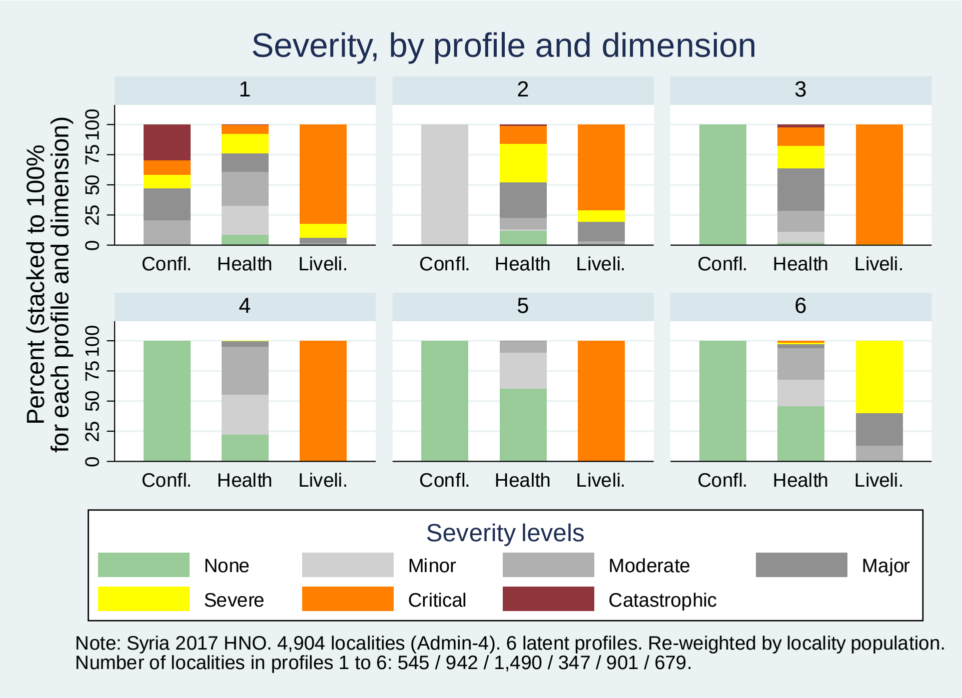
- Livelihoods: between critical and less than critical.
- Health care: where it played a co-defining role: between severe and less than severe.
- Conflict related: between zero-level and minor or worse.

The first two distinctions make sense. The third seems less than optimal. Is the sharpest distinction, as regards the conflict-related severity really at that low level?

Using prior knowledge to predict severity ratings

The 6-class model that includes causal factors produced, as its main result, profiles separated by not one, but two cut-points in the conflict-related severity. This severity dimension thus has become the leading definitional criterion. The distinctions run between localities at “0-None” and “1-Minor”, and between “1-Minor” and “2-Moderate or worse”, which includes all from “2-Moderate” to “6-Catastrophic”.

Figure 11: Six latent profiles - severity ratings in three dimensions



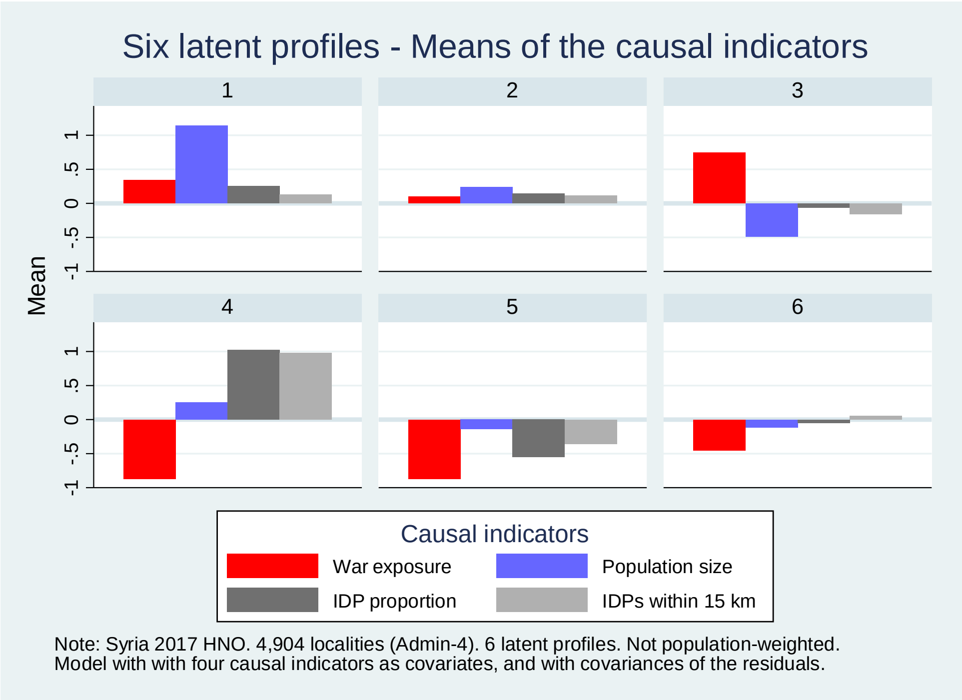
Note: The same graph is used in the Summary.

What makes these six profiles distinct?

- Profiles 1 and 2 gather localities exposed to direct conflict impacts; in # 1 that dimension of severity was rated between moderate and catastrophic. In # 2, the level is uniformly minor.
- Profiles 3 – 6 have localities with conflict-related severity at 0-None level. They are distinguished by the levels of livelihoods severity. It is critical for localities profiles 3 -5. Localities in profile 6 suffer livelihoods severity at various levels lower than "critical".
- The distinctions among profiles 3 to 5 are not crisp. In fact, they are fuzzy if we look only at the severity ratings. The differences are gradual in the composition of the health care severity, with #3 overall showing more severe conditions than #4, and #4 more so than #5.

The profiles show distinct causal signatures.

Figure 12: Causal signatures of the six profiles



Note: The graph is used also in the Summary.

- Membership in **profile 1** is driven strongly by larger population size (cities, larger towns).
- **Profiles 2 and 6** have no strong predictors among the available indicators. The analysts who rated their members must have been guided by other considerations.
- **Profile 3** is the one that, at first glance, is the most strongly driven by war exposure. However, this is chiefly the result of difficult humanitarian access for the vast majority of these 1,490 localities. In fact, on the rating side, the concerned sector analysts gave all of them a "direct-conflict related severity" score of "0-None"[10]. They tend to have smaller populations. One assumes that in their majority they are difficult-to-access rural communities in critical livelihoods and above average difficult health care conditions.
- **Profile 4** membership is driven by good accessibility and high IDP proportions, both in the localities themselves and in their neighborhoods (Notice that the last factor is not a tautology; "IDPs within 15 km" was transformed such that it is statistically independent of the IDP proportion itself.).

[10] There are contradictions in the data. A minority (63) of the 1,490 localities were encircled, and three of them were besieged. Nonetheless, they were all given "direct-conflict related severity" scores of "0-None".

- **Profile 5** assembles localities with no significant current war exposure – all were accessible - and with lower IDP burdens.

It is noteworthy that, whereas Latent Profile Analysis is probabilistic and as such depends on statistical applications, the above indicator signatures can be crafted on the basis of Excel pivot table results. Thus, a simpler, empirical typological approach to profiling, as demonstrated in the table on page 37, *and* to their causal signatures are at the fingertips of every enterprising information management officer.

Probabilistic profile membership

Every locality in the 6-profiles model is assigned six probabilities, one of belonging to each of the six profiles. They sum to 1 since every locality ultimately belongs to exactly one profile.

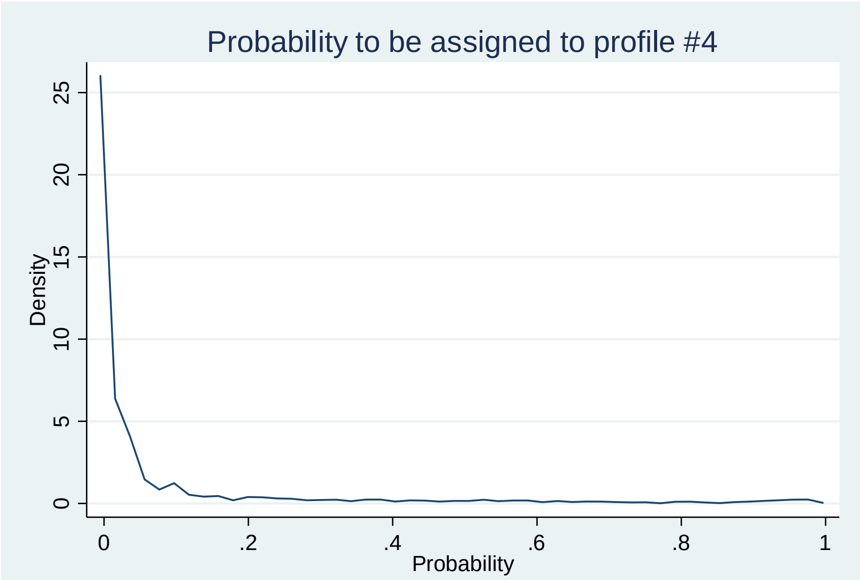
The locality receives its final membership in the profile for which it has the highest of its six probabilities. If this probability is larger than 0.5, the case is trivial; from all the other profiles that "compete" for this locality to become a member, it receives probabilities < 0.5 – "weak invitations", in a manner of speaking, that fail to attract the locality.

Rarely, however, do we find profiles with members that made it into it with probabilities < 0.5. This happens when the remainder of the probability budget is so splintered among the competitors that these are even less attractive.

The highest proportion of members with probabilities < 0.5 are found in profile 4 – 46 of the 347 localities. This profile, as the reader may recall, has the smallest membership of all six profiles. It assembles localities that were all of them rated "0-None" on direct conflict-related severity, and all "5-Critical" on livelihoods severity. The 347 received a wide spectrum of health-care severity ratings, although over 90 percent of them between "0-None" and "2-Moderate".

This profile, therefore, is ideally suited to demonstrate the probabilistic nature of profile analysis. Overall the probability of belonging to profile 4 is small for the 4,904 localities. Most of the localities stand a very low chance to be assigned here, smaller than 0.1 or 10 percent, as this density graph gives away. The mean probability works out as 0.0836, larger than the actual frequency 347 / 4,904 = 0.0708. The difference represents the "wasted efforts" of those who didn't make it into this profile, plus the "unnecessary efforts" of those who got in with probabilities much larger than 0.5.

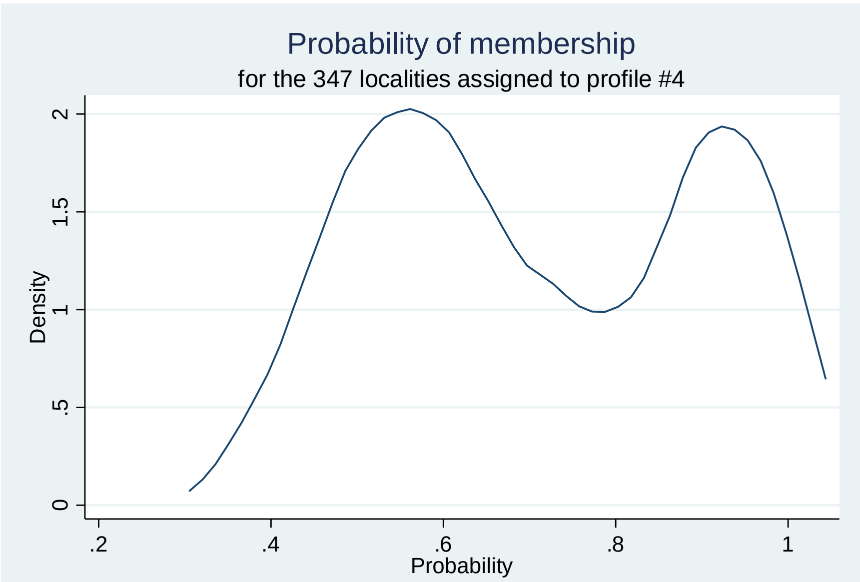
Figure 13: Example of the distribution of probabilities of belonging to a particular profile



Note: Probabilities of all 4,904 localities in the 6-profile model.

The situation changes dramatically when we look at the probability distribution of the 347 who did make it into profile 4. Note the different density scales of the two graphs.

Figure 14: Example - Probability distribution among members of a given profile



Note: Smoothed kernel density function. n = 347. Mean prob = 0.710, min = 0.358, max = 0.991.

The distribution has two peaks. This is suspect of a group that includes subgroups that are distinct on some attributes. Since all members of this profile share the same conflict-related severity ("0-None") and livelihoods ("5-Critical) severity ratings, these attributes must have something to do with the information that the health sector analysts used. As we do not have health sector-specific causal indictors, it is near impossible to say what causes this heterogeneity[11].

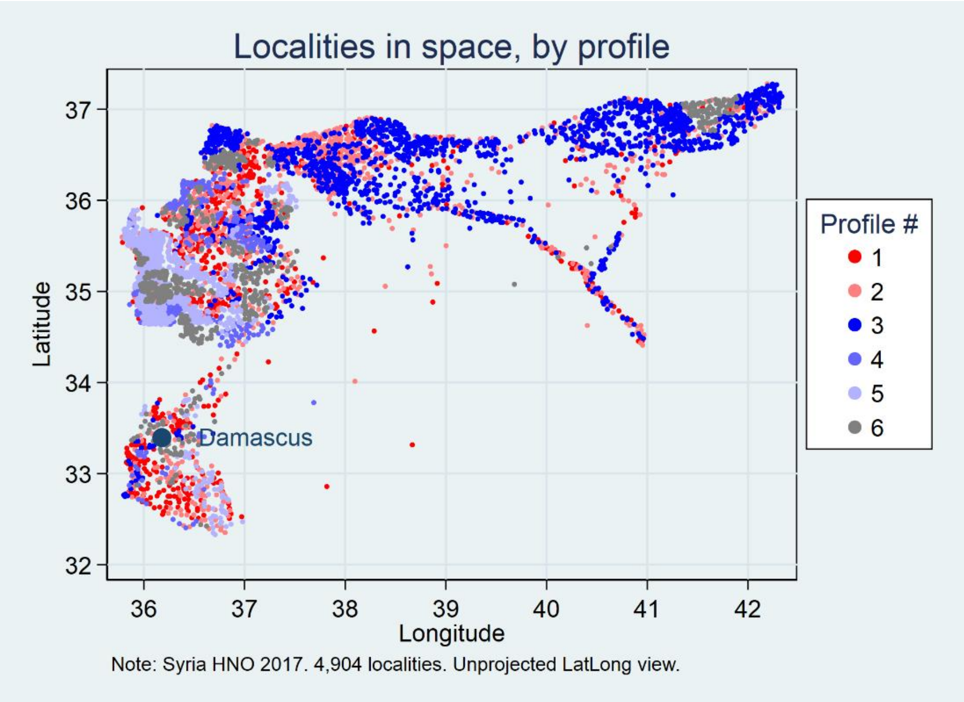
The point to stress here is that we have already obtained good results with the few (four) causal indicators that we have. If the sectors could share with the coordinating unit some of their own trusted and complete sector indicators, the profiling would become more precise and easier to interpret.

Geographical distribution

The distribution of the localities, each assigned to the profile for which it had the highest probability, appears in the map on the next page. The marker colors were chosen such as to indicate that profile #1 (red) tended to represent more severe conditions that #2 (orange), #3 more than #4, and this more than #5 (shades of blue), with #6 (gray) not being comparable in that way to any others.

[11] It can be shown, with different methods and on the basis of the intersectoral indicators, that within this profile there are indeed two distinct groups. However, there is considerable overlap. One group tends to have smaller populations; the other tends to have either higher populations and/or higher IDP proportions.

Figure 15: Geographical distribution of localities, by profile



The overall impression is that regions with fairly homogeneous profile membership alternate with others that mix localities from two or more profiles. The homogeneity may be exaggerated in areas with dense packing of localities; the graphing algorithm superimposed dots from higher profile numbers.

Population estimates

The 4,904 localities have a combined population of 18,609,064. Once the localities have been firmly assigned each to one and only one profile, the distribution over profiles is deterministic and trivial:

Figure 16: Total population, by profiles

Profile	Localities	Population 2017				
		Sum	Minimum	Median	Mean	Maximum
1	545	12,121,579	10	4,500	22,241	1,584,000
2	942	2,556,720	10	1,000	2,714	150,000
3	1,490	1,200,850	10	400	806	35,000
4	347	665,678	20	1,000	1,918	14,560
5	901	932,164	10	620	1,035	12,000
6	679	1,132,073	10	620	1,667	190,000
Total	4,904	18,609,064	10	730	3,795	1,584,000

However, this approach renounces the probabilistic nature of Latent Profile Analysis. It is preferable to compute member and population statistics adjusted for the membership probability distribution of every profile. This reflect the uncertainty of membership.

The sum of the probabilities gives the expected number of localities in the profile. Stata routinely produces a table for all the profiles[12]. Notice the differences in localities per profile between the two tables. The above counts result from ranking probabilities and assigning the given location to the class with the highest; the one below sums over all locations, given the profile. These statistical expectations come with uncertainty measures based on the standard errors of the proportions. They allow us to estimate confidence ranges for the membership of the profiles. For example, we may assume, with a confidence of 95 percent, that profile 1 assembles between 506 and 582 localities. Notice the different width of the intervals. These results are truly probabilistic. If this confuses you, you may notice that the number of localities in every profile in the table *above* is within the corresponding confidence interval in the table just *below*.

Table 13: Expected number of localities, with confidence intervals

Profiles	Absolute numbers			Proportions			
	Expected	LB95%CI	UB95%CI	Expected	Std.Err	LB95%CI	UB95%CI
1	543.1	506.7	581.6	0.111	0.004	0.103	0.119
2	943.9	892.2	998.0	0.192	0.006	0.182	0.203
3	1,510.1	1,413.6	1,610.2	0.308	0.010	0.288	0.328
4	410.2	310.1	538.8	0.084	0.012	0.063	0.110
5	825.8	741.8	917.2	0.168	0.009	0.151	0.187
6	670.9	625.8	718.7	0.137	0.005	0.128	0.147
Total:	4,904.0			1.000			

As for the population estimates, we remember that a given locality contributes population probabilistically to every profile. The contribution to a particular profile equals the product of its population (in absolute numbers) and its probability to belong to that profile. The sum of these products is the expected total population under that profile.

But how uncertain are these population estimates? There are two ways to think about this, depending on where we locate the sources of uncertainty:

- **Method 1:** The populations of the localities are **fixed**. The uncertainty results only from the uncertainty of the profile membership proportions. Thus the *relative*

[12] Known there a "latent class marginal probabilities", which here we call the expected proportions.

width of the confidence intervals for the profile populations is arguably the same as for the above locality table.

- **Method 2**: The locality population is a **random** variable. Both the populations and membership probabilities determine the standard errors. These must be computed from the distribution of *(locality population * probability to belong to the profile)* in each profile.

Table 14: Estimated profile populations, with confidence intervals

Profile	Estimated population	Method 1: Populations fixed		Method 2: Populations as random variable	
		LB95%CI	UB95%CI	LB95%CI	UB95%CI
1	12,118,333	11,307,800	12,979,272	7,560,291	16,676,376
2	2,559,965	2,419,604	2,706,443	2,126,739	2,993,190
3	1,257,268	1,176,923	1,340,567	1,135,861	1,378,675
4	698,310	527,897	917,283	611,809	784,813
5	854,505	767,581	949,103	778,891	930,120
6	1,120,682	1,045,324	1,200,559	681,552	1,559,811
Total:	18,609,063				

However, method 2 is less convincing. To a degree, it can be argued that the war changes the definitions and distinctions among localities, and that both their existence and their populations are volatile – hence a considerable proportion of the raw sample is without population data. In this view, the observed localities are a momentary sample from the cauldron of populations and physical structures that war and displacement continuously refashion.

But that view seems too fluid. Under method 1, the localities are not a random sample; they are the population of localities that were both distinct and (at least remotely) accessible during data collection. Their populations at that moment were fixed, except for measurement errors (of which missing values are extreme instances). The same holds for the other covariates. The randomness enters on the side of the severity ratings. The sector analysts produced severity ratings from incomplete and uncertain information. Moreover, only a small part of that information – the four covariates – was shared with us – hence the uncertainty in identifying the profiles and in predicting their membership.

Note that the confidence intervals of the population estimates are narrower for profiles #1, 2, 3 and 6 under method 1, but wider for profiles #4 and 5. The difference is particularly glaring for profile #1, which includes many of the largest communities.

Nevertheless, the question of how best to gauge the uncertainty of population estimates per latent profile deserves further study. At this stage of our experiment, the reader may want to note this methodological grey area and perhaps come up with better solutions.

[Sidebar:] Latent Profile Analysis vs. other classification methods

Earlier in this note, we placed Latent Profile Analysis in the wider class of models known as mixture models. Mixture models seek to identify sub-populations of which membership cannot be directly observed. It can be inferred from observed attributes, although with uncertainty.

Some readers may perceive – correctly so! - Latent Profile Analysis as a classification method and may wonder how it relates to better known methods such as **Cluster Analysis**.

Classification methods

In the most general terms, classification methods assign members of a sample (or of a completely observed population) to two or more categories, which are represented statistically by consecutive natural numbers, k = 1, 2, .., K. The major interest is in the distinctions among sample members, based on their dissimilarity in the relevant observed attributes. The number K of categories may be *pre*-determined by policy or theoretical concerns. Or it may be the result of selecting from models with various tentative *K after* the analysis, applying some evaluative criterion in terms of information gain or pragmatics (policy, academic). In any such situation, it is not known beforehand to which category a given unit belongs. This is the result of the analysis.

Situations other than classification

Before we talk about Cluster Analysis, let us distinguish two other broad classes of statistical models from classification methods, as understood above.

First, a very large number of models are **focused on variables** rather than on cases, by describing association patterns among variables or estimating the effects of a set of variables on another (dependent) variable. **Regression and factor analysis** are two of the many families of models that are fundamentally variables-oriented.

Second, the situation may arise where the sample members have **already been assigned to categories** of interest. In addition, there is a set of measures believed to be closely related to the categories, yet not directly defining them. The interest is to find out which combinations of values on these measures predict category membership, and how well. **Discriminant Analysis** achieves that. If the researcher is concerned with the sample only, the analysis is descriptive. If (the more interesting case!) a new sample of population members is observed on the same measures, but has not been categorized, the analysis turns predictive. It assigns each new sample member probabilites to belong to the various categories (Unfortunately, Discriminant Analysis is sometimes referred to simply as "classification", which is confusing).

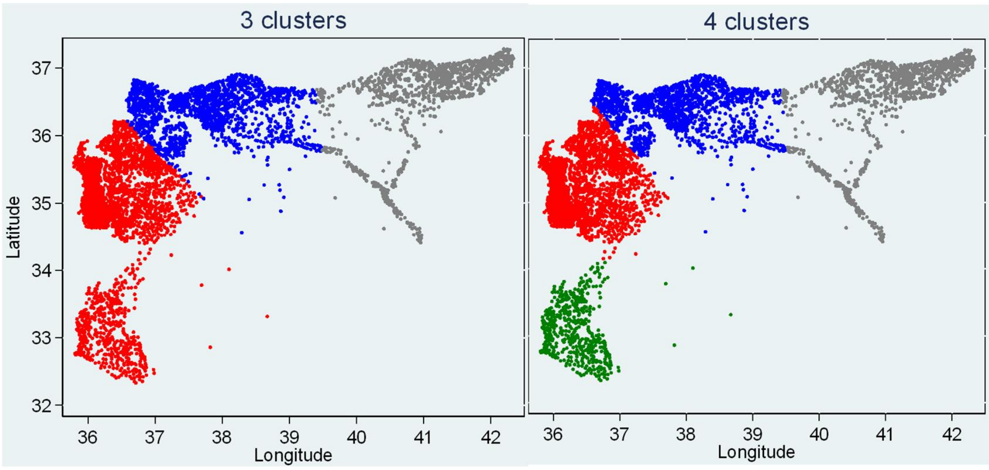
Those two broad classes of models should be carefully distinguished from classification methods like Latent Profile, Latent Class and Cluster Analysis.

Cluster Analysis

Returning to classification methods, in terms of popularity Cluster Analysis stands out. These are descriptive methods that determine natural groupings (called "clusters") of cases based on similar attribute values. The assignment to particular clusters is deterministic. A very large variety of sub-methods and specific options exist. While the deterministic assignment creates an impression of neat distinctions, frequently the results are not robust to even minor changes in the mechanical options that the researcher must choose. There is also a dilemma between methods that have more consistent results between models with different K, but are slow to process large samples ("hierarchical clustering"), and others that are fast and suitable for large samples, but may wildly re-assign members over categories when *K* is changed ("k-median and k-means clustering").

For a rapid and visually impressive, if substantively meaningless demonstration, we ask the k-median algorithm to assign the 4,904 localities to three, then four clusters, based solely on their geographic coordinates. For this demo we do not care that the space is curved, and the map is not projected.

Figure 17: Two k-median cluster analyses



By transiting from a 3- to a 4-cluster solution, the red cluster is split. However, there are also fine changes between red and blue visible. The transition table shows their extent.

Table 15: Member transition from 3- to 4-cluster solution

3 clusters	4 clusters				Total
	Green	Red	Blue	Gray	
Red	511	2,073	0	0	2,584
Blue	0	107	1,295	0	1,402
Gray	0	0	8	910	918
Total	511	2,180	1,303	910	4,904

The red cluster was split through its thin "umbellical cord", which seem intuitive. However, it acquired 107 localities from the blue cluster, which gained 8 from the gray. This happens because the centers of the clusters – the medians of their members' latitude and longitude – change when the red cluster is split. These changes then cascade across all four clusters, decreasing from green to gray.

The clusters of the 4-cluster solution are no longer subsets of, or identical to, the clusters of the 3-cluster solution. They fail a desirable behavior of category refinement, hierarchical association[13].

Commonalities and differences

Coming back to Latent Profile Analysis, there are common points and differences vis-à-vis Cluster Analysis. Both methods classify sample units. For both, the analyst sets the number of profiles, resp. clusters to calculate; and for both there are measures to compare solutions for their better or worse information value (meaning "more or less distinct" clusters / profiles).

[13] Latent Profile Analysis is not hierarchical either, because of its probabilistic character.

Yet Cluster Analysis assigns membership deterministically; in our example a locality either is a full member of a particular cluster or does not belong there at all. Assignment to latent profiles, by contrast, is probabilistic, as we have seen. Moreover, Latent Profile Analysis creates the profiles at the *same* time as it estimates the effects of the covariates ("causal indicators" in this note), thus allowing these to co-define membership. If we wanted to identify causal indicators of k-median clusters, this would happen *after* the clusters were produced. Since their membership is entirely deterministic, the causal model would capture only the ability for the indicators to predict membership, not any uncertainty of membership itself. This would underestimate the uncertainty in the causal effects, compared to the cautious probabilistic approach in Latent Profiles.

Latent Profile Analysis is indeed a classification method – and more. It should be pointed out that with the current rapid advances in so-called machine learning and fuzzy analysis a host of new classification methods have emerged and are still emerging, many of them spearheaded by bio-statistics and gene mapping. An overview is beyond our scope.

Good enough classifications

Those methods all seem sophisticated, some more than others. Still, we need to put in a word for simplicity. If you can do Cluster Analysis, but shy away from Latent Profiles, it is totally ok to explore invisible distinctions with the former, and then check for differences in possible causal variables between the clusters. If you are limited to Excel, you can create purely tabular classifications, then expand your Pivot tables to show averages and standard deviations for each class and check for visually significant differences. These tools may be more limited than probabilistic methods, but given the generally modest data quality in humanitarian assessments, clever discoveries by any method are worth sharing.

outlook

Why the experiment should be repeated

This is strictly an experiment; it is an idea, not a proof of concept, let alone anything supplying results that should be considered in whatever policy debates. In particular, it has nothing to say about the usefulness of the persons-in-need estimates that the 2017 HNO for Syria published. On *statistical* grounds, their distribution over localities and sub-districts in not informative, as we have seen. Yet, there may be sound *policy* reasons for choosing those figures, both countrywide and for particular administrative units.

Methodologically, the experiment attempts something in the field of humanitarian needs assessments that, to our knowledge, has not yet been tried before. It tackles, with methods imported from other fields, the well-known problem that ordinal measures such as severity ratings are difficult to aggregate. They are also difficult to combine with other, continuous or binary, indicators.

The challenge arises in situations where estimates of persons in need are absent or are not satisfactory. The data situation of the Syria 2017 HNO is a case in point. On the upside, we have a set of sectoral severity ratings at the locality level. We also have a minimum of indicators that characterize these communities in terms of size, composition and exposure to the conflict. Latent Profile Analysis offers a way to combine the severity ratings and those indicators. It produces groups of communities – statisticians call them by different names, as "classes" or "profiles" – that are marked off by different combinations of severity and indicator levels. The profiles offer a view of these groups that reflects the greater sectoral diversity of situations across the conflict area. Their populations can be estimated.

Some profiles are clearly dominated by groups in more acute need, others by those in comparatively moderate need, and yet others are mixtures of groups that are more variable on some dimensions. Latent Profile Analysis thus can work as a partial substitute for graded persons-in-need estimates while at the same time preserving greater sectoral specificity.

For this first experiment, we have taken some methodological liberties. We have not considered the structure of the locality sample. It is almost certain that the inaccessible localities differ significantly on some or all variables of interest from the accessible ones that were surveyed. Subsequent Latent Profile Analyses will have to adjust for that.

How to organize for more experiments

There are two approaches in terms of organizing for this type of analysis. Without the intervention of statisticians, mid-level users of MS Excel can perfectly well create simple descriptive profiles and place every community in one of them. With these profiles, they can then associate statistics – means, medians – of the indicators of interest. This already makes for a rich description of the diversity of populations that struggle and survive in different combinations of severity.

The probabilistic approach is more flexible. It leaves the discovery of profiles, and the sets of communities that cluster in them, to the data rather than to pre-defined distinctions. The analyst, however, must query the realism of the distinctions and distributions that the Latent Profile algorithm suggests. This method does require the involvement of somebody equipped to apply the procedure and present the results. Provided this person is given a clean and well-documented dataset, defining, describing, running, and reporting models and results are not extremely labor-intensive. A statistician may be able to achieve that much for a small number of models within two or three workdays.

More important is the quality of the initial briefing and the ability to present output, findings and interpretation in the language of the users. This means: in the language of the analysts and policy makers who are responsible for the data, for the ongoing analysis and ultimately for the messages and meanings that newly emerge from this labor, in order to better inform the humanitarian response.

appendices

Output for the model of six classes

with co-variates and well as with covariances of the residuals

Recoding of the classes in the output

The six classes in the output arrived in an order that was not optimal for presentation. The classes were therefore recoded into a new variable "Profiles". The results are not affected thereby, but orientation in tables and graphs is much easier. This table shows the re-ordering.

```
. tab predclass_E6 profiles_E6
```

predclass_ E6	Profiles, model E6 1	2	3	4	5	6	Total
1	0	0	0	0	0	679	679
2	0	0	1,490	0	0	0	1,490
3	0	0	0	347	0	0	347
4	0	942	0	0	0	0	942
5	545	0	0	0	0	0	545
6	0	0	0	0	901	0	901
Total	545	942	1,490	347	901	679	4,904

For example, all 679 localities in class 1 became the localities of profile 6; the 1,490 of class 2 all went to profile 3. Etc. The "profile" numbering was used to generate tables and graphs; the output below preserves the original class numbers and has not been reordered.

Stata output of the main Latent Profile model

```
Generalized structural equation model           Number of obs     =      4,904
Log likelihood = -13527.913
```

Comparison of causal effects to base outcome (Class 1)

```
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
1.C          |  (base outcome)
-------------+----------------------------------------------------------------
2.C          |
    c_access |    1.57698   .0825994    19.09   0.000     1.415088    1.738872
      c_idps |   .1388091   .0675527     2.05   0.040     .0064082      .27121
    c_neighb |  -.0473693    .064713    -0.73   0.464    -.1742046    .0794659
     c_popul |  -.0448318   .0730845    -0.61   0.540    -.1880748    .0984113
       _cons |    .605344    .081441     7.43   0.000     .4457226    .7649653
-------------+----------------------------------------------------------------
3.C          |
    c_access |  -.6795458   .5832167    -1.17   0.244    -1.822629    .4635378
      c_idps |    .697283   .1126106     6.19   0.000     .4765702    .9179958
    c_neighb |   .5032285    .086416     5.82   0.000     .3338563    .6726008
     c_popul |  -.0531889   .1261402    -0.42   0.673    -.3004191    .1940413
       _cons |  -1.295661   .5228632    -2.48   0.013    -2.320454   -.2708682
-------------+----------------------------------------------------------------
4.C          |
    c_access |   .9836103   .0711948    13.82   0.000     .8440711    1.123149
      c_idps |   .1499608    .058929     2.54   0.011      .034462    .2654595
    c_neighb |   .0927027   .0551068     1.68   0.093    -.0153047      .20071
```

```
     c_popul |   .7336763   .0697155    10.52   0.000     .5970364    .8703163
       _cons |   .4832698     .05946     8.13   0.000     .3667304    .5998092
-------------+----------------------------------------------------------------
5.C          |
    c_access |   1.244239   .0805457    15.45   0.000     1.086372    1.402105
      c_idps |   .0545034   .0711824     0.77   0.444    -.0850116    .1940184
    c_neighb |   .0563323   .0663816     0.85   0.396    -.0737732    .1864378
     c_popul |   1.767447    .084623    20.89   0.000     1.601588    1.933305
       _cons |  -.7730248   .0849887    -9.10   0.000    -.9395997   -.6064499
-------------+----------------------------------------------------------------
6.C          |
    c_access |    -10.156    354.764    -0.03   0.977    -705.4807    685.1687
      c_idps |  -1.166493   .1370758    -8.51   0.000    -1.435156    -.897829
    c_neighb |  -.9552234   .1389276    -6.88   0.000    -1.227516   -.6829304
     c_popul |  -.1331128   .0970019    -1.37   0.170    -.3232331    .0570075
       _cons |  -8.883875   309.1642    -0.03   0.977    -614.8346    597.0669
------------------------------------------------------------------------------
```

Statistics of individual classes

Predicted means of the transformed ratings, the variances and covariances among their residuals

Class : 1

```
Response       : s_liveli
Family         : Gaussian
Link           : identity

Response       : s_health
Family         : Gaussian
Link           : identity

Response       : s_conflict
Family         : Gaussian
Link           : identity
```

```
----------------------------------------------------------------------------------------------
                             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------------------+----------------------------------------------------------------
s_liveli                     |
                       _cons |  -1.963995    .022799   -86.14   0.000     -2.00868    -1.91931
-----------------------------+----------------------------------------------------------------
s_health                     |
                       _cons |  -.6348349   .0301787   -21.04   0.000     -.693984   -.5756858
-----------------------------+----------------------------------------------------------------
s_conflict                   |
                       _cons |  -.6166428   .0067153   -91.83   0.000    -.6298045    -.603481
-----------------------------+----------------------------------------------------------------
              var(e.s_liveli)|   .3422602    .007395                      .3280689    .3570653
              var(e.s_health)|   .6026427   .0135573                      .5766481    .6298091
            var(e.s_conflict)|   .0302546   .0006203                       .029063    .0314951
-----------------------------+----------------------------------------------------------------
   cov(e.s_liveli,e.s_health)|   .0423122   .0065658     6.44   0.000     .0294433     .055181
 cov(e.s_liveli,e.s_conflict)|  -.0060075   .0015062    -3.99   0.000    -.0089596   -.0030555
 cov(e.s_health,e.s_conflict)|  -.0085301   .0019673    -4.34   0.000     -.012386   -.0046743
----------------------------------------------------------------------------------------------
```

Class : 2

```
Response       : s_liveli
Family         : Gaussian
Link           : identity

Response       : s_health
Family         : Gaussian
Link           : identity
```

```
Response       : s_conflict
Family         : Gaussian
Link           : identity

-----------------------------------------------------------------------------------------------
                              |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------------------+----------------------------------------------------------------
s_liveli                      |
                        _cons |   .4771704   .0153732    31.04   0.000     .4470396    .5073013
------------------------------+----------------------------------------------------------------
s_health                      |
                        _cons |    .402529   .0280955    14.33   0.000     .3474627    .4575952
------------------------------+----------------------------------------------------------------
s_conflict                    |
                        _cons |  -.6166428    .004476  -137.77   0.000    -.6254156   -.6078699
------------------------------+----------------------------------------------------------------
               var(e.s_liveli)|   .3422602    .007395                      .3280689    .3570653
               var(e.s_health)|   .6026427   .0135573                      .5766481    .6298091
             var(e.s_conflict)|   .0302546   .0006203                       .029063    .0314951
------------------------------+----------------------------------------------------------------
   cov(e.s_liveli,e.s_health)|   .0423122   .0065658     6.44   0.000     .0294433     .055181
 cov(e.s_liveli,e.s_conflict)|  -.0060075   .0015062    -3.99   0.000    -.0089596   -.0030555
 cov(e.s_health,e.s_conflict)|  -.0085301   .0019673    -4.34   0.000     -.012386   -.0046743
-----------------------------------------------------------------------------------------------
```

```
Class          : 3

Response       : s_liveli
Family         : Gaussian
Link           : identity

Response       : s_health
Family         : Gaussian
Link           : identity

Response       : s_conflict
Family         : Gaussian
Link           : identity

-----------------------------------------------------------------------------------------------
                              |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------------------+----------------------------------------------------------------
s_liveli                      |
                        _cons |   .4799737   .0295109    16.26   0.000     .4221334    .5378139
------------------------------+----------------------------------------------------------------
s_health                      |
                        _cons |  -.5482759   .0629416    -8.71   0.000    -.6716393   -.4249125
------------------------------+----------------------------------------------------------------
s_conflict                    |
                        _cons |  -.6166428   .0085881   -71.80   0.000    -.6334751   -.5998104
------------------------------+----------------------------------------------------------------
               var(e.s_liveli)|   .3422602    .007395                      .3280689    .3570653
               var(e.s_health)|   .6026427   .0135573                      .5766481    .6298091
             var(e.s_conflict)|   .0302546   .0006203                       .029063    .0314951
------------------------------+----------------------------------------------------------------
   cov(e.s_liveli,e.s_health)|   .0423122   .0065658     6.44   0.000     .0294433     .055181
 cov(e.s_liveli,e.s_conflict)|  -.0060075   .0015062    -3.99   0.000    -.0089596   -.0030555
 cov(e.s_health,e.s_conflict)|  -.0085301   .0019673    -4.34   0.000     -.012386   -.0046743
-----------------------------------------------------------------------------------------------
```

```
Class          : 4

Response       : s_liveli
Family         : Gaussian
Link           : identity
```

```
Response       : s_health
Family         : Gaussian
Link           : identity

Response       : s_conflict
Family         : Gaussian
Link           : identity

------------------------------------------------------------------------------------------------
                             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------------------+------------------------------------------------------------------
s_liveli                     |
                       _cons |   .0684968    .019121     3.58   0.000     .0310204    .1059733
-----------------------------+------------------------------------------------------------------
s_health                     |
                       _cons |   .5984918   .0253219    23.64   0.000     .5488619    .6481217
-----------------------------+------------------------------------------------------------------
s_conflict                   |
                       _cons |   .9907419   .0057741   171.58   0.000     .9794249    1.002059
-----------------------------+------------------------------------------------------------------
              var(e.s_liveli)|   .3422602    .007395                      .3280689    .3570653
              var(e.s_health)|   .6026427   .0135573                      .5766481    .6298091
            var(e.s_conflict)|   .0302546   .0006203                       .029063    .0314951
-----------------------------+------------------------------------------------------------------
   cov(e.s_liveli,e.s_health)|   .0423122   .0065658     6.44   0.000     .0294433     .055181
 cov(e.s_liveli,e.s_conflict)|  -.0060075   .0015062    -3.99   0.000    -.0089596   -.0030555
 cov(e.s_health,e.s_conflict)|  -.0085301   .0019673    -4.34   0.000     -.012386   -.0046743
------------------------------------------------------------------------------------------------
```

Class : 5

```
Response       : s_liveli
Family         : Gaussian
Link           : identity

Response       : s_health
Family         : Gaussian
Link           : identity

Response       : s_conflict
Family         : Gaussian
Link           : identity

------------------------------------------------------------------------------------------------
                             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------------------+------------------------------------------------------------------
s_liveli                     |
                       _cons |  -.1071131   .0252788    -4.24   0.000    -.1566587   -.0575675
-----------------------------+------------------------------------------------------------------
s_health                     |
                       _cons |   .5447854   .0334326    16.30   0.000     .4792588    .6103121
-----------------------------+------------------------------------------------------------------
s_conflict                   |
                       _cons |   2.157914   .0075514   285.76   0.000     2.143113    2.172714
-----------------------------+------------------------------------------------------------------
              var(e.s_liveli)|   .3422602    .007395                      .3280689    .3570653
              var(e.s_health)|   .6026427   .0135573                      .5766481    .6298091
            var(e.s_conflict)|   .0302546   .0006203                       .029063    .0314951
-----------------------------+------------------------------------------------------------------
   cov(e.s_liveli,e.s_health)|   .0423122   .0065658     6.44   0.000     .0294433     .055181
 cov(e.s_liveli,e.s_conflict)|  -.0060075   .0015062    -3.99   0.000    -.0089596   -.0030555
 cov(e.s_health,e.s_conflict)|  -.0085301   .0019673    -4.34   0.000     -.012386   -.0046743
------------------------------------------------------------------------------------------------
```

```
Class          : 6

Response       : s_liveli
Family         : Gaussian
Link           : identity

Response       : s_health
Family         : Gaussian
Link           : identity

Response       : s_conflict
Family         : Gaussian
Link           : identity

-----------------------------------------------------------------------------------------------
                             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------------------+-----------------------------------------------------------------
s_liveli                     |
                       _cons |    .476754   .0210226    22.68   0.000     .4355506    .5179575
-----------------------------+-----------------------------------------------------------------
s_health                     |
                       _cons |  -.9903848   .0311185   -31.83   0.000    -1.051376   -.9293937
-----------------------------+-----------------------------------------------------------------
s_conflict                   |
                       _cons |  -.6166428   .0060529  -101.88   0.000    -.6285062   -.6047794
-----------------------------+-----------------------------------------------------------------
              var(e.s_liveli)|   .3422602    .007395                      .3280689    .3570653
              var(e.s_health)|   .6026427   .0135573                      .5766481    .6298091
            var(e.s_conflict)|   .0302546   .0006203                       .029063    .0314951
-----------------------------+-----------------------------------------------------------------
   cov(e.s_liveli,e.s_health)|   .0423122   .0065658     6.44   0.000     .0294433     .055181
 cov(e.s_liveli,e.s_conflict)|  -.0060075   .0015062    -3.99   0.000    -.0089596   -.0030555
 cov(e.s_health,e.s_conflict)|  -.0085301   .0019673    -4.34   0.000     -.012386   -.0046743
-----------------------------------------------------------------------------------------------
```

Latent class marginal probabilities

```
Latent class marginal probabilities             Number of obs     =      4,904

--------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.     [95% Conf. Interval]
-------------+------------------------------------------------
           C |
           1 |   .1368072   .0048328      .1276079    .1465582
           2 |   .3079348    .010229      .2882565    .3283368
           3 |   .0836463   .0118025      .0632335    .1098757
           4 |   .1924845   .0055017      .1819307    .2034982
           5 |   .1107365   .0038948      .1033299    .1186037
           6 |   .1683907   .0091215      .1512613    .1870325
--------------------------------------------------------------
```

Latent class marginal means

```
Latent class marginal means                     Number of obs     =      4,904

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
1            |
    s_liveli |  -1.963995    .022799   -86.14   0.000     -2.00868    -1.91931
    s_health |  -.6348349   .0301787   -21.04   0.000     -.693984   -.5756858
  s_conflict |  -.6166428   .0067153   -91.83   0.000    -.6298045    -.603481
-------------+----------------------------------------------------------------
2            |
    s_liveli |   .4771704   .0153732    31.04   0.000     .4470396    .5073013
    s_health |    .402529   .0280955    14.33   0.000     .3474627    .4575952
```

```
  s_conflict |  -.6166428    .004476  -137.77   0.000    -.6254156   -.6078699
-------------+----------------------------------------------------------------
3            |
    s_liveli |   .4799737   .0295109    16.26   0.000     .4221334    .5378139
    s_health |  -.5482759   .0629416    -8.71   0.000    -.6716393   -.4249125
  s_conflict |  -.6166428   .0085881   -71.80   0.000    -.6334751   -.5998104
-------------+----------------------------------------------------------------
4            |
    s_liveli |   .0684968    .019121     3.58   0.000     .0310204    .1059733
    s_health |   .5984918   .0253219    23.64   0.000     .5488619    .6481217
  s_conflict |   .9907419   .0057741   171.58   0.000     .9794249    1.002059
-------------+----------------------------------------------------------------
5            |
    s_liveli |  -.1071131   .0252788    -4.24   0.000    -.1566587   -.0575675
    s_health |   .5447854   .0334326    16.30   0.000     .4792588    .6103121
  s_conflict |   2.157914   .0075514   285.76   0.000     2.143113    2.172714
-------------+----------------------------------------------------------------
6            |
    s_liveli |    .476754   .0210226    22.68   0.000     .4355506    .5179575
    s_health |  -.9903848   .0311185   -31.83   0.000    -1.051376   -.9293937
  s_conflict |  -.6166428   .0060529  -101.88   0.000    -.6285062   -.6047794
------------------------------------------------------------------------------
```

Stata code

```
************************************************************************************************
cd [set working directory]
set more off

use [datafile], clear

* Needed variables:
des record_id c_access- s_conflict
summ record_id c_access- s_conflict
* c_ = covariates, causes; s = severity ratings, effects.

* D: Models without covariates. D2 means : such a model with 2 groups, etc.
* starting at D5, wouldn't converge.
forvalues i = 2/4 {
di "Model D" `i'
	gsem ( s_* <- _cons), lclass(C `i')  covstructure(e._OEn, unstructured) ///
		startvalues(randomid, draws(5) seed(15))
	estimates store D`i'
	* Tabular statistics:
	estat lcprob // latent class marginal probabilities (proportion cases in class j), with CI
	estat lcmean // marginal predicted means of each observed variable within each class
	* Class membership probability
	predict cpost_D`i'*, classposteriorpr
* Assign locality to class where its predicted probability is the highest.
	egen max = rowmax(cpost_D`i'*)
	gen predclass_D`i' = .
		forvalues j = 1/`i' {
		replace predclass_D`i' = `j' if cpost_D`i'`j' == max
		}
	drop max
}

* E: Models with covariates. E2 means : such a model with 2 groups, etc.

forvalues i = 5/6 {
di "Model E" `i'
	gsem  (  s_*  <-  _cons)(C  <-  c_*),  lclass(C  `i')  covstructure(e._OEn,  unstructured)
	startvalues(randomid, draws(5) seed(15))
	estimates store E`i'
	* Tabular statistics:
```

```
        estat lcprob // latent class marginal probabilities (proportion cases in class j), with CI
        estat lcmean // marginal predicted means of each observed variable within each class
        * Class membership probability
        predict cpost_E`i'*, classposteriorpr

* Assign locality to class where its predicted probability is the highest.
        egen max = rowmax(cpost_E`i'*)
        gen predclass_E`i' = .
                forvalues j = 1/`i' {
                replace predclass_E`i' = `j' if cpost_E`i'`j' == max
                }
        drop max
}

* Compare the models on three information criteria:
est dir
estimates stats D* E*
save [datafile], replace
***************************************************************************************************
```

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An experiment with data from Syria

September 2017