MODERATE NEED, ACUTE NEED

Valid categories for humanitarian needs assessments?

Evidence from a recent needs assessment in Syria

SYRIA

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A note for ACAPS and MapAction

A SYRIA

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1. OVERVIEW

1.1 ACKNOWLEDGEMENT

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All errors, of fact or interpretation, are mine and do not engage the responsibility of ACAPS, MapAction or any other organization connected with the MSNA.

The data used in this study originate from the MSNA team.

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1.2 ACRONYMS AND ABBREVIATIONS

ACAPS	Assessment Capacities Project
IDP	Internally displaced person
NFI	Non-food items
QCA	Qualitative Comparative Analysis
SINA	Syria Integrated Needs Assessment
MSNA	Syria Multi-Sectoral Needs Assessment
OCHA	UNOCHA: United Nations Office for the Coordination of Humanitarian Affairs
zoib	Zero- or one-inflated beta distribution model (a statistical procedure)

1.3 SUMMARY
What this is about

Needs assessments in emergencies seek to establish, among other elements of the situation, the number of persons in need. "Persons in need" is a broad and fuzzy concept; counts, proportions and other measures capturing how many are in need, and how intensely, are necessarily imprecise. Some sectors achieve greater precision by applying specific standards, such as in malnutrition surveys. However, such methods are not feasible in types of assessments that depend largely on local key informant estimates.

Greater depth, if not outright precision, may be achieved in other ways. Categories can be refined. Instead of just the binary "persons in need" / "not in need", needs may be graded. Several recent needs assessments in Syria have done so by distinguishing between "persons in moderate need" and "persons in acute need". This note is about this kind of refinement in persons-in-needs (PiN) estimates in the most recent assessment. The Syria Multi-Sectoral Needs Assessment (MSNA), released in October 2014, provides PiN estimates for 126 of the 270 sub-districts of the country. Persons in moderate and in acute need have been estimated separately for five sectors - food security, shelter, non-food items (NFI), health and safe water.

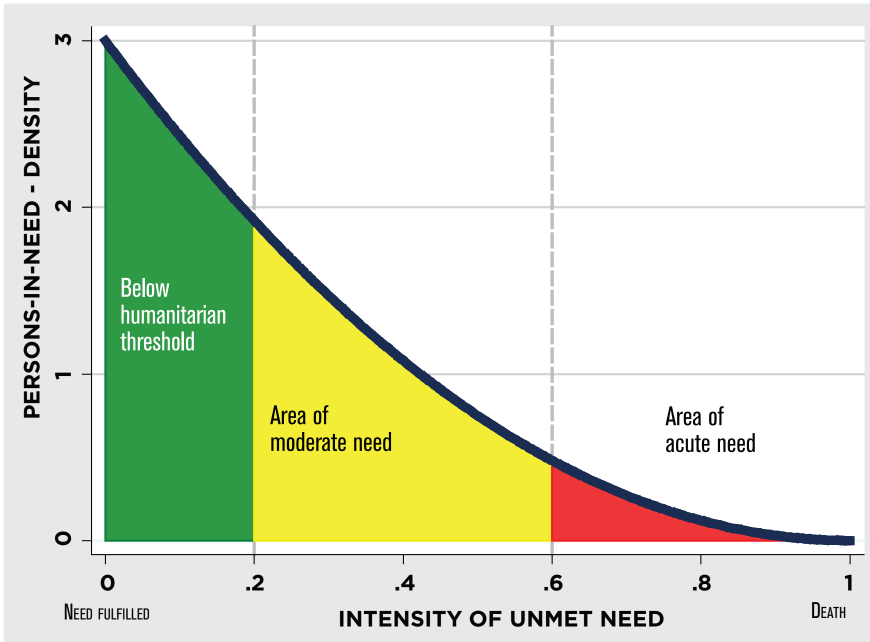


FIGURE 1: Distribution by need intensity and by PiN category

Empirical tests

Whether estimates of persons in acute need add value consistently - in all sectors, and in relation to other measures of need - is an open question. We seek to answer it by submitting the MSNA estimates to two tests:

- Proportions of persons in need, calculated for each assessed area, are correlated among sectors. Areas with relatively more persons in need of food assistance tend of have more persons needing shelter, etc. This is so because extreme events (and even more so persistent crises) trigger cascading deprivations. In groups with multiple deprivations, needs grow acute more rapidly. Thus, in the MSNA, we expect the correlation pattern of persons in acute need to be at least as strong as that of all persons in need.
- Needs assessments produce estimates of the severity of unmet needs in each of several sectors. The enumerators in the MSNA rated the severity on a scale with seven levels. The number of persons in need influenced their judgments. If the enumerators applied the "acute need" category consistently, we expect that the proportions of persons in acute need had a significant influence on their severity ratings. We expect to find this effect even after we take into account, statistically, the effect from all persons in need.

The "acute needs" concept passes both tests. It passes them for all five sectors. This is a strong indication that the enumerators used the concept consistently, and that their estimates of persons in acute need are informative.

What causes acute needs?

That is not enough. One likes to understand what causes acute needs. We expect to find them closely associated with certain factors in the disaster / emergency / conflict environment as well as with the configuration of needs in other sectors.

However, the MSNA data do not exhibit some of the associations that we expect in the Syrian case. Notably, the proportions of IDPs in sub-districts are not, or are negatively, correlated with the proportions of persons in acute need in the different sectors. This may be so because IDPs flock to areas with better conditions. To test for this, we replaced the IDPs with proportions of the pre-conflict population that fled their sub-districts. Statistical estimates confirm the expected effect on the current populations (= the remaining populations plus the IDPs they are hosting) for the shelter and health sectors. However, the opposite tendency was found for acute needs of clean water: the greater the population loss, the lower the proportion of persons currently in acute need.

These tangled associations lead us to conclude that the causal pathways from the conflict environment to acute needs are complex and varied. Also, there is evidence that regional particularities matter. We obtained different patterns across the governorates that the MSNA covered. This diversity shifts the causal validation of acute needs from universal factors to local interpretation.

By contrast, our model estimates confirm, for each sector, the association of acute needs with the "average" need levels in the other four sectors. This is in line with the idea of cascading deprivations that push needs to acute degrees.

Recommendations for future use

Overall, we find theoretical and empirical support for the inclusion of the acute-needs measures in future rapid needs assessments. Such measures, especially the proportion of persons in acute need of assistance in sector X in social group Y and area Z, provide a sharper image of the pattern of unmet needs.

We recommend the inclusion of such measures with these precautions:

- Adopt "persons in acute need" in the design only if assessment workforce and key informants are such as to expect reasonably consistent and reliable estimates.
- Collect estimates of the number of persons in acute need. In the analysis, make meaningful comparisons of proportions of such persons in current populations.
- Compare persons in acute need to all persons in need, rather than to those in moderate need. Statistics in terms of moderate needs can be misleading; low proportions can be due to either low overall impact or to high proportions of persons in acute need.
- Expect a significant number of areas reporting zero persons in acute needs in some or all sectors. While debriefing enumerators, ask specifically why none were reported.
- Limit the analysis of acute needs in the context of other needs and of likely causal variables to tabulations involving not more than three factors. Purposive sampling and other selection effects are likely to make statistical modeling unwieldy, slow or unproductive.

Information about acute needs is helpful for planners and operators. Yet refined categories come at a cost. This is true also of needs assessments that work with three, instead of two, levels: none / moderate / acute. They demand more detailed attention in instrument design, training, supervising, debriefing, processing and reporting. The assessment consumers too need to absorb more complex information.

The nature of this note is conceptual and statistical. There is also an ethical side to it. Category changes in social policies create new information that can motivate new interpretations and new priorities. They can redraw the lines of social inclusion and exclusion. Donors may - incorrectly - conclude that "all persons in need" overestimate the real needs, and that "persons in acute need" are more accurate measures and closer to priorities. Assessment teams must avoid language that might favor such a perception and should focus on the important question of securing humanitarian access to all in need.

The MSNA findings reinforce our belief that "acute needs" is a feasible and productive concept. It can improve the measurement of unmet needs under conditions that rarely permit exact classification. As long as everybody remains aware that the distinctions are fuzzy, and estimates need interpretation in context, such measures will strengthen judgment on humanitarian priorities.

2. INTRODUCTION

2.1 PERSONS IN NEED

"Persons in need" is a vague concept. The number of PiN in a given population can vary widely. It depends on the distribution of units (individuals, households, areas) by actual intensity of needs. And it depends on definitions and measurement techniques by those who count, estimate, deduce or otherwise establish numbers or proportions of those in need.

Of the quantitative claims that needs assessments make most are the result of accumulating local estimates. Fieldworkers such as enumerators contribute estimates for their assigned areas, sites or groups. A local estimate may combine figures that various key informants proffered. Alternatively, a fieldworker may translate an ensemble of qualitative information into some quantitative expression. This translation often involves also a population estimate, which functions as the upper limit or as a denominator.

Designers of needs assessments are aware of the challenges to the validity and reliability of quantitative estimates. One of the strategies for securing both is to refine the categories of the objects whose prevalence we want to estimate. Finer distinctions promise better information. They approximate the underlying concept to be measured more closely. They produce more nuanced estimates than coarser distinctions would achieve.

For PiN estimates, this strategy calls for extensional or intensional refinement. The extensional variety divides the population in focus into smaller units. Estimates are made, for example, for each town, instead of for entire districts only. Intensional refinement defines types and levels of need more specifically. Types are refined by adding or splitting need domains, such as when, within the shelter/NFI sector, separate estimates are produced for shelter and for non-food item needs. Levels of need are refined when additional distinctions are made about the intensity of the needs.

Refined categories impose information costs. Enumerators will ask more questions and record more answers; data processors and analysts process more variables, statistics and interpretations. Readers struggle with yet more information. The more complex questions may confuse enumerators and key informants, adding to estimation error or even derailing an entire interview. Because of these costs, which often are hidden, the value of refined categories cannot be taken for granted. It has to be demonstrated.

[Sidebar:] What is a category? What is a concept?

Traditionally, by "category" we understand a set of objects (or events) that share some attribute of interest. Categories exist in the real world. Concepts are their mental representations; they exist in our heads. We have learned that dogs are animals, have four legs, have fur, and bark. This is not the full "dog concept", though. We add "domesticated", in order to exclude wolves. Not all sets that can be defined in theory form categories. The set of all events that happen on Tuesdays cannot be lumped around a common denominator beyond the set definition. It takes a socially shared essence in order to elevate objects or events to a usable category. This requirement will preoccupy us presently when we turn to "persons in need" as a category.

The naïve realism of categories in the world and concepts in our minds does not go very far. Even simple categories that provide accurate, effective summaries of the world (such as "dog") require an observer that subsumes an instance under the correct concept (as a dog, not a cat or wolf). He communicates this observation such that other persons can act upon the essence of the category (because the dog is a domestic animal, it will not bite) - until disproved. All the more when it comes to abstract entities, concepts are harder to distinguish from categories. Both exist as social realities. Usage changes, chiefly from outside world vs. inner mind to taxonomic relations between sets and subsets. The concept may be "domestic animals"; its categories include "cat", "dog", and others. Similarly for the concept of "person in need", which, in one of many possible categorizations, includes the categories that concern us in this note - "persons in acute need", those in "moderate need" as well as the complement "persons not in need".

Categories and concepts are of a great variety. Besides simple object concepts for which people use names or nouns ("dog"), there are event concepts (e.g., a "party"), script concepts (an event with rules for types and sequences of behaviors - a "children's birthday" has food, drinks, invited guests, but no alcohol; guests will leave at a time that fits with parenting rhythms), concepts combining thematic categories ("bee" and "honey"; "dog" and "leash"), abstract concepts, particularly in scientific and institutional realms.

For our purposes, two other types of concepts/categories are relevant. They have been investigated particularly by the psychologist Lawrence Barsalou (Barsalou 1983, 1991):

- Ad-hoc categories are short-lived ensembles created in a context that is special and value-wise not neutral. For illustration, Barsalou looked at categories of things to carry from a burning home. They include the children, pets, photo albums, the wife's jewelry, perhaps a labtop computer - but not the big TV screen mounted on the wall. The essence is that these objects are portable, valuable, and irreplaceable, with strong emotional attachment.
- Goal-derived categories hinge on solutions to a common problem. Barsalou gives the example of inexpensive long-distance travel (the problem), for which hitchhiking, taking a bus, or flying standby are some of the solutions.

Members of these categories tend to form heterogeneous lists, have little in common beyond the context, and cannot be described with a simple word. The important difference is that ad-hoc categories are not normally committed to long-term memory (home fires are rare; most families will occasionally think of the possibility, but will not rehearse lists of things to carry from the burning house. Compare that to the scripted category "airplane evacuation" with its "in the event .. do not take any personal belongings with you"). By contrast, goal-derived categories are remembered long-term, notably because occasions and needs repeat themselves during a person's lifetime.

For the concept of "person in need" with its affiliated categories, the question, therefore, is not whether such persons are real or exist only in our imagination. At issue is the question whether the concept is used purely ad-hoc, or with goal-derived reinforcement that secures it a role in future needs assessments. In assessing its long-term chances, three dimensions must be distinguished - substantive, social, and temporal:

- **Substantive**: Is the concept useful despite the heterogeneity among and within its categories? It is obvious that "persons in acute need of health support" as a category mixes medical caseloads of different nature. Can those who make or use estimates of such persons have any practical use for them?
- **Social:** Who shares the concept? How many? Is the writing and talking about persons in need, and all the more so about those in acute need, limited to a narrow circle of needs assessment specialists, or is it part of the language of a wider community including donors, responders, even the media?
- **Temporal**: Have the assessment that so far have used the concepts of "persons in need" and "persons in acute need" created an expectation that it will be applied in future needs assessments? Is the expectation normative, enshrined in institutional guidance, training syllabi, even in standardized vocabulary in several languages?

Apparently, "person in need" is in good company, among the types of categories that psychologists and cognitive scientists recognize. As an ad-hoc category, it would be legitimate, if ephemeral. To be a fully goal-derived category, it has to earn this status.

[Adapted in part from Murphy (2010)]

2.2 PRODUCING PIN STATISTICS

To better understand how PiN information is collected and processed, we need to slip into the shoes of the enumerators who collect it and of the analysts who analyze it. For simplicity we assume that each enumerator is responsible to collect needs assessment information in one sub-district. We choose this administrative unit - and use it throughout the rest of this note - because in our empirical part the enumerators actually were assigned to sub-districts. In other contexts, enumerators might look after provinces, districts, refugee camps or mixtures thereof.

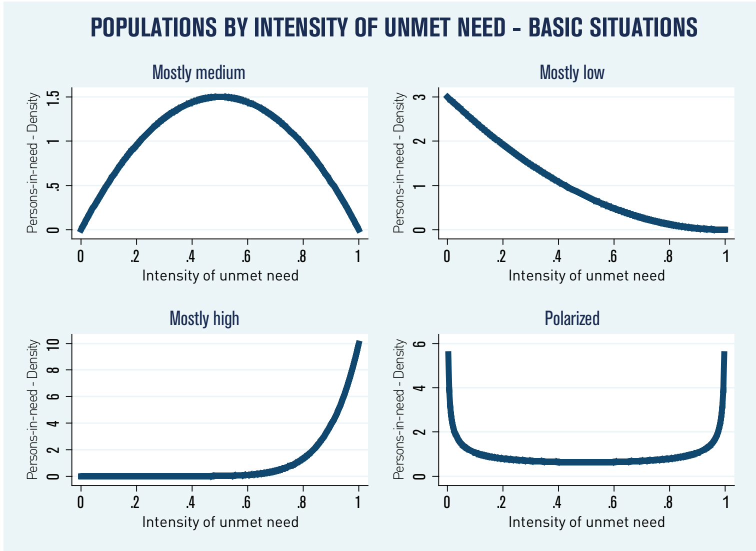
Similarly, we posit an analyst who is responsible for the data from all sub-districts in the assessed region. We do not care about intermediate levels or team structures. For the time being, we do not bother about the different sectors either. This will come later.

The enumerator

The enumerator knows that humanitarian needs assessments focus on unmet needs. He also knows that in his sub-district needs are being fulfilled to differing degrees. The distribution of persons by intensity of unmet need varies. It varies by area of need, social group, recent history and more. The enumerator does not know the precise distribution, and he may know it barely at all. However, when he looks at the entire information at hand, he may discern the overall shape of the distribution.

He may conclude that it conforms to one of four basic situations: The unmet needs in the population may be mostly low, mostly medium, mostly high, or polarized between high and low. This graph represents these situations in terms of probability plots. A degree of zero means that a member's basic need is fully met; a degree of one denotes deprivation that leads to death. Although these are quantitative expressions, the interpretation is chiefly qualitative: mostly low, mostly medium, mostly high, or polarized.

FIGURE 2 - Basic situations by intensity of need



Even if the enumerator is sure of the basic shape of the distribution, he cannot communicate it in one single PiN figure. Expressions such as "50 percent of the population are in need" do not tell the analyst how intense their needs are. For most purposes, there is no precisely defined cut-off point between needy and not needy. Therefore any proportion of PiN is compatible with every one of the four shapes. For other purposes, standards may exist, such as in poverty lines or Sphere standards, together with representative data from the time before the emergency. However, it may not be possible for key informants, and through them for the enumerator, to know the current distribution. We should therefore expect that the standards of need are highly variable. A single PiN number or proportion is not an effective signal of the humanitarian urgency.

That changes for the better when the enumerator can report PiN quantities at more than one level of need intensity. The shape of the distribution is no longer arbitrary. For example, the statements *"50 percent are in acute need; 20 percent are in moderate need"* are not compatible with a "mostly low" or "mostly medium" scenario. They may permit the "polarized" interpretation, although with some difficulty, but "mostly high" is the most plausible shape.

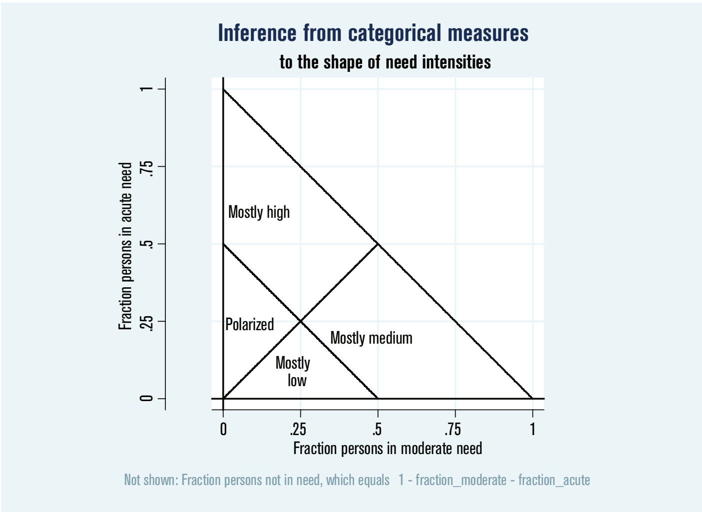
The point is: Categories have been refined. The refinement appears minimal - from two to three categories (including the persons not in need). Yet it enables the enumerator to send the analyst information which, if still not very precise, is of much higher qualitative value. The analyst now can assess the urgency of the needs in the sub-district population more meaningfully.

The analyst

For each area with refined estimates, the analyst can now infer the likely basic shape of the need intensity curve. She may use some classification scheme to aid the inference, such as the one proposed in this chart. Regardless of where she draws the lines, she uses two quantitative measures - PiN proportions - and maps them to a qualitative type.

Yet, the analyst cannot yet be satisfied. Certainly, she can now aggregate PiN figures for moderate and acute needs. She can produce distributions over all assessed sub-districts and can provide a rich description of needs across the assessed region. However, she cannot be sure that definitions for

FIGURE 3 – Inference to the shape of need intensities



"moderate" and "acute" were applied consistently. Also, the total number of PiN will be driven by the more populous sub-districts. The analyst knows that she has only as many independent observations as there were enumerators. This creates a dilemma: Should she sum the PiN numbers, then divide by the total population, in order to find the overall proportions of persons in moderate and acute need? This is what the assessment users want, but then the results are heavily influenced by the standards and estimation errors of the large sub-districts. Or should she do without population weighting and treat the PiN proportions from all sub-districts as equally important and, barring other evidence, equally reliable? In this case, her findings may be rejected as giving undue weight to smaller sub-districts.

To make things worse, the analyst may fall into the fallacy of compositional data. This means that she fails to see that the proportions of persons in acute need, in moderate need and not in need always sum to 100 percent. As the deprivation grows in ongoing emergencies, initially the persons in moderate needs will multiply ahead of those in acute need. As things worsen further, those in acute need will overtake the milder form. When the proportion in acute need keeps growing, eventually the proportion of those in moderate need is bound to fall[1]. Stand-alone aggregates of persons in moderate need therefore are misleading. They are mixture of situations that are genuinely mild with bad situations in which acute needs crowd out the moderate .[2]

Consequences

We draw three analytic consequences from the mechanisms of PiN estimation:

- **"All in need" and "in acute need"**: We will not compare moderate vs. acute needs situations. Rather, we work with "all persons in need" and "persons in acute need". Obviously, in a three-category set-up, "all persons in need" are the sum of persons in moderate and in acute need. The number of all PiN is always equal to or larger than that of persons in acute need. This does not eliminate the compositional data problem, but it mitigates it for our purposes. Plausibly, assessment users are interested to have ready access to statistics of all PiN and of persons in acute need; they have less use for the "moderate" figures.
- **Population-weighting**: We will not always use population-weighted statistics. Aggregate PiN numbers are necessary; they are de-facto population-weighted (sub-district proportions multiplied by sub-district populations). However, needs are specific, and therefore PiN correlations across sectors are important in order to detect clusters of needs. These correlations we leave unweighted, to take into account that, regardless of size, each sub-district is only one observation.
- **Tests of the information value:** While three categories (acute / moderate / not in need) capture the humanitarian urgency better than two (in need / not in need), this does not by itself ensure that the refined categories create valid measures. We need to demonstrate that the addition of "acute need" produces relevant information. This requires tests by relating PiN statistics to other assessment variables. These tests will be proposed and run below.

1 This is a purely definitional statement. Once the proportion of persons in acute need crosses the 50 percent threshold, the proportion of those in moderate need is bound to be less. It is an altogether different, i.e. an empirical question whether the growth of unmet needs will meet any intrinsic limits, and where these limits will arise ahead of the theoretical extreme of an entire population in acute need (thanks to Wilhelmina Welsch for pointing out this difference).

2 Compositional data are a headache for the analyst and require special attention and statistical instruments (Aitchison 1986).

3. SYRIA MULTI-SECTORAL NEEDS ASSESSMENT (MSNA)

Theoretically, methods to estimate PiN can work with infinitely many variations in categories and criteria. Practically, little is known about the validity and value of different categorizations. Recently, however, several assessments of humanitarian needs have tried out a simple refinement beyond the basic in-need / not-in-need distinction. To our knowledge all of these experiments have been done in Syria. As already noted, they introduced, for the PiN estimates, the categories "moderate" vs. "acute" needs.[1]

The latest assessment pursuing this line of investigation is the Syria Multi-Sectoral Needs Assessment (MSNA) (Humanitarian Liaison Group 2014). Enumerators working for the MSNA collected information in 126 of the country's 270 sub-districts. They combined key informant data to produce estimates of the number of persons in acute, respectively in moderate "need of humanitarian assistance". They reported such estimates separately for five sectors - food security, shelter, non-food items (NFI), health support, and safe water.

The MSNA benefitted from a well-educated enumerator workforce, from previous experiments with these categories, as well as from contact with multiple key informants in every assessed sub-district. Not all needs assessments will enjoy these advantages.

The MSNA data thus offer an opportunity to test whether a refinement of the simple "in need" vs. "not in need" adds true value to the PiN estimates, and ultimately to the needs assessment as a whole. Since the MSNA report is publicly available[2] , we dispense with a summary of substantive findings here. We present statistics only as far as they are needed for the methodological argument. We concentrate on tests to determine whether the distinction between "moderate" and "acute" needs yield a sharper image of the humanitarian situation.

There are several potential test criteria. Two stand out:

- **Humanitarian needs are correlated across sectors.** As crises linger unresolved, deprivations cascade, and unmet needs soar. We expect the proportions of persons in needs between any two sectors to move together. The strength of these associations is manifest in the correlation pattern. The patterns for all PiN and that for persons in acute need will likely differ. If the latter makes sense, this is an indication that graded measures of need are productive. They produce a richer image of the needs situation.
- The MSNA rates the severity of **unmet needs** on a scale with seven levels. The severity ratings too are separate by sector. Plausibly, in every rated sector, higher proportions of PiN go hand in hand with higher severity ratings. We expect the proportion of persons in acute need to have predictive value for the severity score. Ideally, this proportion should improve the prediction after the effect of all PiN has already been accounted for. If it does so, the case for graded measures is even stronger.[3]

Before discussing the findings from the two tests, we describe the extent of the needs, as far as the estimated numbers of all PiN and of the persons in acute need reveal them.

1 The origins of the «moderate need - acute need» vocabulary are unclear. «Acute needs» are claimed in numerous institutional domains, but the pairing with «moderate needs» does not seem common. In the humanitarian field, «moderate malnutrition» and «acute malnutrition» have a longer tradition.

2 http://www.humanitarianresponse.info/operations/stima/assessment/syria-multi-sectoral-needs-assessment-msna-final-report

3 The predictive value of additional categories has been investigated particularly in medical testing, under the heading of «net reclassification improvement (NRI)». See, for example, Pencina et al. (2011).

3.1 PERSONS IN NEED IN SYRIA

The MSNA estimated the current populations of the 126 assessed sub-districts. These estimates provide the denominators for the proportions of persons in need. This table gives global statistics for the entire assessed area. They were calculated, in each sector, using the sums of populations in the sub-districts with valid observations on persons in need. Interested readers find the sample sizes detailed in a table in the appendix.

Table 1: Proportions of persons in need, by sector

PERSONS IN NEED	SECTOR				
	Food	Shelter	NFI	Health	Water
All persons in need	4,452,334	1,647,685	2,769,637	2,402,556	4,616,530
Of the population	28.5%	10.6%	17.9%	16.9%	29.7%
Persons in acute need	192,164	94,830	205,345	136,205	901,080
Of the population	1.2%	0.6%	1.4%	1.0%	5.9%

The number of persons in acute need is a fraction of that of all PiN - less than a fifth in the case of water, and less than one in 23 in food security. This divergence might lead some to think that the MSNA massively under-estimated acute needs. However, such a conclusion is not compelling. For one thing, "in acute need for assistance" implies that only those persons were included who will suffer devastating consequences, including death, if they are not assisted in the near future. The enumerators must have applied this standard restrictively. Moreover, the precise distribution of the intensity of needs within sub-districts was not known to the enumerators. Between sub-districts, the understanding of "acute" may have varied. How exactly, this again we do not know.

Thus, all we have are two measures of need, instead of just one, for each sub-district and for each sector.

[Sidebar:] Classifying areas by the likely distribution of need intensity

The refined PiN measures allow us to infer the likely shape of how the population of an area is distributed by intensity of the need. We cannot derive the full distribution - for this, the information is too coarse - but we can assign areas to qualitative types. These types were introduced in Figure 5 above. Here we exemplify them with the MSNA estimates for persons in need of safe water support.

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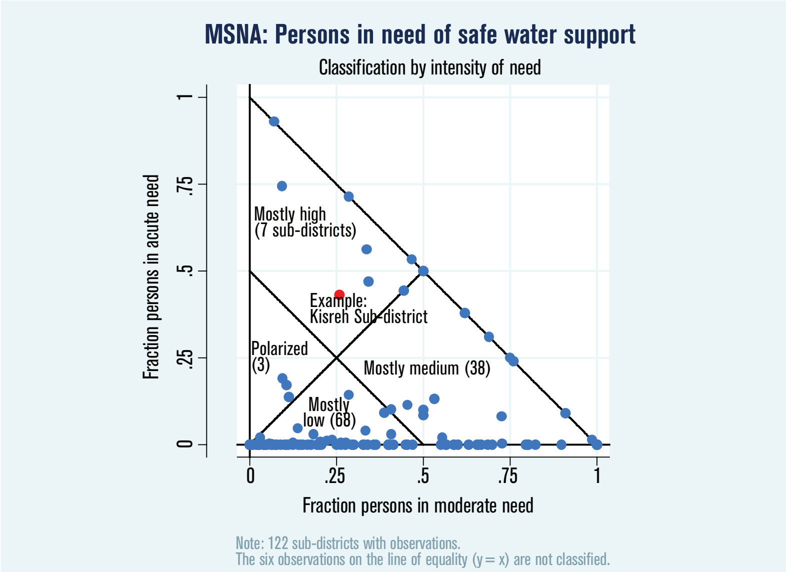


FIGURE 4 - Sub-districts classified by intensity of need for safe water

Each dot represents a sub-district. The positions of the dots can be explained with an example: Kisreh Sub-district in Deir-ez-Zor Governorate (the red dot) reported a population of 116,000. The enumerator brought back estimates of 30,000 persons in moderate need of safe water support (approx. 26 percent), and of 50,000 in acute need (43 percent). This leaves out 31 percent who then were not in need of this support.

We classify this sub-district as belonging to the type of population with mostly high intensity of this particular need. The reasons are: The "acute" category takes the largest of the three population shares. The exact category boundaries on the intensity scale are not known; the difference between the "no need" and "moderate need" proportions is too small to suggest a polarized situation.

This example also shows that the classification is more credible the closer a dot lies to one or the other corner of the big triangle. Those positioned farther inside - including all three instances of "polarized" - call for additional information on "what's going on here".

Nevertheless, the overall distribution by intensity classes - over half of the sub-districts in "mostly low", with consecutively smaller numbers in "mostly medium", "mostly high", and "polarized" - makes intuitive sense. We expect something like this from careful, parsimonious PiN estimates.

3.2 EMPIRICAL TESTS

Test #1: Correlations across sectors

Above we gave summary statistics of the proportions of PiN for the entire assessed region. Below we detail the distribution of this statistic by sub-district and sector. We show them for all PiN (top row of plots) and for the persons in acute need (bottom row). The histograms arrange these proportions in ten-percent intervals; the height of the bars indicates the number of sub-districts with PiN proportions in the interval. For the reason stated earlier, the frequencies are not population-weighted.

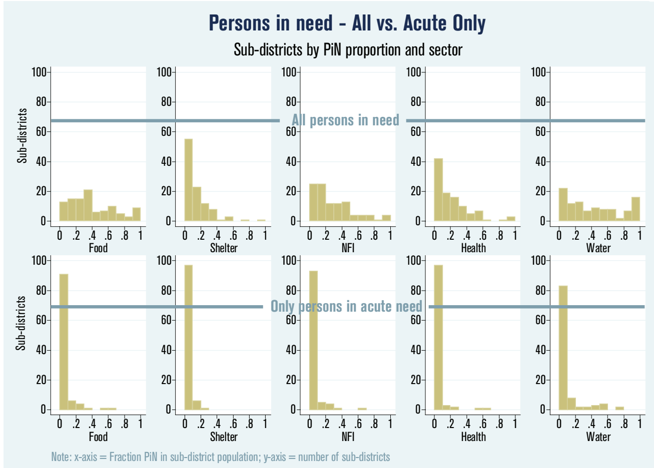


FIGURE 5 - Persons in need across sub-sectors

The distributions between the two rows are very different. They differ also among the plots of each row:

- When we look at all persons in need, the distributions for shelter, NFI and health are dominated by sub-districts with relatively low proportions. The distribution of water needs is more polarized. In the case of food, three peaks can be recognized.
- Regarding the persons in acute need, the distributions are radically different from those of all PiN. For the majority of sub-districts, the enumerators reported zero persons in acute need. This holds for every sector. A minority of the sub-districts did report acute needs, but only in the case of safe water did a sizeable number of sub-districts have elevated proportions.

How do these PiN proportions cohere among the sectors? As we reasoned above, the correlation patterns for persons in acute need, compared to that of all PiN, will indicate if the graded need measures are superior to the simple in-need / not-in-need. Because the distributions are skewed, we establish the correlations between sectors based on the ranking of proportions, rather than on their absolute values. The statistical measure used here is the so-called Spearman's rank correlation coefficient (Wikipedia 2012). A coefficient of one indicates that the rankings of the two variables are identical while zero would mean that the rankings are independent.

Table 2: Correlations of PiN proportions among sectors

	ALL PERSONS IN NEED					PERSONS IN ACUTE NEED ONLY				
SECTORS	Food	Shelter	NFI	Health	Water	Food	Shelter	NFI	Health	Water
Food	1.00					1.00				
Shelter	0.51	1.00				0.68	1.00			
NFI	0.63	0.44	1.00			0.69	0.77	1.00		
Health	0.31	0.25	0.39	1.00		0.63	0.46	0.47	1.00	
Water	0.51	0.29	0.53	0.46	1.00	0.59	0.62	0.55	0.39	1.00

We find that on both measures - all PiN and persons in acute need - all inter-sectoral correlations are positive. With one exception (water x health), the correlations of acute needs are stronger than those of the broad-based needs. In some cases, the differences are large. Thus, the coefficient between shelter and NFI for all PiN is a moderate 0.44; it rises to a strong 0.77 for persons in acute need. Similarly, food and health as well as shelter and water display considerably differences in correlation strength between the two measures.

The greater strength of correlations among the acute needs supports the belief that "persons in acute need" as an additional measure does indeed contribute value.

This correlation pattern offers additional insights. Three things stand out for acute needs:

- Food is strongly correlated with all other sectors.
- Food, shelter and NFI form a strongly correlated core.
- Water needs too are fairly strongly tied to that core while health shows a greater degree of independence.

The factors that produced this pattern are not known in detail One may speculate that displacement deprives households simultaneously of their normal livelihoods, thus of access to food, as well as of household infrastructure (shelter, NFI). Water needs become acute particularly where supply systems were damaged. Health support needs may surge sharply where health care facilities were destroyed, and where numerous trauma patients cannot be treated. This interpretation may not be correct because it rests on developments over time. The MSNA data are only cross-sectional.

Test #2: Acute needs inform judgments on severity

The enumerators provided a rating of how serious they thought the situations was in each of the needs areas in their assigned sub-districts. The MSNA designed severity scales for every sector. The scales used an identical range and formal definitions across sectors, but different substantive guidance for what it meant to assign the observed level of unmet needs and coping mechanisms. The common elements correlated the gravity of problems with the need for assistance:

Table 3: The common elements of sector severity scales

No need of external assistance	0	No problem
	1	Minor Problem
Need of humanitarian assistance	2	Moderate problem
	3	Major Problem
Acute and immediate need of humanitarian assistance	4	Severe Problem
	5	Critical Problem
	6	Catastrophic Problem

The overall rating pattern shows that the median value was uniformly 3 ("Major problem"). Because the sector-specific guidelines were different[1], the inter-sectoral comparability is limited. Still one is led to conclude that overall the situation in the health and water sectors was more severe than in the other areas of need.

Table 4: Severity ratings, by sector

RATING	FOOD	SHELTER	NFI	HEALTH	WATER
0	0	0	0	0	0
1	5	7	7	4	4
2	39	47	45	32	33
3	62	58	60	45	53
4	16	11	13	33	30
5	4	1	1	10	3
6	0	0	0	1	0
N =	126	124	126	125	123

1 Here are two examples for catastrophic problems: Food: «At least 20% of the population in the sub district is experiencing catastrophic food gaps.» - Water: «At least 70% of the population doesn't have access to improved water.»

For the purposes of our test, the intersectoral comparability, however, does not matter. What we need to know is to what extent, in each sector, the information on persons in acute need contributed to the severity rating after the enumerator had already taken into account the total PiN figure. Did the addition of an estimate of acute needs have any effect on the rating?

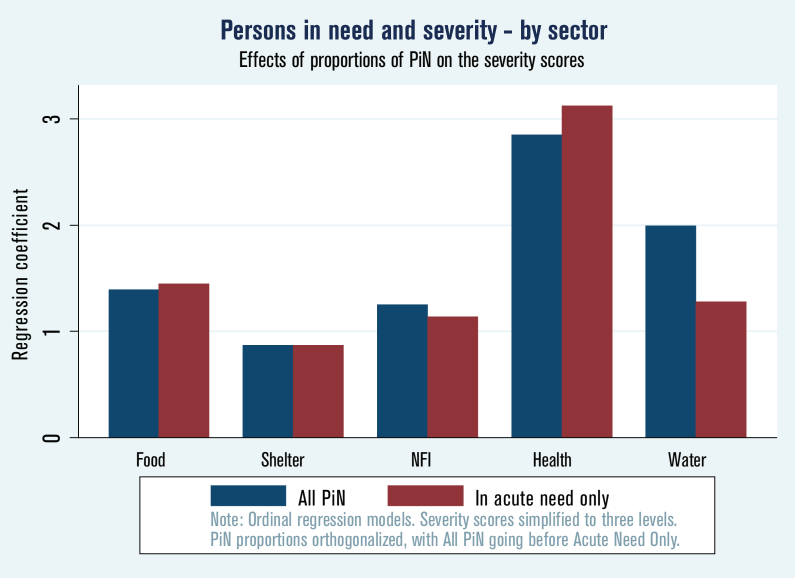


FIGURE 6 - Effects of PiN proportions on severity ratings

We use a statistical transformation of the PiN proportions that ensures that the "acute needs" information is used only to the extent that goes beyond the information already contained in the "all persons in need" information. Also we make sure that, despite the much larger number of all PiN than of those in acute need, the effects of the two information pieces are comparable. The technical device for this is described in the appendix. Above we inserted a chart that, for each sector, compares the effect of the all-PiN proportion to the additional effect of the acute-only PiN.

The result is telling: In four of the five sectors, the proportion of persons in acute need has an additional effect on the severity that is very similar to the effect that the proportion of all PiN makes in the first place. Only in the water sector does the-acute needs information contribute noticeably less. Yet this contribution is still statistically significant.

We are tempted to conclude that the addition of an "acute need" category has passed this second test too. In combination, the results for the five sectors suggest so strongly. However, the uncertainty in the regression coefficients is considerable, given that the estimates are based on a relatively small number of observations (N = 123).

3.3 WHAT CAUSES ACUTE NEEDS?

The two tests that we claim speak to the validity of the "persons in acute need" support the use of this measure in needs assessment. We will have even more confidence if we understand what causes higher or lower proportions of persons in acute need. With this in mind, we estimated various models. They work with the variables that the MSNA, and in part also the preceding Syria Integrated Needs Assessment (SINA) (AWG 2013), provided. Unfortunately, no clear favorite has emerged.

The effects of conflict and of other unmet needs

We started from the assumption that the proportions of persons in acute need in a particular sector vary with the conflict environment as well as with the entire configuration of all unmet needs.

But some of the expected relationships did not hold. In particular, we expected that the proportions of persons in acute need and of internally displaced persons (IDPs) in the current population would be positively correlated, even strongly so. This is not so, and for some sectors it is negative. One may argue that displaced persons flocked, wherever possible, to sub-district with better conditions. But to the extent that they did, as a result, one would think, the host areas grew over-burdened, with more persons falling into acute needs. The IDP proportions, however, do not show this effect. Nor did the change in proportion over the ten months between SINA and MSNA drive acute needs in any clear direction.

We eventually replaced IDPs with the proportion, in the pre-conflict population, of persons who fled their sub-districts. Its unweighted mean is approx. 29 percent. We also considered whether a sub-district was rural or urban because of the assumed differences in access to livelihoods and in exposure to shelling and bombardment.

As for the total needs configuration, in each sector model we formed a summative index of the needs in the sectors other than the one in focus. For example, for the acute-need-of-food assistance model, we formed a score from PiN statistics in shelter, NFI, health and water. We outline technicalities in the appendix, where we present also the model estimates.

Complex relationships

Here we exemplify a segment of these complex relationships with the help of a combined graph. We chose the shelter sector because here the acute needs vary both with the needs in the other sectors and with the extent of the flight of the pre-conflict population. Also we enumerate a number of findings from other sectors.

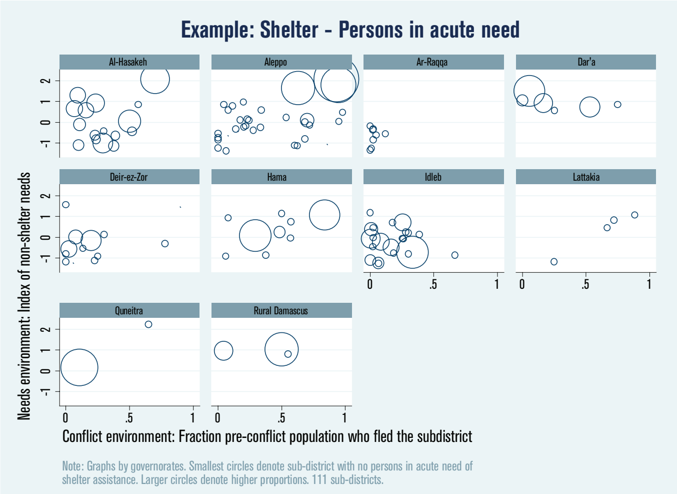


FIGURE 7 – Persons in acute need for shelter, by location, population flight and other needs

The substantial differences among governorates are conspicuous. They may render the assumed direct relationships between population flight and other needs on one side and acute needs for shelter assistance on the other spurious. The relationships are at least in part due to differences in the governorate sample sizes. Aleppo and to a smaller extent Al-Hasakeh contribute strongly to the positive associations; Idleb has a dampening effect; some of other governorates might have affected the overall result had more of their sub-districts been covered. We are moving in a complex maze of interactions that linear models may not be able to unravel.

Comparing sector models, we find that the extent of the population flight can have opposite effects. Sub-districts who lost larger fractions of their original reported greater acute needs for shelter assistance and for health support. There is no such relationship with food and NFI. The acute needs for safe water are greater in sub-districts that have retained a higher proportion of their pre-war population.

We find opposite effects also of the rural/urban split. Rural sub-districts tend of have greater acute needs for shelter assistance than urban areas. The opposite holds for the other four sectors.

We find better consistency in the effects of needs configurations. Acute needs in each sector are driven up by the combined needs in the other four sectors. This effect is statistically significant for all sectors except health. It is not surprising, given what we know of the correlations among acute needs.

The sum of all this is that, yes, needs go hand in hand in many expected ways, but the conflict environment fashions acute needs differently from sector to sector. There can also be important regional (governorate-level) modifications.

[Sidebar:] Detecting complex causes of acute needs

The preceding segment told us, in so many words, that multi-variate regression models have had limited success in explaining what causes acute needs. Localized factors matter.

Analyst can therefore be tempted to abandon the search for patterns. They may opt for a purely descriptive approach, such by comparing numbers or proportions by region. Demonstrating regional differences is a key part of the assessment. Yet, in themselves alone, regions - such as governorates - explain little of the interesting variation at the lower levels.

Analysts may use spreadsheet tools - pivot tables - to explore regional differences jointly with differences in other factors of interest, and their combined effect on acute needs. Because of the modest sample size, such cross-tabulations quickly produce cells with no observations, and others with very small numbers. They rarely reveal firm patterns.

Here we briefly want to mention an analytic method specifically devised to detect complex interactions in relatively small samples. Fuzzy Qualitative Comparative Analysis, or Fuzzy QCA, is a case-based (as opposed to variables-based) method. It assigns cases (here: sub-districts) a degree of membership in the variables of interest. For example, a sub-district in Aleppo Governorate, is a member of Aleppo to a degree of 1, and of all other governorates to the degree of 0. Sub-districts exposed to a lot of fighting over the past thirty days may be said to be included in the contested areas to a degree of 1, those seeing sporadic fighting perhaps to a degree of 0.3, and those undisturbed to a degree of 0. "A degree of 0.3", set by the analyst for the middle category, exemplifies the fuzziness of the membership.

QCA seeks to establish to what degree a combination of attributes is 1. necessary, and 2. sufficient, in order to produce the outcome of interest, i.e. high proportions of acute needs. It reviews the outcome distribution for all combinations of high/low attribute values, marks combinations that result in high outcomes and then simplifies them to the minimum set of high-outcome combinations.[1]

In principle this is not very different from what the analyst does with pivot tables. But QCA's logical reduction algorithm is powerful. The analyst can tell it to be indifferent to combinations with very few cases and proceed with the reduction regardless of whether those infrequent combinations were associated with high or low outcomes.

We exemplify this with the results from a Fuzzy QCA analysis of the proportion of persons in acute need of health support. We fed QCA the data on these tentative explanatory variables:

- The sub-district is either in Aleppo or Al-Hasakeh Governorates
- The sub-district is rural or urban
- The proportion of the pre-conflict population who had fled the sub-district
- The intensity of the fighting in the past thirty days (3 levels)
- An index of the unmet needs in the four sectors other than health

The initial solutions (combinations that are associated with higher proportions of persons in acute need of health support) proposed by the QCA algorithm were:

1 The Wikipedia article on QCA is not very good (Wikipedia 2014b). The authors of the STATA procedure fuzzy provide a more instructive introduction also for non-users (Longest and Vaisey 2008); this article is now publicly available at http://www.stata-journal.com/sjpdf.html?articlenum=st0140.

Table 5: Combinations of attributes that produce acute needs

Solution #	Combination of attributes
1	Urban AND high proportion fled AND low-contest AND high other needs
2	In Aleppo or Al-Hasakeh AND urban AND high proportion fled AND low contest
3	In Aleppo or Al-Hasakeh AND high proportion fled AND low contest AND high other needs

At first glance the common denominator seems to be "High proportion fled" AND "low contest".

However, by telling the algorithm to be indifferent to elemental combinations of all five variables that include three or fewer sub-districts, the algorithm comes up with one final set that is simpler and different from what we expected:

Final set #	Combination of attributes
1	In Aleppo or Al-Hasakeh AND high proportion fled

Urban/rural, level of contestation, and needs in other sectors are no longer relevant. See the appendix for some more technical detail.

QCA's strong side is the ability to identify higher-order interactions and to simplify them through indifference to the effects of infrequent combinations. The downside is in the difficulty of explaining the mechanism as well as the findings in terms of which members (in our case: which sub-districts) clearly belong to the final set(s), and which not. The membership remains fuzzy, by design. The robustness of findings too is in question.

This method is best suited to generate new hypotheses that had been blind spots in spreadsheet-based or variables-based statistical analysis. It is applicable to the distributions of acute needs, but also to those of other elements of needs assessments for which an explanation in terms of other observed variables is desired.

4. CONCLUSION AND RECOMMENDATIONS

Summary of evidence

The MSNA provides moderately strong evidence that "persons in acute need" is a productive concept. It should be incorporated into the tools of needs assessments. Estimates, by enumerators relying on local key informants, of persons in acute need may sharpen humanitarian intelligence. Such estimates complement, but do not replace, estimates of all PiN, who include the persons in moderate need.

The acute-needs estimates of the MSNA passed two tests:

- They present a plausible correlation pattern.
- They inform the sectoral severity ratings, beyond the influence of the estimates of all PiN.

The factors that cause acute needs to emerge and then to expand are less obvious. The conflict environment and the configuration of needs in other sectors are plausible drivers. However, to the extent that we expressed these factors through a small number of indicators, we found that the link from them to the prevalence of acute needs varies from sector to sector. In Syria, as much as the MSNA data tell, associations between causal factors and sector-specific acute needs are further complicated by regional particularities. While this is hardly any less true of all persons in need - moderate plus acute -, it shatters any hopes that acute needs can be more keenly discerned and thus more dependably predicted along a uniform set of causal pathways. Localized factors matter.

Technical recommendations

Assessment designers who include persons-in-acute-need measures may want to heed these points in particular:

1. The MSNA results are encouraging because this assessment had the benefit of a well educated workforce and multiple key informants in every assessed area. Assessments that work in less favorable conditions may not be able to produce consistent and reliable estimates.

2. Rather than comparing absolute numbers of PiN, it may be more productive to contrast sectors, areas and groups of affected persons on the basis of proportions. This is instructive both for all PiN and for those in acute need.[1]

3. "Moderate need" is a logical complement to "acute need", assuming one wants to work with three ordered categories (no need, somewhat needy, very needy). For technical reasons ("compositional variables"), numbers of persons in moderate need and those in acute need should not be compared systematically. The comparison should be between all persons in need and those in acute need.

4. In the MSNA, surprisingly high proportions of sub-districts reported zero persons in acute need, in most sectors. During debriefings, enumerators should be asked why they think that in area X and sector Y, key informants did not signal acute needs. Conversely, if persons in acute needs are reported, a brief qualitative explanation may add to our understanding of causes, forms and distribution.

5. Similarly, outliers - areas that report distinctly high proportions of persons in acute need - should be discussed. Even if they are demonstrably exaggerated (and need to be corrected downwards), they signal special situations that should be noticed, monitored and, if justified and feasible, receive appropriate relief.

6. Analysts can find associations between context variables and acute needs quickly with the means of spreadsheet pivot tables. These relationships must remain simple and descriptive. Because the number of assessed areas (126 sub-districts in the MSNA) will be modest, tabulations involving more than three factors will soon accumulate empty cells - combinations of factor levels that were nowhere observed. Statistical modeling may run into problems with the purposive nature of the sample, missing values not-at-random, and ignorance of appropriate functional form. Its major benefit is in gauging the extent of uncertainty in the conclusions.

Information costs and ethical considerations

The coherence of the acute-needs estimates in the MSNA recommends working with measures of acute need in future needs assessments. This recommendation is purely statistical. Two potential objections may be noted:

This information has a cost. Refined categories involve more distinctions, therefore more detailed attention in instrument design, training, supervising, debriefing, processing and reporting. This may displace attention from other important details, such as during key informant interviews. "All persons in need", "those in moderate need", and "those in acute need" - these concepts need to be translated consistently across hierarchical, language and functional boundaries. Functional challenges may arise, for example, in aggregating estimates from several key informants in an area, some of whom may have offered plainly invalid estimates or none. The assessment designers should evaluate the expected costs and benefits of the proposed acute-need measures. If they find - during questionnaire translation, enumerator training or pre-test - that the concept itself or the questions to ask key informants are confusing, the measures should not be included.

There is an ethical side to it. Category changes in social policies create new information that can motivate new interpretations and new priorities. They can redraw the lines of social inclusion and exclusion (Bowker and Star 2000; Monahan 2010). Donors may - incorrectly - conclude that "all persons in need" overestimate of the real needs. They may take "persons in acute need" to be more accurate and closer to priorities in times of scarcity, fatigue and incessant calls for better targeting. Response planners, conscious of the correlated acute needs across sectors, may make inferences from the sub-district level (for which numbers were estimated) to small neighborhoods or even families - inferences that are not warranted. They may prescribe delivery formats with too much or too little inter-sectoral integration before in-depth assessments and beneficiary participation identify effective synergies.

Informed priorities

Nevertheless, the concept of "acute needs" is valuable. It can improve the measurement of unmet needs under conditions that rarely permit exact classification. As long as everybody remains aware that the distinctions are fuzzy, and estimates need interpretation in context, such measures will strengthen judgment on humanitarian priorities.

[1] This concerns the analysis. What about the data collection? Enumerators, working with key informants, may find it easier to elicit estimates of absolute numbers, but, to our knowledge, there are no studies about which work better with key informants - proportions or absolute numbers.

1. APPENDIX

Tables and graphs in the appendix are not captioned.

1.1 PERSONS IN NEED - EXTENDED INFORMATION

	SECTOR				
	Food	Shelter	NFI	Health	Water
ALL PERSONS IN NEED					
Sub-districts with valid observations	126	125	122	119	125
Population in these sub-districts	1.56E+07	1.56E+07	1.55E+07	1.42E+07	1.56E+07
Persons in need	4,452,334	1,647,685	2,769,637	2,402,556	4,616,530
Fraction	28.5%	10.6%	17.9%	16.9%	29.7%
PERSONS IN ACUTE NEED					
Sub-districts with valid observations	123	121	117	116	122
Sub-districts reporting some persons in acute need	54	44	41	73	44
Population in observed sub-districts	1.54E+07	1.52E+07	1.49E+07	1.40E+07	1.54E+07
Persons in acute need	192,164	94,830	205,345	136,205	901,080
Fraction	1.2%	0.6%	1.4%	1.0%	5.9%

1.2 EFFECTS OF ALL PIN AND PERSONS IN ACUTE NEED ON THE SEVERITY SCORES

These models advanced in three steps:

- Simplifying the severity scales
- Computing the residual component of the "acute needs" information
- Regressing the severity scores on the PiN proportions

Simplifying the severity scales

Across the five sectors, the level zero ("No problem") was never used. Level six ("Catastrophic") appeared only once, in health. Level one and five were rarely used. These low frequencies would make sector-specific regression models unstable.

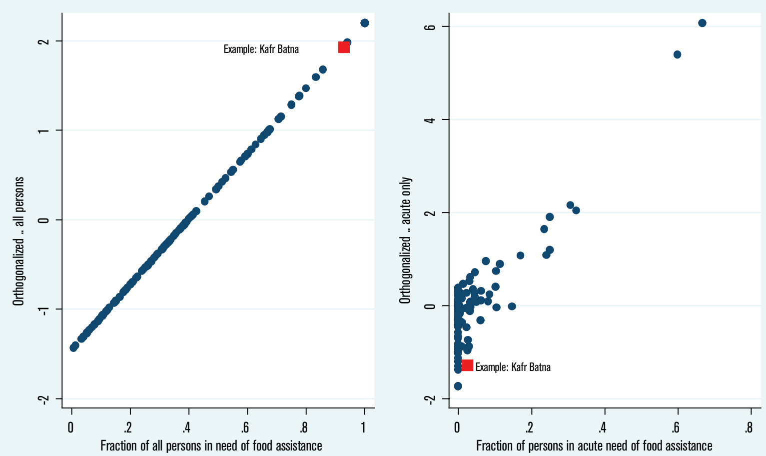
The scales were therefore recoded as: (0,1,2) → 2; 3 → 3; (4, 5, 6) → 4, leaving three levels 2, 3, and 4 for use in the regression models. Substantively, this is justified by the scale design, which makes a substantive break between level 3 ("need for assistance") and level 4 ("acute and immediate need"). In hindsight, it might have been better to leave 1 and 2 separate, in order to respect the substantive break between them.

Orthogonalizing the PiN proportions

The statistical procedure that ensures statistical independence between the proportions of all PiN and those of persons in acute need is known as *orthogonalization* (Wikipedia 2014a). The procedure *orthog* in the statistical application STATA standardizes the orthogonalized variables to mean zero and variance one. This makes the effect of the all-PiN proportions (the first variable passed to *orthog*) and the additional effect of the persons in acute needs proportions (second to *orthog*) comparable. The procedure was run separately for each sector.

To make this more understandable, this chart shows the transformation in one sector. The first entered variable underwent a simple linear transformation that achieved the standardization. Its information content remains undiminished. The second resulted from regressing it on the first, then standardizing its residuals. Thus it retains only the information not yet contained in the first variable. The (Pearson moment) correlation between the two transformed variables is zero.

Orthogonalization example: Persons in need of food assistance



Note: 123 sub-districts. 69 reported zero persons in acute need of food assistance. The example marked red - the sub-district of Kafr Batna - reported 93 percent of its population in need of food assistance, and 2.5 percent in acute need.

An example of an observation makes this clear. The sub-district of Kafr Batna reported a high proportion of its people in need of food assistance, but a very low proportion in acute need. This large discrepancy causes the transformed value of the proportion in acute need to be pushed into the negative. As a result, it will lower the predicted value of the food severity score in the next step.

Ordinal regressions

For each sector, the recoded severity scores are regressed on the orthogonalized PiN proportions. The severity scores are ordinal variables; therefore ordered logistic regressions are computed. The regression coefficients are recovered and visualized in the bar chart in the main part of the note.

By way of illustration, we print the output from one of the models, the one of the food severity score:

Variable definitions

```
variable name      type   format   label      variable label

-----------------------------------------------------------------------------------------

C1_1               byte   %10.0g              Food severity score

SeverRecodFood     byte   %9.0g               RECODE of the original Food severity score
                                               (reduced to three levels)

allfractC2_c_1     float  %9.0g               Fraction of all persons in need of food
                                                    assistance

fractionC2_a_1     float  %9.0g               Fraction of persons in acute need of food
                                               assistance

orthog1Food        double %10.0g              orthogonalized proportion all PiN of food

orthog2Food        double %10.0g              orthogonalized prop. p. in acute need of
                                               food
```

Descriptive statistics

Recoding of the severity score:

```
     Food |  RECODE of C1_1 (Food severity score)
 severity |
    score |         2          3          4 |     Total
----------+---------------------------------+----------
        1 |         5          0          0 |         5
        2 |        39          0          0 |        39
        3 |         0         62          0 |        62
        4 |         0          0         16 |        16
        5 |         0          0          4 |         4
----------+---------------------------------+----------
    Total |        44         62         20 |       126
```

PiN proportions of the effective sample:

```
    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
allfractC2~1 |       123    .3980751    .2746773   .0063226          1
fractionC2~1 |       123    .0389967    .0992226          0   .6666667
 orthog1Food |       123    4.91e-18     1.00409  -1.432062   2.200352
 orthog2Food |       123   -2.96e-18     1.00409  -1.736186   6.068158
```

Ordered logistic regression

```
Ordered logistic regression                       Number of obs   =        123
                                                  LR chi2(2)      =      46.35
                                                  Prob > chi2     =     0.0000
Log likelihood = -101.06289                       Pseudo R2       =     0.1865

------------------------------------------------------------------------------
SeverRecodFood |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+--------------------------------------------------------------
   orthog1Food |   1.391073   .2916197     4.77   0.000     .8195094    1.962638
   orthog2Food |   1.445332   .4285136     3.37   0.001      .605461    2.285203
---------------+--------------------------------------------------------------
         /cut1 |  -1.119419   .2435608                      -1.59679   -.6420489
         /cut2 |    1.95273    .320807                      1.323959      2.5815
------------------------------------------------------------------------------
```

Note the wide confidence intervals on the coefficients of the transformed PiN proportions.

Quantity of interest

The research question is whether the proportion of persons in acute need of food significantly informs the severity rating of the food sector after the proportion of all PiN has been taken into account. The coefficient of *orthog2Food* is statistically significant, with p = 0.001. However, because of the wide confidence interval, we want to see how the effects of the two proportions compare. We thus seek a confidence interval for the expression

(_coef[orthog2Food] / _coef[orthog1Food] - 1)

which we compute with the help of STATA's *nlcom* procedure for non-linear combinations of parameter estimates (the ratio of the coefficients is an instance of non-linear):

```
nlcom (_coef[orthog2Food] / _coef[orthog1Food] - 1)

       _nl_1:  _coef[orthog2Food] / _coef[orthog1Food] - 1
------------------------------------------------------------------------------
SeverRecod~d |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |    .039005   .2289574     0.17   0.865    -.4097432    .4877532
------------------------------------------------------------------------------
```

The result tells us that the two effects are not significantly different, and that, with a probability of 95 percent, the effect of the transformed proportion of persons in acute need of food assistance is between 1 -.4097 = 59 percent and 1 + .4878 = 149 percent of the effect of the proportion of all PiN.

We take from this that the persons in acute need clearly do inform the severity judgment. However, when we consider the size of its effect compared to all PiN, there remains considerable uncertainty. This is not surprising because 123 sub-districts is a relatively small sample (not in regards to the total of 270 sub-districts in the country, but in a hyper-population of infinitely many areas). If this seems hard to visualize, imagine that the reported estimates of PiN proportions and severity scores in some sub-districts were incorrect, and that their true values were equal to those of some neighboring sub-districts. If we did this substitution exercise sufficiently many times over, we would find that the effects on the severity scores vary to an extent similar to the confidence intervals above.

In fact, it turns out that the proportion of persons in acute need is informative for the severity scores in all sectors. The effects are significantly greater than zero with p = 0.001 or better, with the exception of the need for clean water, for which p = 0.013. Details are not shown for space reasons. However, the uncertainty in the sector estimates needs to be pointed out:

SECTOR	EFFECTS ON THE SEVERITY SCORE "acute need" effect in percent of "all PiN" effect:		
	Estimated	LCI95%	UCI95%
Food	104%	59%	149%
Shelter	100%	36%	164%
NFI	91%	45%	137%
Health	110%	88%	131%
Water	64%	28%	101%

With the exception of the health sector, the uncertainty is considerable.

1.3 CAUSAL FACTORS IN ACUTE NEEDS

As noted in the main body, the relationships between conflict environment and the proportion of persons in acute need is complex.

The conflict environment was captured by a demographic shift variable - the proportion of the pre-conflict population that had fled the sub-district -, by the intensity of the fighting in the last thirty days, as well as by whether the sub-district is rural or not.

Descriptive statistics (not population-weighted) for the entire 126 sub-districts are:

```
variable name   type   format      label       variable label
---------------------------------------------------------------------------------
Fled_prop_pre~l float  %9.0g                   Proportion of pre-conflict population
                                               that fled from sub-district
isRural         byte    %8.0g      isRural     Rural vs. urban sub-district
fight30days     long    %19.0g     fight30days
                                               Contested area in the last 30 days

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
Fled_prop_~l |       126    .2914256    .2790768          0   .9804878
     isRural |       126    .6190476    .4875595          0          1

 Contested area in |
  the last 30 days |      Freq.     Percent        Cum.
-------------------+-----------------------------------
1-Frequent fighting |        49       38.89       38.89
2-Sporadic fighting |        52       41.27       80.16
       3-No fighting |        25       19.84      100.00
-------------------+-----------------------------------
             Total |       126      100.00
```

From the final regression models, we dropped the contested-area variable after it failed to show significant effects.

In order to separate effects of the needs assessment process from those of the conflict environment, we needed a combined cross-sectoral needs index. The persons in acute need were not suitable as indicators because of the numerous zero values. Moreover, the proportion of all PiN in the same sector as the dependent proportion of persons in acute need could not be included in the index because of the compositional dependency. We settled eventually on a factor analysis model that proceeded as follows:

In each sector model,

- Use the four sectoral proportions of all PiN other than the sector's in point
- Use their sigmoid transforms[1] (to dampen the effect of outliers)
- Factor-analyze the four variables
- Retain the scores of the first factor as the combined needs index.

1 Sigmoid = (-1exp(-V)) / (+1exp(-V)), where V=[x_i-(x)mean)]/sigma, sigma = standard deviation.

The proportions of persons in need were then fitted as a zero-inflated beta distribution in response to

- whether the sub-district was rural
- the fraction of the pre-conflict population that had fled
- the combined needs index.

The models were estimated using the STATA procedure zoib (Buis 2012). zoib estimates coefficients of two aspects of the causal effects. Both are reported in the following table:

- The section called "proportion" collects coefficients that influence the proportion directly.
- The section "zeroinflate" concerns the difference between zero and any positive number of persons in acute need. Note that positive coefficients mean higher probabilities that there are zero persons in acute need.

In describing findings in the main body, we did not make the difference between these two aspects. They would have confused the reader.

Zero-inflated beta distribution, five sector models:
Dependent variable: Proportion of persons in acute need

Variable	Food	Shelter	NFI	Health	Water
			Sector		
proportion					
Rural	0.138	0.448*	0.273	0.359	0.186
Fled subdist	0.309	1.040***	-0.506	1.814***	-1.551**
Combined needs in sectors other than					
Food	0.718***				
Shelter		0.505***			
NFI			0.717***		
Health				0.187	
Water					1.050***
_cons	-2.747***	-3.946***	-2.469***	-3.883***	-1.518***
zeroinflate					
Rural	0.860*	0.207	0.833*	0.985**	1.146**
Fled subdist	-0.330	0.682	0.474	-0.414	1.441
Combined needs in sectors other than					
Food	-0.688**				
Shelter		-0.583**			
NFI			-0.612**		
Health				-0.281	
Water					-0.946***
_cons	-0.168	0.320	0.103	-1.073**	-0.476
ln_phi					
_cons	2.385***	3.837***	2.396***	2.447***	1.603***
Statistics					
N	112	111	110	111	113
p	<0.0001	<0.0001	0.0003	0.0003	<0.0001

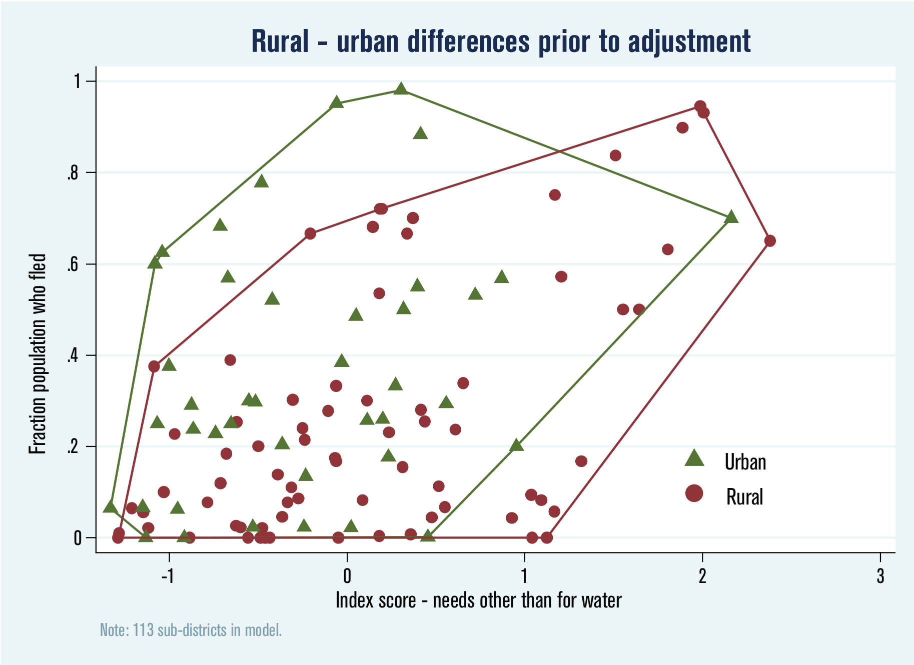
legend: * p<.1; ** p<.05; *** p<.01

[Sidebar:] Can statistical models tell us anything about the causes of acute needs that we don't know yet?

Let us exemplify the insights that such a multi-variate model offers. In the table above, the coefficient of being a rural sub-district on having zero persons in acute need of safe water is 1.146. Two stars indicate that it is moderately significant. What does this say?

Coefficients in the inflation part are log odds ratios; here this is the log odds ratio of having zero persons in acute need in rural sub-districts compared to urban ones. When we exponentiate, the odds ratio is a steep 3.15. This is incredibly high, at first glance anyway. Let us find the observed ratio: Of the 113 sub-districts in the model, 72 are rural, 41 urban. 69.44 percent of the rural areas have zero acute water needs, as compared to 56.1 in urban areas. The observed odds ratio thus works out as (0.6944 / (1 - 0.6944)) / (0.561 / (1- 0.561)) = 1.778.

Thus the observed odds of having at least some persons in acute needs of water in cities are roughly twice the odds in the countryside. However, the model predicts that, if all else were equal, the urban odds would be over three times the rural ones. What is "if all else were equal"? It means: if urban and rural areas were the same in terms of population who fled and in terms of non-water needs. But, of course, they are not the same. Urban areas lost (unweighted) 36 percent of their pre-conflict population, rural areas 26 percent. Non-water needs in rural areas are, on average, higher than in urban areas.



Were these needs and the population loss the same between city and countryside, we would observe that cities have an even stronger tendency to develop acute needs for water. For this scenario the difference in terms of probabilities is 0.256:

```
Conditional marginal effects                      Number of obs    =        113

Expression    : probability of having value 0, predict(pr0)
dy/dx w.r.t. : isRural
at           : isRural              =     .6371681 (mean)
               Population loss      =     .2958958 (mean)
               Index of other needs =     .0087265 (mean)

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     isRural |    .256481   .1053978     2.43   0.015      .049905     .463057
----------------------------------------------------------------------------
```

The observed difference, as we saw, is 69.44 percent - 56.1 percent = 0.133.

In other words, cities are even more vulnerable to acute water needs than the observed differences vis-à-vis the rural areas suggest. Is this due to the larger, more interdependent water supply infrastructure in cities (compared to more decentralized, smaller systems in the villages, some of which may survive the hostilities)?

At the same time, the claim of higher urban vulnerability is speculative. The predicted odds ratio itself is uncertain. Its estimate is 3.14, but its 95% confidence interval ranges from 1.24 to 7.98 (not shown in the table). The observed ratio of 1.78 is well within it.[1]

Such model estimates do not replace direct observational results. However, they can stimulate new thinking in interpreting needs assessments. No model is correct, but some are useful. All need careful checking against other evidence and common sense.

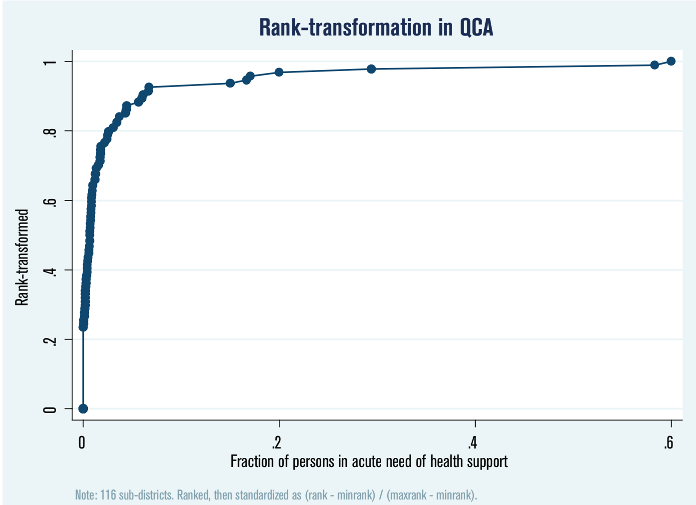
1 Speculative, but not unlikely:

```
nlcom [zeroinflate]_b[isRural] - ln(1.78)
------------------------------------------------------------------------------
fractionF2~1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   .5698439   .4751821     1.20   0.230    -.3614959    1.501184
------------------------------------------------------------------------------
```

1.4 THE FUZZY QCA MODEL OF ACUTE HEALTH SUPPORT NEEDS

This segment documents STATA output from a model using the procedure *fuzzy* (Longest and Vaisey 2008). The substantive results were presented starting on page 11-12.

fuzzy requires variables to be named with a single capital letter. Both dependent and independent variables must express degrees of membership in sets. The degrees are in the interval [0, 1]. We transformed the dependent variable "Fraction of persons in acute need of health support" and two of the explanatory variables to their ranks and hence proportionately to [0, 1] such that the highest original value = 1, and the lowest = 0 (see graph as well as further below). For the fighting intensity in the previous 30 days, we set the values 1 for high, 0.3 for intermediate, and 0 for no fighting.



Another notational convention is necessary to know. *fuzzy* examines the consistency (see below) between the outcome (fraction persons in acute need of health support) and each combination of high and low values of the explanatory variables. Such a combination is called a *configuration* and is described by a combination of uppercase letters for high values and lowercase letters of low values. This is best explained by way of example. The configuration written as

```
ArPco
```

is the set of all cases (sub-districts) characterized by:

- Is in Aleppo or Al-Hasakeh Governorate (uppercase A for membership degree = 1 of being part of one or the other of those governorates)
- Is urban (lowercase r for the degree = 0 in "Is rural")
- High proportion of people fled (uppercase P for high membership degree in P)
- None or sporadic fighting (lowercase c for low membership degree in contestation)
- Low fractions of PiN in sectors other than health (lowercase o for low degree of membership in the other-needs index).

Descriptive statistics

variable name	type	format	label	variable label
fractionE2_a_1	float	%9.0g		Fraction of persons in acute need of health support
H	float	%9.0g		Health (prop. persons in acute need rank-transformed
A	byte	%8.0g		Al-Hasakeh or Aleppo
R	byte	%8.0g	isRural	Rural vs. urban sub-district
P	float	%9.0g		Proportion pre-conflict population who fled sub-district [rank transformed]
C	float	%9.0g		Intensity scores fighting last 30 days
O	float	%9.0g		Factor score other needs, std [rank transformed]

Variable	Obs	Mean	Std. Dev.	Min	Max
fractionE2~1	111	.0287136	.0879513	0	.6
H	111	.3942879	.3523635	0	1
A	111	.4234234	.4963421	0	1
R	111	.6306306	.4848229	0	1
P	111	.4806438	.3055634	0	1
C	111	.3315315	.3685307	0	1
O	111	.501022	.2921006	0	1

The variable C has three levels, the fuzzy membership value for the intermediate category (sporadic fighting) arbitrarily set to 0.3:

Intensity scores fighting last 30 days	Freq.	Percent	Cum.
0	42	37.84	37.84
.3	46	41.44	79.28
1	23	20.72	100.00
Total	111	100.00	

The fuzzy command used for this model

```
fuzzy H A R P C O, matx(coincid suffnec) standard settest(yvv yvn) greater(col1) conval(.700)
common reduce remainders(3)
```

Two choices need to be noted:

- We set the consistency criterion for the tests at a liberal level (0.70; *fuzzy's* default standard for this is 0.80).
- The option "remainders(3)" was taken. This means that any configuration with three or fewer best-fitting cases was excluded from the first logical reduction, and was treated indifferently in the second, simplified one. The remainder feature is one of *fuzzy's* major strengths for small and medium sample sizes. It makes the second logical reduction independent from the presence or absence of very rare combinations of values in the explanatory variables.

See Longest et al. (op.cit., 83sqq.) for explanations of the other command options.

Bivariate relationships

Coincidence Matrix

Conincidence measures the degree of overlap in two fuzzy variables and is operationalized as $sum_i(min(x_i, y_i)) / sum_i(max(x_i, y_i))$.

	H	A	R	P	C	O
H	1.000					
A	0.525	1.000				
R	0.665	0.608	1.000			
P	0.813	0.539	0.542	1.000		
C	0.472	0.569	0.648	0.510	1.000	
O	0.805	0.520	0.726	0.756	0.566	1.000

Sufficiency and Necessity Matrix

The triangle below the diagonal holds the sufficiency statistics, the one above the necessity statistics.

Sufficiency is the degree to which membership in x produces membership in y and is operationalized as $sum_i(min(x_i, y_i)) / sum_i (x_i)$.

Necessity is the degree to which membership in y depends on membership in x and is operationalized as $sum_i(min(x_i, y_i)) / sum_i (y_i)$.

	H	A	R	P	C	O
H	1.000	0.475	0.539	0.705	0.371	0.699
A	0.442	1.000	0.596	0.569	0.443	0.501
R	0.337	0.400	1.000	0.429	0.330	0.554
P	0.578	0.501	0.562	1.000	0.360	0.737
C	0.442	0.565	0.628	0.522	1.000	0.554
O	0.550	0.424	0.697	0.707	0.366	1.000

Tests of explanatory power

Each configuration had to pass two tests in order to qualify as consistently associated with high proportions of acute need for health support. The first test probes which configurations are more consistent with the dependent variable (its membership degree y) than with y's fuzzy opposite (1 - y). The second probes which have a consistency value higher than the set standard (0.70).

Y-CONSISTENCY vs N-CONSISTENCY

Set	YCons	NCons	F	P	NumBestFit
arpcO	0.751	0.710	0.04	0.835	3
arPcO	0.761	0.612	0.70	0.404	6
arpCO	0.758	0.719	0.03	0.860	1
ArPco	0.801	0.624	1.15	0.285	5
ArPcO	0.811	0.554	1.60	0.208	5
ARPcO	0.771	0.587	0.76	0.386	7

Y-Consistency vs. Set Value

Set	YConsist	Set Value	F	P	NumBestFit
arpcO	0.751	0.700	0.19	0.666	3
arpCo	0.750	0.700	0.16	0.688	0
arPco	0.726	0.700	0.07	0.797	3
arPcO	0.761	0.700	0.42	0.519	6
arpCO	0.758	0.700	0.22	0.639	1
aRpCO	0.740	0.700	0.19	0.663	1
Arpco	0.801	0.700	0.46	0.498	1
ArpCO	0.706	0.700	0.00	0.970	0
ArPco	0.801	0.700	1.36	0.247	5
ArPcO	0.811	0.700	1.01	0.317	5
ArPCo	0.797	0.700	0.95	0.331	3
ArPCO	0.740	0.700	0.06	0.800	0
ARPco	0.718	0.700	0.02	0.879	3
ARPcO	0.771	0.700	0.42	0.516	7

Common Sets
arpcO arPcO arpCO ArPco ArPcO ARPcO

Logical reduction

Complex solutions (remainders excluded)

```
Complexity Solution: Remainders (arpcO arpCo arpCO arPco arPCo arPCO aRpCo aRpCO
aRPCo aRPCO Arpco ArpcO ArpCo ArpCO ArPCo ArPCO ARpco ARpcO ARPco ARPCo ARPCO)
Excluded

4 Solutions Entered as True

Minimum Configuration Reduction Set
rPcO ArPc APcO

Final Reduction Set
Coverage
Set          Raw Coverage     Unique Coverage      Solution Consistency
r*P*c*O         0.200             0.100                 0.762
A*r*P*c         0.186             0.085                 0.785
A*P*c*O         0.259             0.159                 0.796

Total Coverage = 0.444
Solution Consistency = 0.764
```

Simplified solution (indifferent to remainders)

```
Parsimony Solution: Remainders (Bestfit<=3) Included As Do Not Cares

4 Solutions Entered as True
21 Solutions Treated as Do Not Cares

Minimum Configuration Reduction Set
ACo rP rO AP Ar aC rC CO PC


Final Reduction Set

Coverage
Set         Raw Coverage     Unique Coverage      Solution Consistency
A*P                0.430               0.430                     0.714

Total Coverage = 0.430
Solution Consistency = 0.714

And One of the Following
ACo rP rO Ar aC rC CO PC
```

A * P is the final simplified solution described in the main part of the note: Subdistricts "*in Aleppo or Al-Hasakeh AND with a high proportion of people who fled*" are the ones that tend to have high proportions of persons in acute need of health support.

REFERENCES

Aitchison, J. (1986). The statistical analysis of compositional data. Dordrecht Springer.

AWG (2013). Syria Integrated Needs Assessment (SINA) [December 2013], Assessment Working Group for Northern Syria.

Barsalou, L.W. (1983). "Ad hoc categories." Memory & Cognition 11(3): 211-227.

Barsalou, L.W. (1991). Deriving categories to achieve goals. The Psychology of Learning and Motivation. G. H. Bower. New York, Academic Press. 27. 1-64.

Bowker, G. C. and S. L. Star (2000). Sorting things out: Classification and its consequences, MIT press.

Buis, M. L. (2012). ZOIB: Stata module to fit a zero-one inflated beta distribution by maximum likelihood. Berlin and St.Louis, WZB Berlin and IDEAS - Research Division of the Federal Reserve Bank of St. Louis.

Humanitarian Liaison Group (2014). MSNA. Syria Multi-Sectoral Needs Assessment [October 2014], Prepared by OCHA, REACH and SNAP on behalf of the Humanitarian Liaison Group based in Turkey.

Longest, K. C. and S. Vaisey (2008). "fuzzy: A program for performing qualitative comparative analyses (QCA) in Stata." The Stata Journal 8(1): 79-104.

Monahan, T. (2010). Surveillance in the Time of Insecurity, Rutgers University Press.

Murphy, G. L. (2010). What are categories and concepts. The making of human concepts. D. Mareschal, P. C. Quinn and S. E. G. Lea. Oxford, Oxford University Press. 11-28.

Pencina, M. J., R. B. D'Agostino, et al. (2011). "Extensions of net reclassification improvement calculations to measure usefulness of new biomarkers." STATISTICS IN MEDICINE 30(1): 11-21.

Wikipedia. (2012)."Spearman's rank correlation coefficient." Retrieved 20 November 2012, from http://en.wikipedia.org/wiki/Spearman%27s_rank_correlation_coefficient.

Wikipedia. (2014a)."Orthogonalization." Retrieved 14 November 2014, from http://en.wikipedia.org/wiki/Orthogonalization.

Wikipedia. (2014b)."Qualitative comparative analysis." Retrieved 24 November 2014, from http://en.wikipedia.org/wiki/Qualitative_comparative_analysis.