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# Measuring Malnutrition and Dietary Diversity: Theory and Evidence from India

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**Abstract**
Adequate nutrition constitutes one of the most basic dimensions of human well-being. Ample evidence exists for the functional link between a diverse diet and health outcomes or economic performance. However, a concise measure to capture nutritional diversity that utilizes typical household-level data, often the only data available in developing countries, is yet to be developed. In this paper, I propose a theoretical framework for such a measure by extending the Alkire-Foster (AF) methodology. The new framework enables the calculation of both the incidence and intensity of nutritional deprivation. Applying this framework, I construct a Nutritional Deprivation Index (NDI) for Indian states using household survey data on food consumption. The NDI is unique, and, compared to existing measures, it is more effective in both identifying the inadequately nourished and revealing the extent of food deprivation.

**Keywords**: health; nutrition; malnutrition; dietary diversity; developing countries

**JEL classification**: I10, I14, I15, I32, Q18

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# 1 Introduction

"[H]ealth is among the most important conditions of human life and a critically significant constituent of human capabilities which we have reason to value" (Sen, 2002). Within the capability space of health, being well-nourished to enjoy a life free of hunger and starvation is certainly the most basic functioning.[1] In this context, while arguing for the right to food, the United Nations (1999) states in Comment No. 12: "The right to adequate food is realized when every man, woman and child, alone or in community with others, has the physical and economic access at all times to adequate food or means for its procurement."

I want to discuss two key points of this Comment. One, the focus is on the *access* to food and not just the availability of food. Sen (1981) argues for such a distinction. "Starvation is the characteristic of some people not having enough food to eat. It is not the characteristic of there being not enough food to eat. While the latter can be a cause of the former, it is but one of many possible causes." Existing measures of food availability within a country fail to account for the question of adequate access and can be misleading due the inherent and "inevitable" inequality in terms of access to food (Barrett, 2010). Second, the Comment concerns the right to *adequate* food and not just some quantity of food. There is widespread consensus that merely meeting standardized calorie norms, as set for example by the Food and Agriculture Organization (FAO), does not translate into adequate food or nutrition. Instead, measuring adequate nutrition involves measuring access to dietary diversity (Deaton and Drèze, 2009). According to Gopalan (1992), there are two practical ways to measure undernutrition that, in combination, provide valuable information to combat undernutrition: anthropometric data collection or surveys of diets. This paper focuses on utilizing the latter.

Both intrinsic as well as functional arguments make the case for the importance of dietary diversity. Studies on nutrition in India show that diets have become somewhat more diverse with increasing income levels over the last decades, though not much (Deaton and Drèze, 2009). Trends of the "nutrition transition" in industrialized countries across continents during the last century reveal preferences for diverse diets, even across income groups (Drewnowski and Popkin, 1997; Smith et al., 2016; Tilman and Clark, 2015). In this paper, the reason for measuring progress in dietary diversity in poor societies of low income countries (LICs) is to examine the extent and occurrence of a shift away from the traditional staple-based diets, which are based on just a few food groups and contain mostly just starchy roots and coarse grains (Drewnowski and Popkin, 1997). Therefore, problems arising with more diverse but more sugary or fat diets are not discussed here (Tilman and Clark, 2015). Besides the intrinsic value and pleasure in a diverse diet, there is ample evidence for the functional link between a diverse diet and health outcomes, and between a diverse diet and economic performance. Alderman et al. (2005), for instance, highlight the long chain between diverse childhood nutrition and cognitive development, physical stature, strength, earlier school enrollment, more regu-

[1] For more on Amartya Sen's capability approach and the terminology, see for instance Sen (1981, 1992, 2002).

lar school attendance, greater learning, and eventually greater adult productivity. Similarly, various studies using cross-sectional data for sub-Saharan African and South Asian countries, including India, show a direct link between dietary diversity and the nutritional adequacy of a diet, per capita consumption, total per capita caloric availability, household per capita daily caloric availability from staples, and household per capita daily caloric availability from nonstaples (Hoddinott and Yohannes, 2002; Ogle, 2001; Bhargava, 2015; Hatloy et al., 1998). Further, Steyn et al. (2006) show that dietary diversity correlates with micronutrient intake. Arimond and Ruel (2004) show that dietary diversity does predict height-for-weight z-scores (HAZ), weight-for-age (WAZ) z-scores, and undernutrition.[2] For the Indian context, Menon et al. (2015) use nationally representative data (National Family Health Survey 3, 2005–06) to show that dietary diversity of children aged 6–23 months is "strongly and significantly associated with HAZ, WAZ, stunting and underweight." Their results are robust to the inclusion of controls for household wealth. Earlier studies, too, establish such a correlation and praise the usefulness of a dietary diversity index or child feeding index to predict anthropometric outcomes in settings ranging from Latin America to rural Kenya (Onyango et al., 1998; Ruel and Menon, 2002, for instance). Thus, one may infer a great deal about anthrometrics from dietary diversity even when data on the former are not available.

The most widely used method to measure dietary diversity is to capture the simultaneous consumption of food groups via "a simple count of food groups over a given reference period" (Ruel, 2003).[3] This can be summarized in the dietary diversity index (DDI). For a diet to qualify as diverse it must include the minimum number of food groups defined as mandatory.[4] The ratio of those consuming less than the threshold to overall population yields the DDI. Some studies count the number of individuals whose number of diverse food groups is *at least as high or above* the threshold. In such cases, the DDI is the ratio of those obtaining a diverse diet to the overall population. In this paper, however, I consider the DDI as the incidence of those *not* obtaining a diverse diet. The DDI is considered a promising indicator of dietary quality in the field of development economics (Villa et al., 2011).

However, there are several drawbacks to this approach. For one, the DDI reflects merely the incidence of inadequate food consumption and neglects the extent of inadequacy. In doing so, the DDI treats the absence of a diverse diet in such a way that the extent of nutritional

[2]Definition as given by Barrett (2010): "[...] hunger refers to the physical discomfort caused by a lack of food and can only be properly gathered at the individual-level. Underweight summarizes individual anthropometric measures–such as weight-for-height, weight-for-age, or mid upper-arm circumference–at least two standard deviations below global reference values. Undernutrition reflects insufficient dietary energy (caloric) intake, according to internationally agreed standards. Malnutrition refers to undernutrition, obesity, and micronutrient (mineral and vitamin) deficiencies."

[3]See, for example, the U.S. Agency for International Development (USAID)'s Food and Nutrition Technical Assistance Project (FANTA) at http://www.fantaproject.org/monitoring-and-evaluation/household-dietary-diversity-score. The FAO has carried out much research using such a counting score, and provides guidelines to conduct dietary diversity surveys. See, for example, http://www.fao.org/publications/card/en/c/5aacbe39-068f-513b-b17d-1d92959654ea/.

[4]The mandatory number is arbitrary and context-dependent.

deprivation across different food groups is not accounted for. For instance, individuals consuming very few diverse food groups are considered as equally deprived as those consuming just below the required minimum of groups.[5] The second weakness relates to minimum requirements of a food group. By not considering the quantity consumed of a food group but merely counting incidences of consumption, the DDI may underestimate the number of inadequately nourished individuals. For example, an individual may consume a food group in a quantity that is insufficient for a healthy life, but sufficient to be counted within the framework of the DDI. The third weakness is related to the previous one. The DDI neglects idiosyncratic variations in food requirements. While every person is in need of a diverse diet, the extent of minimum requirements varies greatly by age, gender, health status, and occupation (Gopalan, 1992; Kakwani, 1992); there are also other individual factors and even varying intra-individual requirements (Srinivasan, 1992; Kakwani, 1992). Therefore, a dietary measure should ideally apply person-specific thresholds for each food group.[6]

In this paper, I develop a framework for a Nutritional Deprivation Index (NDI) to measure access to diverse diets using individual-level data. An alternative framework is also defined for when only household-level data are available. I apply the household framework to compute an NDI using household-level data on food consumption from India's 2011–12 National Sample Survey (NSS). The NDI overcomes the above-mentioned weaknesses of the DDI by adapting and extending the Alkire-Foster counting approach (Alkire and Foster, 2011), which is a technique widely used in multidimensional poverty measurement. The NDI addresses the first two weaknesses of the DDI by accounting for the actual amount consumed of each food group as well as the number of under-consumed food groups. By doing so, the framework yields both the incidence and intensity of nutritional deprivation. The absence of idiosyncratic thresholds in the DDI is also addressed by the NDI. It allows for minimum food group requirements that vary by food group as well as by individual characteristics such as age, gender, and occupation. Overall, the NDI is superior to the DDI in measuring dietary diversity for a variety of reasons. First, it overcomes the three weaknesses of the DDI. Second, it provides information about both the incidence and intensity of nutritional deprivation. Third, the NDI framework inherits several properties of the AF methodology that allow for useful decompositions of the NDI and its components (the incidence and the intensity of nutritional deprivation).

This is demonstrated in the paper by applying the NDI and DDI frameworks to the household-level data on food consumption amongst India's rural population. The analysis reveals that the DDI underestimates the extent of food inadequacies. According to the DDI approach, 67 per cent are deprived in at least one food group. In contrast, applying the NDI framework yields that around 60 per cent are nutritionally deprived in at least five of eight food groups. Further, the NDI highlights that the nutritionally deprived are primarily de-

[5] This violates dimensional monotonicity.

[6] Kakwani (1992) and Osmani (1992) discuss possible errors when average requirements are used despite given inter-individual variation in dietary requirements.

prived of leafy vegetables, fruits, and dairy products. Finally, the NDI reveals that the average intensity of nutritional deprivation amongst those lacking a diverse diets is nearly 70 per cent. Decomposing the NDI by state and social subgroups highlights considerable variation in the kinds of food deprivation. For example, in the northern state of Punjab, nutritional deprivation in cereals contributes to overall nutritional deprivation. In the most populous state of Uttar Pradesh, however, cereals are sufficiently consumed while the consumption of leafy vegetables and fruits is insufficient. Decompositions by social groups reveal that almost 50 per cent of the Scheduled Tribes are inadequately nourished in five of eight food groups, whereas it is just 22 per cent for the "Others". I also find that larger households are less adequately nourished according to the headcount ratio of the NDI than smaller ones. In this manner, the NDI addresses the gaps in the existing measure (DDI) and proves to be a more accurate tool to quantify access to diverse diets, using data that are readily available in a significant number of surveys. It is a step forward in measuring the most basic functioning of human well-being in the capability space of health.

At the outset of this paper, a few caveats to using household data to measure dietary inadequacies have to be mentioned. Household-level data on consumption, such as NSS data for India, may not map onto nutritional adequacy for a number of reasons. One, intra-household inequalities in food consumption cannot be accounted for. There is a large literature on intra-household allocation of nutrients showing that individual consumption or nutrient intake responds differently to, say, changes in income, and that the response can be gender-specific (e.g. Behrmann, 1992). Second, person-specific differences in metabolism exist (Gopalan, 1992), and thus individual nutritional needs vary beyond age, gender, and occupation. Since such differences are not captured by the household data, the applied thresholds may serve as reasonable rule-of-thumb yardsticks but are certainly not sufficiently precise to capture individual needs. Third, the household-level data on food consumption do not show an individual's ability to convert the consumed resources into functionings. Thus, we do not know after all whether a certain realized diet improves the functioning of, say, being well-nourished. Fourth, there is non-sampling measurement error in the NSS data as in any other household survey. In particular, for purposes of measuring dietary diversity, it matters that rich households are less likely to be captured by the household survey. Also, despite a relatively short recall period of seven days, the quantity of food groups consumed are likely to suffer from measurement error, and "[q]uite likely, there is some underestimation of consumption in the NSS data, particularly among higher-income groups [...]"(Deaton and Drèze, 2009).

Ideally, I would employ nationally representative individual-level data. These should include information on both daily individual consumption of all food groups (in grams) and individual metabolism. However, to my knowledge, such data do not exist. Thus, while the method presented in this paper is unique and optimally suited for individual-level data, the application to household-level data is second best.

The paper is structured as follows. First, Section 2 introduces the NDI framework. Section 3 presents an application using data on food consumption from India's National Sample Survey. It exemplifies how widely available household survey data can be applied to compute an NDI and its various decompositions. In Section 4, I compare the NDI with the traditional measure of a DDI in terms of accuracy in identifying inadequately nourished households. The final Section 5 concludes with a discussion on further research.

# 2 Towards a Nutritional Deprivation Index: The General Framework

In this section, I explain the counting approach to measure nutritional deprivation in a multi-dimensional manner following the AF methodology. As presented in Alkire and Foster (2011), the AF methodology has been widely adopted to measure multidimensional poverty. In particular, for the global Multidimensional Poverty Index (MPI) the AF methodology is applied to monitor multidimensional poverty using ten indicators spanning health, education, and living standard across more than 100 countries (Alkire and Santos, 2014). Since 2010, the global MPI has been published by the United Nations Development Programme (UNDP) in its annual Human Development Reports (HDR)[7]. Numerous governments have applied the AF methodology to design and compute their own country-specific multidimensional poverty measures, for example Colombia, Mexico, and Bhutan. Besides poverty measurement, the AF methodology has been applied in other fields of research as well, for example, to measure access to modern energy in sub-Saharan Africa (Bensch, 2013) and to measure women empowerment (Alkire et al., 2013), to name a few.[8]

In Subsection 2.1, the key features of the AF methodology are briefly presented, before I introduce an extension to the AF methodology in Subsection 2.2 for individual-level data. In Subsection 2.3 I show how the framework can be adjusted in such a way that household-level data on food consumption, too, can be applied to compute an NDI.

## 2.1 The Alkire-Foster Methodology

The methodology and terminology as presented in Alkire et al. (2015) are straightforward.[9] I follow both entirely. The aim of the AF methodology is to provide for a framework that allows the measurement of joint (simultaneous) deprivations in various dimensions using a counting approach. After collecting all achievements of each individual in each dimension, a dual cut-off approach is used to first translate achievements into deprivations and to then determine if an individual is jointly deprived or not deprived in a given number of dimensions. Ultimately, this yields the incidence ($H$) of the jointly deprived and the intensity ($A$)

[7]At http://hdr.undp.org/en/reports a list of all Human Development Reports can be found.
[8]More studies can be found at: http://www.ophi.org.uk/resources/
[9]Consult http://multidimensionalpoverty.org/contents/ for an online version of the book.

of joint deprivations. In the framework of poverty measurement, it yields the incidence and intensity of multidimensional poverty. The product of $H$ and $A$ yields an index score, $M_0$. In the following, the dual cut-off approach of the AF methodology is shown. Based on this and an extension to the first cut-off, I construct the NDI.

According to the notation given by Alkire et al. (2015), think of an $n \times d$ dimensional achievement matrix $X$ with $n$ individuals and $d$ dimensions, with achievements $x_{ij}$ of individual $i$ in dimension $j$. The dual cut-off approach is applied as follows. To apply the first cut-off entails using dimension thresholds. These are collected in the $d$-dimensional vector $z$, such that

$$z = (z_1, ..., z_d). \tag{1}$$

Applying the thresholds to determine whether achievement $x_{ij}$ lies above or below $z_j$, the so-called deprivation matrix $g^0$ is constructed with its elements $g^0_{ij} = 1$ whenever individual $i$ is deprived in dimension $j$, i.e. when $x_{ij} < z_j$, and $g^0_{ij} = 0$ whenever $x_{ij} \geq z_j$. Given a $d$-dimensional vector of weights, $w = (w_1, ..., w_d)$, each dimension is weighted accordingly. Adding up the number of weighted deprivations $w_j g^0_{ij}$ for each individual $i$ yields individual $i$'s deprivation score, $c_i = \sum_{j=1}^{d} w_j g^0_{ij} = \sum_{j=1}^{d} \overline{g}^0_{ij}$. Ultimately, $n$ deprivation scores are collected in the vector of deprivation scores $c_i = (c_1, ..., c_n)$.

Applying the second cut-off of the AF method entails 'censoring' those individuals who have fewer deprivations than the minimum threshold $k$, and by identifying those who are jointly deprived in at least $k$ deprivations. Formally, an identification function $\rho_k$ is applied such that $\rho_k(x_i; z) = 1$ if $c_i \geq k$, and $\rho_k(x_i; z) = 0$ otherwise. Applying the identification function to all entries, $w_j g^0_{ij}$ , yields the censored matrix of deprivations, $g^0_{ij}(k)$, which is the product of $g^0_{ij}$ and $\rho_k(x_i; z)$. Counting the censored deprivations yields the censored deprivation score vector $c(k)$, which includes $n$ deprivation scores, denoted for individual $i$ by $c_i(k) = \sum_{j=1}^{d} w_j g^0_{ij}(k)$.

In order to calculate the multidimensional headcount ratio $H$ (or the incidence of the multidimensionally deprived), the number of individuals with non-zero entries in the censored deprivation score vector $c(k)$ sum up to $q$, so that $H = q/n$. In order to measure the intensity of deprivations, the average deprivation share of the multidimensionally deprived, $A$, is defined as $A = \sum_{i=1}^{q} c_i(k)/q$. Multiplying these two measures, $H \times A$ yields the adjusted headcount ratio $M_0$. It is also the mean of the censored deprivation score $c(k)$ or the mean of the censored deprivation matrix $g^0_{ij}(k)$. Thus, it can be formally notated as both:

$$M_0 = \mu(c(k)) = \frac{1}{n} \times \sum_{i=1}^{n} c_i(k) \tag{2}$$

and

$$M_0 = H \times A = \frac{q}{n} \times \frac{1}{q} \sum_{i=1}^{q} c_i(k) = \frac{1}{n} \sum_{i=1}^{n} c_i(k) = \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{d} w_j g^0_{ij}(k) \tag{3}$$

*Properties of the AF Methodology*

The AF methodology has several attractive properties. I show the most basic and useful ones here, as I will apply them in the empirical part. Broadly, one can think of components of the $M_0$, $H$, and $A$. For instance, instead of a headcount ratio for the entire country, one may be interested in $H$ for the country's regions. Likewise, one may be interested in the dimensions of $M_0$ and the question arises which dimension contributes most to $M_0$. What is the dimension with the highest deprivation rates? Thus, with the censored deprivation matrix in mind, one is interested in $M_0$, $H$, and $A$ by columns (dimensions) and rows (sub-groups). The AF methodology allows such "decompositions" to take place in a coherent manner as the $M_0$ measure satisfies both the properties of population subgroup decomposibility and dimensional breakdown (Alkire et al., 2015; Foster et al., 1984).

To begin with dimensional decomposition, the censored headcount ratio of dimension $j$ is defined as

$$h_j = \frac{1}{n}\sum_{i=1}^{n} g_{ij}^0(k), \tag{4}$$

which is the mean of the $j^{th}$ column of the censored deprivation matrix $g^0(k)$. The dimensional contribution of each dimension $j = 1, ..., d$ to $M_0$ is defined as

$$\phi_j^0 = w_j \frac{h_j(k)}{M_0}. \tag{5}$$

Importantly, the sum of all censored headcount ratios yields $M_0$. Decomposing the censored deprivation matrix by subgroups(rows) yields subgroup-specific values $M_0$, $H$, and $A$. Multiplied by respective population shares, the sum of all subgroup-specific values yields the overall measures. Formally, given $m$ subgroups and the population share of subgroup $l$ given by $v^l = n^l/n$, the overall $M_0$ is

$$M_0 = \sum_{l=1}^{m} v^l M_0^l \tag{6}$$

Similarly, both overall incidence and overall intensity satisfy the property of subgroup decomposibility, so that

$$H = \sum_{l=1}^{m} v^l H^l \tag{7}$$

$$A = \sum_{l=1}^{m} v^l A^l \tag{8}$$

## 2.2 A Nutritional Deprivation Index: Extending the Alkire-Foster Methodology

In order to construct the NDI that is sensitive to idiosyncratic food requirements, the AF method as presented above needs to be adjusted. In terms of notation and within the AF framework, one can think of the $d$ dimensions as food groups of interest, for example those recommended by the FAO. The $n \times d$ dimensional achievement matrix $X$ thus contains entries of $x_{ij}$, which represent achievements of consumption for individual $i$ in food group $j$ (see matrix 9).

$$X = \begin{bmatrix} x_{11} & \dots & x_{1d} \\ \vdots & \ddots & \vdots \\ x_{n1} & \dots & x_{nd} \end{bmatrix} \tag{9}$$

In order to allow for idiosyncratic food requirements, I adjust the AF methodology by introducing idiosyncratic minimum requirements for each food group $j$. Recall, that for the first cut-off in the AF methodology, a $d$-dimensional row vector $z$ of thresholds is applied. If the dimensions are food groups, this would imply that all individuals are treated equally in terms of food requirements. However, it is widely known that food requirements vary from person to person and by age, gender, health status, and occupation (Gopalan, 1992; Kakwani, 1992; Deaton and Drèze, 2009). In fact, requirements may even vary intra-individually, depending on health status or activity level (Srinivasan, 1992; Kakwani, 1992). Dimension cut-offs, however, neglect these idiosyncratic requirements. For example, dimension cut-offs may be average thresholds for the entire population across all age groups. This would results in two types of errors. Either, for example, the consumption of fruits by infants could be below the cut-off, but the infants' consumption might in fact be adequate. Or, for example, the relatively high consumption of cereals by laborers could be inadequate to cover nutritional requirements but would be above the threshold. Hence, in both cases dimension cut-offs yield wrong estimates, which may be overestimates (infants) or underestimates (laborers) of the inadequately nourished. Therefore, I account for idiosyncratic differences in food requirements by including person-specific thresholds, i.e. $n$ different cut-offs. I thus employ an $n \times d$-dimensional cut-off matrix $Z$ (see matrix 10), instead of just the $d$-dimensional row vector $z$, shown in equation 13. This adjustment is crucial and presents the major adjustment to the classical AF method.

$$Z = \begin{bmatrix} z_{11} & \dots & z_{1d} \\ \vdots & \ddots & \vdots \\ z_{n1} & \dots & z_{nd} \end{bmatrix} \tag{10}$$

I use $Z$ to determine whether individual $i$ consumes less in dimension $j$ than individual $i$'s specific threshold $z_{ij}$. Applying the cut-off matrix $Z$, I compute a deprivation matrix $g^{0_z}$. This represents the first step of the dual cut-off approach. The elements of $g^{0_z}$ are then: $g_{ij}^{0_z} = 1$ when $x_{ij} < z_{ij}$, and $g_{ij}^{0_z} = 0$ whenever $x_{ij} \geq z_{ij}$. All subsequent steps of the AF methodology (including the second step of the dual cut-off method) remain the same, such that I ultimately calculate $M_{0N}$ as the product of the headcount ratio of the nutritionally deprived, $H_N$, and the average deprivation share of the nutritionally deprived, $A_N$.

It might seem that having a matrix of vectors would fundamentally alter the properties satisfied by the AF methodology, given that the original paper requires the cut-offs to be "fixed and given." However, in the case of nutrition, in fact, far from generating incomparabilities between individuals, a characteristic-specific cut-off creates comparability whereas a uniform vector of cut-offs would not do so. Thus the cut-offs create comparable deprivations in the space of nutritional functionings. For this reason they can be applied whilst maintaining the same properties of the AF methodology. In the following section, I show how the NDI can be computed when only household-level data are available.

## 2.3 Adjustment to Allow for Household-level Data

Most national surveys collect data at the household-level. That implies that information on, say, food consumption is not available for each individual but is aggregated at the household-level. Thus it is not possible to apply individual food reference lines. However, if the survey provides information on the number of individuals in a household, their gender, age, and occupation, as most household surveys do, then individual-level reference lines can be summed up at the household-level. Doing so yields household minimum requirements for each food group. The $Z$ matrix can be written as a $Z^h$ matrix with household-level thresholds for each food group as its entries.

The following example shall highlight this simple point. Typically, one observes for the entire household $i$ a row vector of food consumption (achievements), capturing food intakes (in grams) for, say, three food groups including cereals (C), vegetables (V), and pulses (P), so that hypothetically for household $i$:

$$x_i = \begin{pmatrix} 1360 & 300 & 450 \end{pmatrix}.$$

Knowing the composition of the household yields the $Z$-matrix containing individual requirements, for example:

$$Z = \begin{pmatrix} 600 & 100 & 120 \\ 480 & 100 & 90 \\ 300 & 100 & 60 \end{pmatrix}.$$

Adding up these requirements by food group yields the $z^h$ vector for household $i$:

$$z_i^h = \begin{pmatrix} 1380 & 300 & 270 \end{pmatrix},$$

or more generally the $d$-dimensional $z^h$ vector for household $i$:

$$z_i^h = (z_{i1}^h, \ldots, z_{id}^h). \tag{11}$$

Repeating this for every household and collecting all rows of household-wise $z^h$ vectors yields matrix $Z^h$:

$$Z^h = \begin{bmatrix} z_{11}^h & \ldots & z_{1d}^h \\ \vdots & \ddots & \vdots \\ z_{n1}^h & \ldots & z_{nd}^h \end{bmatrix}, \tag{12}$$

the threshold matrix of household food group requirements. Built on this first and adjusted step of the dual cut-off methodology for household-level data, a nutritional deprivation index is constructed. Applying the elements of $Z^h$ as household-specific thresholds yields $g^{0_z}$, $g^{0_z}(k)$, $H_N$, $A_N$, and $M_{0N}$ (NDI), as before in the framework for individual-level data .

To comment briefly on the household-specific thresholds: First, the adjustment of using household-specific cut-offs comes close to the idea of using equivalence scales in poverty measurement. Such a technique is often applied when data on only household consumption expenditure are available and per capita expenditures are to be computed using age and gender-specific weights – equivalence scales. Second, the measure is sensitive to household composition and needs. As the individual thresholds are summed up at the household-level, household-specific needs are captured, even though intra-household allocations and inequalities cannot be captured.

# 3 Application: An NDI for Rural India

In this section, I present results of applying the NDI to household-level data for India. Being one of the fastest growing countries during the last decades, it makes for an interesting example. In particular, a nutritional index for India is of great interest since, despite considerable advances in poverty alleviation, India still accounts for the highest number of malnourished children in the world.[10] In particular, compared to its South Asian neighbors, India is lagging behind in many indicators related to health and nutrition (Drèze and Sen, 2013). Multidimensional poverty in India as measured by Alkire and Seth (2015) varies greatly by state and sub-population. Alkire and Seth show that the progress in poverty alleviation between 1999

[10] http://www.economist.com/blogs/graphicdetail/2015/07/daily-chart-0

and 2006 has not been even. Richer states were able to reduce multidimensional poverty at much higher rates than the relatively poorer ones. Likewise, poverty rates for Hindu families and upper caste families reduced relatively faster than for more disadvantaged groups of Muslim families and scheduled tribes. Building on the study by Alkire and Seth (2015), I construct an NDI and decompose the index by states and sub-groups. This shall serve the mainly illustrative purposes of the new measure while also providing evidence on nutritional deprivation in rural India.

## 3.1 Data

I use data from India's National Sample Survey Organization (NSSO) for the year 2011–12. With more than 100,000 households interviewed the sample is representative at the national as well as at the state level. In its 68th round, the NSSO collected consumption data on prices and quantities using a seven as well as a 30-day recall period. In the following, I make use of the seven day recall period assuming that it is the most accurate in terms of reflecting quantities of food products. Since the data are collected year-round, all agricultural seasons are equally covered. Thus, one may rule out seasonal artefacts in the data. I focus on rural India, only, for two reasons. First, given the high rate of undernutrition in rural India (Drèze and Sen, 2013), it is important to shed light on one of the major causes of undernutrition in the very same region. Second, given that a large share of India's rural population consumes home-cooked food and, less frequently, outside meal options (Deaton and Drèze, 2009), which are more difficult to measure and convert into food groups, I do not cover urban areas in this paper. For all estimations of aggregates, I apply the standard NSS survey weights.

## 3.2 Indicators, Cut-offs, and Weights

In order to measure food inadequacies in several food groups simultaneously using the framework outlined above, it is necessary to make important judgment calls on four interchangeable and "flexible" parameters. First, what indicators best capture a diverse diet in rural India? Second, what are the indicator and person-specific cut-offs? Third, what dimensional weights ought to be used? And fourth, what $k$-value is most appropriate?

*Choice of Indicators*

Most measures of dietary diversity, like the DDI, use broad food groups as indicators, instead of micro-nutrients, for example. I follow the Indian National Institute of Nutrition's (NIN) guidelines and focus on food groups. NIN's argument is that, since "people consume food, it is essential to advocate nutrition in terms of foods, rather than nutrients. Emphasis has, therefore, been shifted from a nutrient orientation to the food based approach for attaining optimal nutrition" (National Institute of Nutrition, 2011). It has been common practice by NIN since 1998 to report on dietary intake in India and provide for dietary guidelines in India. Based on that, NIN publishes detailed statistics on food intakes for eight broadly categorized food groups. These are cereals, pulses and meat, dairy products, leafy vegetables, other vegetables, fruits, oils and fats, roots and tubers. I utilize these eight categories to measure nutritional inadequacy via the NDI framework.

*Choice of Cut-offs*

In order to create a $Z^h$ matrix – the threshold matrix containing household food reference lines – I exploit two sources of information. First, I employ household-level information given in the survey data (NSS 2011–12) on the number of individuals within a household, each member's age, gender, and occupation. Second, I utilize information provided by NIN (2011) on "recommendations for a healthy diet." These recommended daily allowances (RDAs) are age, gender, and occupation-specific based on what NIN considers as "nutrient-centred." The "guidelines promote the concept of nutritionally adequate diets and healthy lifestyles from the time of conception to old age." Since these RDAs are widely used, for example by the Kennedy et al. (2011), I consider these guidelines to be justifiable cut-offs. Therefore, to create the $Z^h$ matrix I sum up the food reference lines, as given in Table 1, at the household-level and as per household composition. However, since the RDAs are meant as guidelines for a "healthy diet" for the average Indian person, they are likely to be relatively high for households living in poverty. Thus, in order to measure (non)access to nutrition of an "acceptable" minimum that guarantees avoidance of hunger and starvation, much lower RDAs may be considered. I do so in the subsequent analyses by applying the RDAs of only a quarter of their value (RDA 25 per cent) and one half (RDA 50 per cent).

*Choice of Weights*

In terms of choosing weights for each food group, I apply equal weights of 1/8 for each food group. I do so, since NIN and FAO consider these eight food groups as equally essential for a diverse diet. If, however, the focus is on measuring access to the most essential and vital food groups to, for example, avoid undernutrition, one could easily change the weights. For instance, one may consider that cereals, vegetables, and proteins are the most vital food groups of the eight. Following this logic, one could set the food group weights in such a way that the said three groups are weighted at 1/4 each and the remaining five at 1/20 each. Since such a procedure requires as much justification as choosing equal weights, I restrict the analysis in this paper to an application of only equal weights. After all, this paper's application of NSS data shall mainly serve illustrative purposes for the new NDI framework and is by no means ideal.

*Choice of k-values*

In the subsequent analyses, I report the various parameters of the NDI for several $k$ values. Recall that in this application of household-level data and eight food groups, a household is nutritionally deprived if it is deprived in more than $k$ food categories. Counting those households which are deprived in more than $k$ food groups and taking the mean of the sub-sample of interest yields the headcount ratio of nutritional deprivation, or $H_{Nk}$. Calculating the average deprivation count of the nutritionally deprived (in $k$ food groups) yields $A_{Nk}$. The product of $H_{Nk}$ and $A_{Nk}$ yields $NDI_k$.

**Table 1: Recommended Daily Allowances (RDAs)**

| | Activity and Gender | | | | Age and Gender | | | | | | Age Only | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Sedentary | | Heavy | | 16–18 | | 13-15 | | 10–12 | | 7–9 | 4–6 | 1–3 | Infant |
| **Items** | **M** | **F** | **M** | **F** | **M** | **F** | **M** | **F** | **M** | **F** | | | | |
| Cereals | 375 | 270 | 600 | 480 | 450 | 330 | 420 | 330 | 300 | 240 | 180 | 120 | 60 | 15 |
| Pulses & Meat | 75 | 60 | 120 | 90 | 90 | 75 | 75 | 60 | 60 | 60 | 60 | 30 | 30 | 7.5 |
| Dairy Products | 300 | 300 | 300 | 300 | 500 | 500 | 500 | 500 | 500 | 500 | 500 | 500 | 500 | 400 |
| Leafy Vegetables | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 50 | 50 | 25 |
| Other Vegetables | 200 | 200 | 200 | 200 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 50 | 25 |
| Fruits | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| Oils & Fat | 25 | 20 | 40 | 30 | 50 | 35 | 45 | 40 | 35 | 35 | 30 | 25 | 25 | 20 |
| Roots & Tubers | 200 | 200 | 200 | 200 | 200 | 200 | 150 | 100 | 100 | 100 | 100 | 100 | 50 | 25 |

Notes: All figures are in grams and are recommendations per day.
Source: NIN (2008).

## 3.3 Findings for Rural India using 2011–12 NSS Data

The following trends emerge from Indian NSS data (2011–12) for rural areas. Table 2 depicts state and so-called raw headcount ratios for all food groups. These headcount ratios are 'raw' in the sense that they show the deprivations for the population, irrespective of how many deprivations a household may face. According to Table 2, in almost every food group there is considerable variation across states. For instance, the North Eastern states of Manipur, Meghalaya, Mizoram, Nagaland, and Assam are hardly deprived at all in cereals, whereas states like Maharashtra and Karnataka account for incidences of about eight per cent. While such incidences are rather small in magnitude, they appear much higher for the pulses food group. Here, the highest rate is above 80 per cent (Rajasthan) and the lowest as low as four per cent (Nagaland). Average deprivations in leafy vegetables are very high in comparison and reach up to 100 per cent (Puducherry).

Raw headcount ratios do not inform about the joint deprivations households face in several food groups simultaneously. They do, however, provide information on average intake of each food group and provide a good starting point to think about and calculate joint deprivations. These are captured using the counting approach described above and the respective results for rural India are reported in Table 3. It presents all ratios of interest – $H_N$, $A_N$, $M_{0N}$ – for $k$-values ranging from one to eight. It is apparent that $H_N$ decreases with

**Table 2: NDI using Household Data: Raw Headcount Ratios by State**

| | Cereals | Pulses | Dairy P. | Leafy Veg. | Other Veg. | Fruits | Oils | Roots |
|---|---|---|---|---|---|---|---|---|
| Andaman and Nicobar | 4.46 | 5.12 | 89.42 | 63.3 | 10.95 | 51.97 | 6.45 | 98.44 |
| Andhra Pradesh | 5.57 | 22.1 | 73.03 | 95.25 | 11.33 | 55.83 | 15.12 | 99.33 |
| Arunachal Pradesh | 2.7 | 14.94 | 91.69 | 43.76 | 28.88 | 67.31 | 60.02 | 77.8 |
| Assam | 1.52 | 15.65 | 96.51 | 68.63 | 19.15 | 74.43 | 38.69 | 77.7 |
| Bihar | 0.59 | 41.86 | 74.28 | 80.75 | 9.71 | 76.85 | 34.89 | 29.18 |
| Chandigarh | 9.99 | 27.56 | 24.52 | 95.82 | 9.26 | 54.5 | 9.42 | 76.55 |
| Chhattisgarh | 2.54 | 47.14 | 94.97 | 72.27 | 8.37 | 82.96 | 29.73 | 88.14 |
| Dadra and Nagar Haveli | 14.97 | 29.67 | 74.37 | 99.93 | 26.88 | 77.52 | 19.97 | 96.88 |
| Daman and Diu | 16.43 | 11.38 | 68.94 | 100 | 21.07 | 71.39 | 9.57 | 87.22 |
| Delhi | 11.81 | 37.79 | 26.86 | 91.51 | 14.97 | 56.96 | 9.76 | 76.23 |
| Goa | 6.23 | 9.76 | 52.49 | 85.37 | 27.09 | 7.67 | 16.86 | 99.38 |
| Gujarat | 8.81 | 55.2 | 46.33 | 94.23 | 12.01 | 70.49 | 4.71 | 88.12 |
| Haryana | 4.7 | 63.53 | 16.6 | 85 | 7.38 | 51.26 | 29.74 | 75.69 |
| Himachal Pradesh | 3.01 | 19.25 | 29.85 | 85.76 | 15.34 | 64.92 | 12.94 | 87.31 |
| Jammu and Kashmir | 1.41 | 31.8 | 24.05 | 41.48 | 17.26 | 66.67 | 8.79 | 91.29 |
| Jharkhand | 3.48 | 46.93 | 83.44 | 81.3 | 17.72 | 86.65 | 40.83 | 32.3 |
| Karnataka | 8.31 | 34.5 | 71.71 | 88.19 | 22.94 | 39.37 | 20.32 | 99.9 |
| Kerala | 10.5 | 12.96 | 74.21 | 98.74 | 25.67 | 11.23 | 36.9 | 99.35 |
| Lakshadweep | 6.55 | 12.39 | 99.29 | 100 | 36.82 | 2.56 | 25.37 | 98.86 |
| Madhya Pradesh | 2.82 | 54.23 | 69.89 | 92.66 | 20.92 | 72.14 | 25.98 | 86.22 |
| Maharashtra | 8.29 | 33.57 | 69.25 | 86.5 | 22.78 | 56.76 | 9.41 | 97.82 |
| Manipur | 1.09 | 31.75 | 99.89 | 64.87 | 44.54 | 84.39 | 67.73 | 94.68 |
| Meghalaya | 2.25 | 21.44 | 96.88 | 71.88 | 31.46 | 81.69 | 53.42 | 86.18 |
| Mizoram | 0.1 | 12.9 | 92.22 | 30.36 | 26.17 | 81.56 | 20.8 | 84.11 |
| Nagaland | 0 | 3.61 | 98.42 | 31.37 | 19.75 | 77.23 | 82.64 | 87.01 |
| Orissa | 2.35 | 41.21 | 91.91 | 79.71 | 13.28 | 79.36 | 49.25 | 62.04 |
| Puducherry | 11.34 | 12.65 | 47.44 | 99.95 | 15.99 | 39.57 | 18.62 | 97.73 |
| Punjab | 6.78 | 58.04 | 18.37 | 88.8 | 6.53 | 67.03 | 9.86 | 75.59 |
| Rajasthan | 2.34 | 81.84 | 35.03 | 92.6 | 22.39 | 71.82 | 27.59 | 92.03 |
| Sikkim | 5.89 | 45.15 | 39.58 | 48.67 | 14.78 | 90.62 | 14.77 | 81.86 |
| Tamil Nadu | 9.46 | 22.73 | 65.56 | 95.96 | 20.55 | 42.61 | 27.06 | 99.78 |
| Tripura | 1.06 | 17.47 | 95.45 | 47.52 | 5.2 | 65.71 | 42.43 | 84.23 |
| Uttar Pradesh | 2.09 | 46.26 | 63.05 | 92.39 | 18.15 | 74.67 | 25.56 | 35.6 |
| Uttaranchal | 1.81 | 31.84 | 32.51 | 77.55 | 9.05 | 66.16 | 8.27 | 73.27 |
| West Bengal | 4.78 | 28.43 | 91.07 | 76.64 | 20.5 | 78.15 | 20.45 | 27.34 |

Calculated from NSS Round 68, Consumption Module 2011-12. 50 per cent of Food Reference Value applied.

**Table 3: NDI using Household Data: $H_N$, $A_N$, $M_{0N}$, and $H_D$ over $k$-values**

| k | $H_N$ | $A_N$ | $M_{0N}$ | $H_D$ |
|---|---|---|---|---|
| 1 | 99.62 | 48.57 | 0.484 | 67.32 |
| 2 | 96.28 | 49.82 | 0.48 | 27.78 |
| 3 | 83.32 | 53.68 | 0.447 | 5.99 |
| 4 | 59.07 | 60.33 | 0.356 | 1.51 |
| 5 | 31.52 | 69.36 | 0.219 | 1.34 |
| 6 | 12.26 | 80.13 | 0.098 | 1.3 |
| 7 | 4.01 | 90.71 | 0.036 | 1.14 |
| 8 | 1.03 | 100 | 0.01 | 0.71 |

Calculated from NSS Round 68, Consumption Module 2011-12.

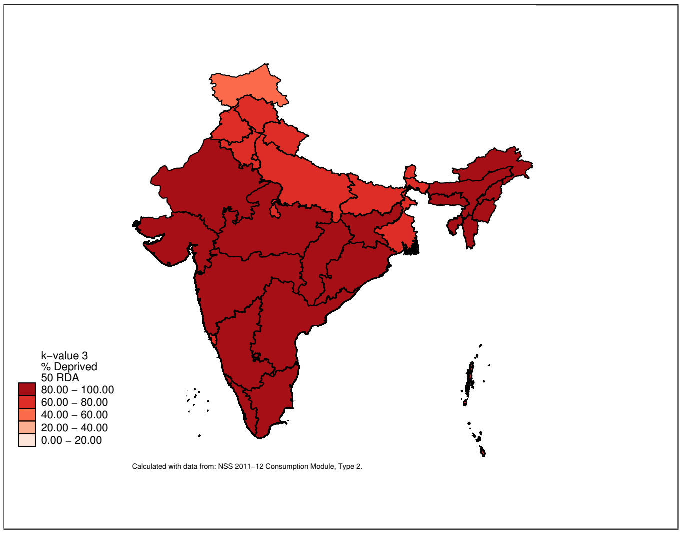
increasing $k$-values, while $A_N$ increases. For low $k$-values $H_N$ is almost 100 per cent, implying that the entire rural population is inadequately nourished in at least one food group. $A_N$ for a $k$-value of one is about 50 per cent, implying that those who are inadequately nourished in at least one food group are on average inadequately nourished in four of eight food groups. At a $k$-value of five, $H_N$ is around 30 per cent and $A_N$ is at 70 per cent, implying that a third of India's rural population is inadequately nourished in at least five food groups, and, on average, in 5.6 food groups.

*Decomposition by States*

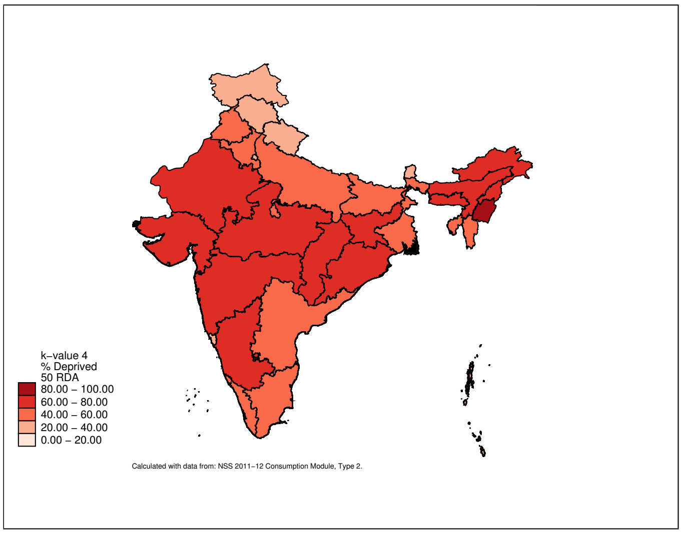
Figure 1 presents maps depicting headcount ratios, $H_N$, for $k$-values ranging from three to eight.[11] At higher $k$-values, one particular region appears to be particularly exposed to nutritional deprivation. The belt stretches from Rajasthan in the North West via Madhya Pradesh and Jharkhand to Orissa. These regions are known to be the most disadvantaged areas in other aspects, too, be it monetary or multidimensional poverty, health, education, or living standards (Alkire and Seth, 2015). In the following, I stick to presenting results for a $k$-value of five.

[11] I exclude maps for and lower and higher $k$-values here, as there is hardly any variation across states at such levels of $k$.

(a) $k = 3$




(b) $k = 4$




(c) $k = 5$

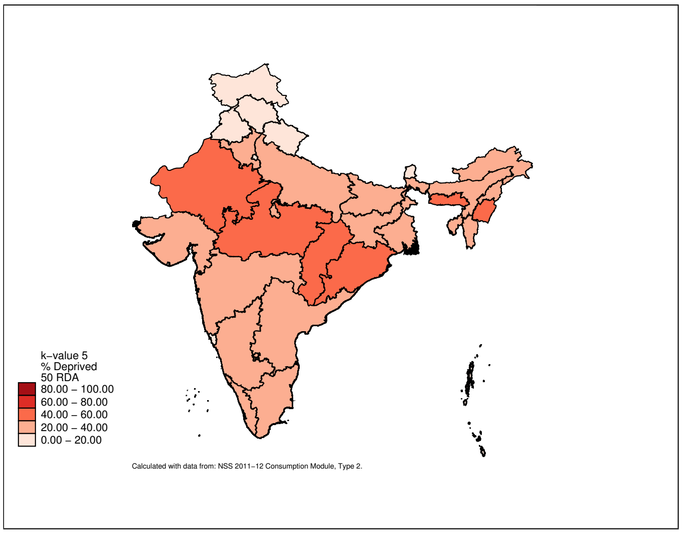



**Figure 1: States' $H_N$ for $k$-values 3–5**

*Breakdown and Contribution by Food Group*
In Figure 2, I show censored headcount (CH) ratios for every food group and for the $k$-value of five.

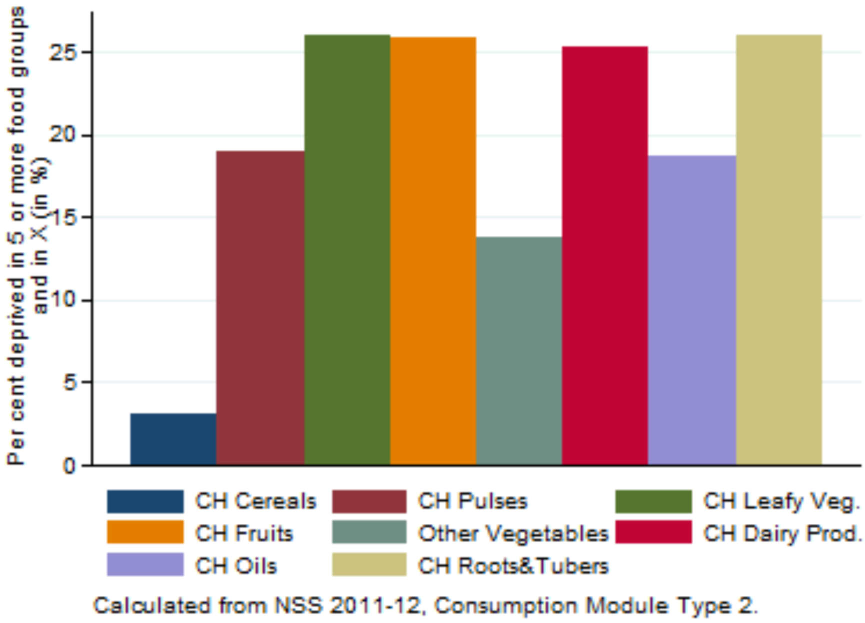



**Figure 2: Censored Headcount Ratios for $k$=5**

Being nutritionally deprived and deprived in, say, cereals yields the CH for cereals. The CH of cereals is the lowest in comparison to the other seven, which can reach values of more than 25 per cent. The highest ones are found for the groups of leafy vegetables and roots. Related to Figure 2 is Figure 3. It presents contributions of food groups by state to the overall NDI. The broad pattern reveals that food group contributions to food inadequacy are broadly similar but still vary by state. Similarly, but not the same as the raw headcount ratios, I find that the contribution of cereals to the overall measure is near zero, but is about five per cent in some states (Delhi, Kerala). Across states, the highest contributions to nutritional inadequacies can be found for pulses (a notable exception are the North Eastern states), leafy vegetables, and fruits.

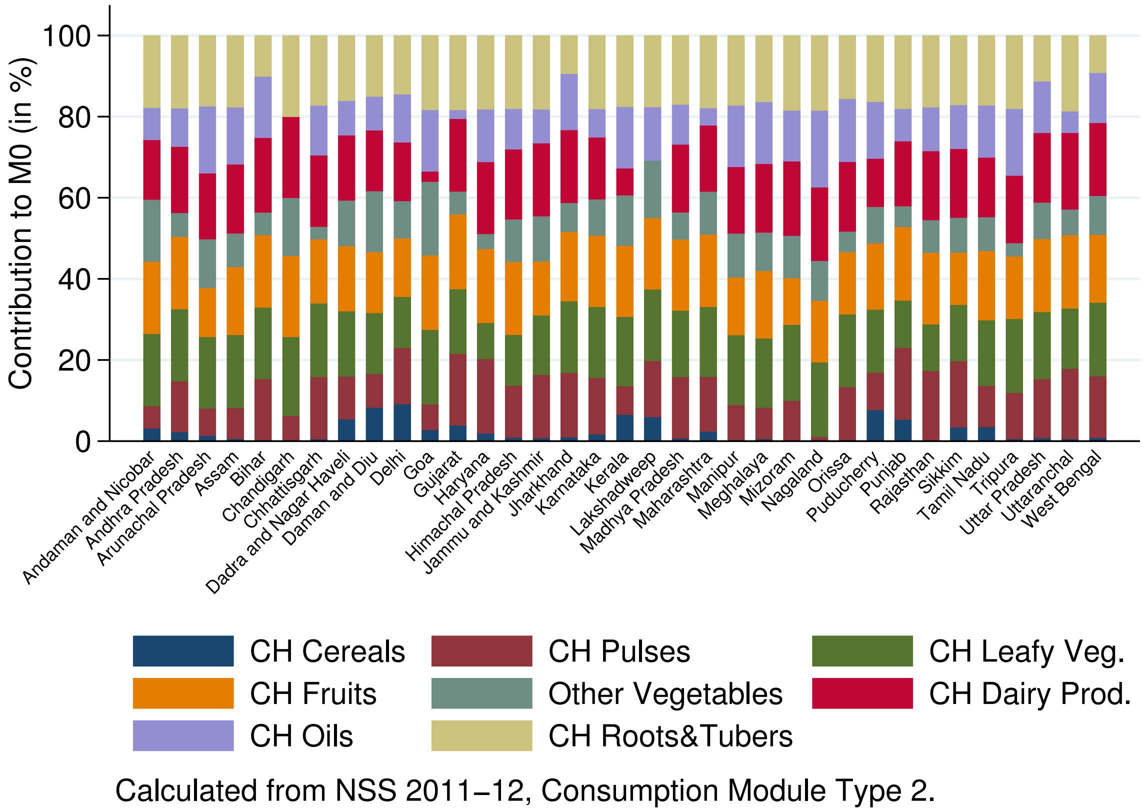



**Figure 3: Percentage Contribution of Food Groups to $M_0$ for $k = 5$**

*Decomposition by Socioeconomic Subgroups*

Besides large regional differences across rural India there exist large inequalities across socioeconomic subgroups such as caste, gender, and religion among others (Drèze and Khera, 2013; Alkire and Seth, 2015). In Table 4, I present the three measures of the NDI ($H_N$, $A_N$, $M_{0N}$) along with the censored headcount ratios of each food group, given a $k$-value of five. It is apparent that the traditionally most disadvantaged groups have also the least access to an adequate nutrition. Therefore, households belonging to Scheduled Tribes, the landless, or very large households account for the highest $H_N$ (above 40 per cent). While $A_N$ does not vary much across subgroups, it is around 70 per cent, $H_N$ varies substantially. For instance, among caste groups, $H_N$ for higher castes (other) (22 per cent) is less than half the value of $H_N$ for Scheduled Tribes. Across landholding classes, the pattern is quite clear: the more landholding the less chances of being inadequately nourished. Also across censored headcount ratios, the large landowners are the least likely to be deprived in any of the eight food groups while being at the same time nutritionally deprived in at least five of them. A similar pattern is evident for the decomposition by household size. The larger the household the higher the chances of being inadequately nourished. With increasing household size censored headcount ratios increase, almost continuously.

**Table 4: Subgroup Decomposition for $k$-value = 5**

| Subgroup | $H_N$ | $A_N$ | $M_{0N}$ | CH Cereals | CH Pulses | CH Dairy P. | CH Leafy V. | CH Other V. | CH Fruits | CH Oils | CH Roots &. T. |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *Caste* | | | | | | | | | | | |
| Scheduled Tribes | 46.8 | 72.0 | 0.337 | 4.5 | 36.9 | 44.5 | 43.3 | 21.8 | 44.2 | 30.8 | 43.5 |
| Scheduled Castes | 37.2 | 69.1 | 0.257 | 2.6 | 29.8 | 34.4 | 36.0 | 14.2 | 35.0 | 23.7 | 29.6 |
| Backward Classes | 29.7 | 68.5 | 0.203 | 2.2 | 22.9 | 27.0 | 29.1 | 11.8 | 27.1 | 17.5 | 25.2 |
| Other | 22.4 | 69.3 | 0.155 | 2.2 | 17.0 | 19.7 | 21.6 | 11.7 | 20.4 | 12.6 | 18.8 |
| *Religion* | | | | | | | | | | | |
| Hinduism | 32.5 | 69.5 | 0.226 | 2.7 | 26.0 | 29.7 | 31.4 | 13.6 | 30.1 | 19.5 | 27.8 |
| Islam | 25.5 | 68.1 | 0.173 | 1.3 | 16.5 | 24.0 | 24.7 | 12.0 | 23.8 | 17.5 | 18.8 |
| Christianity | 32.5 | 72.0 | 0.234 | 5.0 | 19.3 | 31.8 | 30.4 | 18.6 | 27.0 | 25.7 | 29.7 |
| Other | 23.6 | 67.3 | 0.159 | 2.4 | 18.9 | 18.7 | 22.8 | 8.1 | 22.2 | 11.0 | 23.0 |
| *Landholding Class* | | | | | | | | | | | |
| Landless | 46.1 | 68.3 | 0.314 | 6.8 | 39.8 | 42.7 | 45.0 | 12.9 | 43.6 | 21.8 | 39.0 |
| Marginal | 32.1 | 68.7 | 0.220 | 1.6 | 24.8 | 30.0 | 30.8 | 12.8 | 29.9 | 20.2 | 26.1 |
| Small | 27.5 | 68.1 | 0.188 | 0.3 | 20.7 | 23.5 | 27.0 | 11.9 | 26.5 | 13.9 | 26.3 |
| Semi-Medium | 24.2 | 66.3 | 0.161 | 0.3 | 18.0 | 18.3 | 23.4 | 11.2 | 23.1 | 10.6 | 23.5 |
| Medium | 25.0 | 68.3 | 0.171 | 0.0 | 21.0 | 18.5 | 24.8 | 16.1 | 22.0 | 10.5 | 23.5 |
| Large | 18.7 | 65.4 | 0.123 | 0.2 | 15.4 | 9.4 | 18.7 | 12.4 | 14.7 | 8.7 | 18.4 |
| *Household Size* | | | | | | | | | | | |
| Less than 3 Members | 22.4 | 76.9 | 0.172 | 9.7 | 20.9 | 20.3 | 21.6 | 12.8 | 18.3 | 13.2 | 20.9 |
| 3-4 Members | 25.2 | 67.6 | 0.170 | 1.0 | 19.3 | 23.2 | 24.2 | 9.2 | 23.6 | 14.7 | 21.1 |
| 5-6 Members | 38.0 | 68.6 | 0.260 | 1.5 | 28.5 | 34.7 | 36.3 | 15.7 | 35.4 | 24.4 | 31.8 |
| More than 6 Members | 42.7 | 69.1 | 0.295 | 1.0 | 33.0 | 38.8 | 41.9 | 19.5 | 40.7 | 25.4 | 35.5 |

Calculated from NSS Round 68, Consumption Module 2011-12. Applied RDA: 50 per cent of RDA.
Landholding classes in hectares: 0.002 < land ≤ 1 (Marginal), 1 < land ≤ 2 (Small), 2 < land ≤ 4 (Semi-Medium), 4 < land ≤ 10 (Medium), land >10 (Large)

# 4 Comparison between NDI and DDI

In this Section, I compare the NDI and the DDI in two ways. First, I compare the conceptional frameworks of the two approaches. For this purpose, I show how the DDI is constructed and how its weaknesses are overcome in the NDI framework. Second, I show empirically the differences in outcomes the two approaches yield.

## 4.1 The DDI Framework

In most studies, the DDI serves as a count of food groups and yields the ratio of those not consuming a diverse diet to the total sample population. Traditionally, neither food-specific nor person-specific thresholds are set. Only incidences of joint non-consumption in several food groups are counted. For comparison with the NDI framework, I construct the DDI as close as possible to the NDI using the dual cut-off methodology. The latter has not been referred to as such in DDI studies. Since the DDI normally does not include any explicit dimension thresholds it would not have two cut-offs. The $z$-vector contains the dimensional cut-offs and can be thought of as only containing zeros for each dimension. The minimum threshold to determine dietary diversity in food groups is in effect a $k$-value, similar to the one from the NDI framework built on the AF methodology. Therefore, I present the DDI framework using the dual cut-off approach that will exemplify the differences between the NDI and DDI.

To begin with, in the DDI framework the threshold vector $z_D$ for $d$ food groups is

$$z_D = (z_1, ..., z_d), \tag{13}$$

with all entries being zero. As in the NDI framework, one can think of an achievement matrix,

$X$, with $x_{ij}$ entries reflecting realizations in food consumption for person $i$ in food group $j$. Now, in order to count incidences of consumption and collect this information in a deprivation matrix, say $g^{0_D}$, the following holds: given that the threshold vector includes only zeros, elements $g_{ij}^{0_D} = 1$ if $x_{ij} = z_j$, and $g_{ij}^{0_D} = 0$ if $x_{ij} > z_j$. Building on this, a vector of deprivation counts, $c^D$, contains row-wise counts of deprivations. Ignoring dimensional weights, its entries $c_i$ are $c_i = \sum_{j=1}^{d} g_{ij}^{0_D}$. Regarding the second cut-off, a person is considered as deprived in dietary diversity (not consuming a diverse diet) if she is deprived in at least $k$ food groups. Applying $k$ to the $c^D$-vector thus yields the $c^D(k)$-vector with entries $c_i(k) = 1$ if $c_i \geq k$ and $c_i(k) = 0$ if $c_i < k$. Now, traditionally the DDI framework has been used only to report the incidence of those not consuming a diverse diet, which is $H_D$. The latter can be written as: $H_D = \frac{\sum_{i=1}^{n} c_i(k)}{n}$.

Viewing the DDI in such an Alkire-Foster type framework, the DDI resembles the NDI in two ways. One, joint deprivations in food groups are considered. Thus, both the NDI and the DDI account for simultaneous deprivations in food inadequacies at the individual-level. Second, both the NDI and the DDI framework yield a headcount ratio of the inadequately nourished, $H_N$ and $H_D$, respectively.

However, the DDI framework has three major shortfalls, which the NDI framework overcomes. First, the DDI does not reveal anything beyond the incidence of food inadequacy. While $H_D$ is certainly very informative as such, it does not inform about the intensity of food inadequacy. Therefore, inequalities in food diversity among those not consuming a diverse diet may be stark but overlooked by focusing only on $H_D$. In fact, $H_D$ identifies everyone as equally deprived in dietary diversity as long as they consume less than $k$ different food groups, even though some may consume much less than the minimum $k$ while others consume just below $k$. Formally, $H_D$ violates the monotonicity principle, according to which, in the context of the DDI, additional deprivations should increase food inadequacy and thus the value of $H_D$. The violation of the monotonicity principle is a well-known problem in poverty measurement. To overcome it, other poverty measures go beyond the headcount ratio and estimate the intensity of poverty (Foster et al., 1984; Ray, 1998; Alkire et al., 2015). The NDI framework, too, overcomes this problem by accounting for the average intensity of food deprivation, $A_N$. The headcount ratio $H_N$, similar to $H_D$, still violates the dimensional monotonicity. But since both the incidence as well as the intensity of food inadequacy are calculated, the NDI framework provides for much richer information. Further, the ultimate NDI figure, $M_0$, which is the product of $H_N$ and $A_N$, does not violate dimensional monotonicity.

Second, the DDI framework does usually not include dimensional thresholds. Recall, the $z_{DDI}$-vector contains only zeros. By doing so, the DDI does not control for heterogeneous food requirements and thus ignores the extent of food deprivations within food groups. The DDI framework could easily allow for the inclusion of food-group specific thresholds as these could be collected in the $z_D$-vector. However, this is rarely done. The NDI framework, on the other hand, does account for dimensional thresholds.

Third, the DDI framework does not include any individual-specific thresholds for the various food groups. Similar to not including dimensional thresholds, not accounting for idiosyncratic differences in food requirements underestimates the incidence of food inadequacies and neglects the extent of food inadequacy entirely. For instance, food requirements vary immensely by age, gender, occupation, and other factors (Gopalan, 1992; Kakwani, 1992), but the DDI ignores all of these by only counting incidences of consumption irrespective of any thresholds. The NDI overcomes this weakness by accounting for idiosyncratic thresholds. The $n \times d$-dimensional $Z$-matrix combines both idiosyncratic and dimensional thresholds.

## 4.2 Empirical Differences in NDI and DDI Applications

Given the fundamental differences in the two conceptual frameworks described above, empirical outcomes can be expected to be different. To show this, I utilize the NSS household-level data for rural India (2011-12), as before.

Headcount ratios for any given $k$-value will always be higher for $H_N$ than for $H_D$, or at least as high. This is due to the $z$-cut-offs which are always zero in the DDI framework and are always greater than zero in the NDI framework. Therefore, under the DDI framework, by counting tiny amounts of food consumption one would identify these as "no deprivation," whereas under the NDI one would identify these tiny amounts as a food shortfall and a deprivation, given that they are below the household-specific threshold of $z_h$.

Table 3 presents both $H_N$ and $H_D$. Clearly, $H_N$ is always higher than $H_D$ across all $k$-values. In terms of levels, the two headcount ratios are very different, especially for lower $k$-values. For a $k$-value of 1, the $H_D$ figure is 67 per cent, implying that 67 per cent of India's rural population do not ever consume at least one of the eight food groups. $H_D$ then drops sharply to 28 per cent given a $k$-value of 2. In contrast, for the same $k$-values, $H_N$ is much higher at about 100 per cent and 96 per cent, respectively. This means that almost all rural households are inadequately nourished in at least two food groups given the $z_h$-cut-offs. The $H_D$ figures drop much further and faster than the $H_N$ figures, so that already at a $k$-value of 4 the incidence figure is close to 1 per cent, which $H_N$ reaches only at a $k$-value of 8. These differences are also visible and even more pronounced in the decomposition by state of $H_N$ and $H_D$ (Table 5). For example, at a $k$-value of one, $H_N$ is as high as 100 per cent in almost every state, whereas $H_D$ can be as low as 42 per cent (Karnataka).[12] Similar to the national figures, state' $H_D$ reduces much faster than $H_N$ with increasing $k$. In Karnataka, for instance, $H_D$ decreases to 9 per cent at a $k$-value of two and declines further to two per cent at a $k$-value of four. In contrast, $H_N$ reduces at a much smaller rates with higher $k$-values, so that only at a $k$-value of eight it is at a level of two per cent.

$H_N$ and $H_D$ are similar in magnitude at the national and state level at two specific $k$-values. At a $k$-value of two for $H_D$ and at a $k$-value of five for $H_N$, the national incidence rates are not

[12]For completeness, Appendix Figure 5 includes maps showing the state variation, in levels of $H_D$ for all $k$-values up to six.

**Table 5: Headcount Ratios $H_N$ and $H_D$ for $k$-value = 5, by State**

| | $k=1$ | | $k=2$ | | $k=3$ | | $k=4$ | | $k=5$ | | $k=6$ | | $k=7$ | | $k=8$ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| State | $H_N$ | $H_D$ | $H_N$ | $H_D$ | $H_N$ | $H_D$ | $H_N$ | $H_D$ | $H_N$ | $H_D$ | $H_N$ | $H_D$ | $H_N$ | $H_D$ | $H_N$ | $H_D$ |
| Andaman & N. | 100.00 | 56.22 | 97.19 | 22.62 | 79.39 | 5.35 | 38.96 | 1.76 | 9.74 | 1.76 | 3.60 | 1.76 | 1.76 | 1.76 | 0.60 | 0.60 |
| Andhra P. | 99.97 | 59.40 | 98.58 | 23.87 | 87.08 | 7.25 | 58.84 | 3.42 | 24.30 | 2.85 | 7.36 | 2.70 | 4.32 | 2.67 | 2.36 | 1.98 |
| Arunachal P. | 99.27 | 80.39 | 92.12 | 50.42 | 82.01 | 28.51 | 62.99 | 15.12 | 38.37 | 5.53 | 16.60 | 1.99 | 7.04 | 1.61 | 1.65 | 1.59 |
| Assam | 99.76 | 58.69 | 96.29 | 23.20 | 84.04 | 4.98 | 63.09 | 1.06 | 33.42 | 0.94 | 13.57 | 0.94 | 4.01 | 0.89 | 0.95 | 0.89 |
| Bihar | 98.68 | 77.19 | 92.20 | 30.40 | 75.15 | 4.19 | 49.07 | 0.11 | 25.70 | 0.08 | 7.89 | 0.08 | 1.70 | 0.08 | 0.08 | 0.07 |
| Chandigarh | 99.92 | 97.72 | 90.78 | 32.49 | 69.90 | 0.00 | 26.36 | 0.00 | 11.17 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Chhattisgarh | 99.89 | 81.69 | 98.22 | 44.53 | 93.41 | 7.39 | 77.29 | 1.25 | 44.13 | 0.93 | 17.80 | 0.93 | 3.47 | 0.93 | 1.24 | 0.92 |
| Dadra & N. | 100.00 | 91.68 | 100.00 | 76.13 | 96.18 | 37.78 | 93.58 | 16.60 | 49.23 | 16.60 | 25.39 | 16.60 | 17.98 | 16.60 | 16.53 | 16.53 |
| Daman & Diu | 100.00 | 79.67 | 99.76 | 44.00 | 82.96 | 14.64 | 57.73 | 9.02 | 16.37 | 9.02 | 9.02 | 9.02 | 9.02 | 9.02 | 9.02 | 9.02 |
| Delhi | 97.78 | 69.24 | 97.78 | 12.12 | 61.48 | 6.31 | 28.19 | 6.31 | 9.98 | 6.31 | 7.28 | 6.31 | 6.31 | 5.53 | 5.53 | 5.53 |
| Goa | 100.00 | 54.63 | 94.35 | 13.95 | 68.29 | 0.08 | 35.13 | 0.00 | 14.66 | 0.00 | 6.53 | 0.00 | 0.08 | 0.00 | 0.00 | 0.00 |
| Gujarat | 99.95 | 73.78 | 98.72 | 22.02 | 90.36 | 4.43 | 68.63 | 1.43 | 34.09 | 1.43 | 9.97 | 1.43 | 3.05 | 1.42 | 1.42 | 1.11 |
| Haryana | 99.51 | 75.00 | 95.58 | 28.29 | 78.13 | 3.42 | 53.82 | 0.53 | 23.46 | 0.42 | 6.09 | 0.34 | 1.03 | 0.34 | 0.46 | 0.34 |
| Himachal P. | 98.25 | 69.20 | 91.42 | 16.08 | 68.06 | 1.72 | 38.46 | 0.75 | 15.73 | 0.75 | 5.36 | 0.75 | 1.85 | 0.71 | 0.43 | 0.43 |
| Jammu & K. | 99.06 | 48.67 | 87.70 | 8.87 | 56.06 | 0.63 | 28.74 | 0.48 | 11.42 | 0.48 | 3.16 | 0.37 | 1.42 | 0.36 | 0.24 | 0.22 |
| Jharkhand | 99.70 | 89.32 | 96.71 | 57.35 | 87.95 | 18.53 | 64.38 | 2.19 | 39.73 | 1.63 | 14.98 | 1.63 | 4.80 | 1.63 | 1.32 | 1.31 |
| Karnataka | 99.96 | 42.33 | 98.29 | 8.69 | 86.90 | 2.82 | 60.68 | 2.16 | 32.47 | 2.07 | 11.18 | 2.00 | 4.39 | 2.00 | 1.35 | 0.51 |
| Kerala | 100.00 | 61.50 | 99.43 | 20.14 | 84.24 | 5.23 | 49.12 | 3.02 | 22.21 | 2.53 | 9.20 | 2.47 | 4.12 | 2.10 | 2.03 | 1.33 |
| Lakshadweep | 100.00 | 83.93 | 100.00 | 23.22 | 98.83 | 11.57 | 44.34 | 6.45 | 19.05 | 6.45 | 6.45 | 6.45 | 6.45 | 0.00 | 0.00 | 0.00 |
| Madhya P. | 99.67 | 74.60 | 98.01 | 30.47 | 90.34 | 7.02 | 73.74 | 0.94 | 49.84 | 0.85 | 24.16 | 0.85 | 6.70 | 0.72 | 0.98 | 0.66 |
| Maharashtra | 99.56 | 44.01 | 96.69 | 17.22 | 88.04 | 7.55 | 67.31 | 3.97 | 36.55 | 3.84 | 13.79 | 3.83 | 4.87 | 2.71 | 1.79 | 1.73 |
| Manipur | 100.00 | 76.27 | 98.85 | 47.83 | 94.27 | 9.61 | 80.84 | 1.50 | 57.05 | 1.38 | 33.28 | 1.24 | 11.58 | 1.24 | 1.13 | 1.13 |

| | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Meghalaya | 99.92 | 51.13 | 98.93 | 24.21 | 90.76 | 2.14 | 70.69 | 1.50 | 49.00 | 1.50 | 28.71 | 1.50 | 11.43 | 1.50 | 1.50 | 1.50 |
| Mizoram | 99.83 | 67.53 | 96.67 | 25.35 | 86.14 | 7.73 | 57.53 | 2.87 | 28.90 | 1.22 | 8.82 | 0.35 | 1.41 | 0.00 | 0.00 | 0.00 |
| Nagaland | 99.78 | 62.02 | 98.71 | 15.99 | 94.08 | 3.77 | 72.16 | 0.51 | 28.35 | 0.00 | 7.47 | 0.00 | 0.28 | 0.00 | 0.00 | 0.00 |
| Orissa | 99.86 | 66.23 | 97.78 | 34.56 | 88.62 | 6.37 | 70.07 | 0.79 | 43.40 | 0.62 | 20.22 | 0.55 | 4.33 | 0.40 | 0.64 | 0.16 |
| Puducherry | 100.00 | 59.46 | 94.57 | 20.19 | 78.67 | 8.76 | 36.04 | 5.91 | 13.61 | 5.91 | 6.84 | 5.91 | 5.91 | 5.91 | 2.52 | 2.12 |
| Punjab | 99.79 | 83.28 | 93.88 | 31.85 | 76.67 | 2.50 | 45.84 | 1.98 | 16.77 | 1.98 | 5.50 | 1.98 | 2.04 | 1.51 | 0.17 | 0.17 |
| Rajasthan | 99.89 | 74.94 | 98.17 | 33.62 | 93.05 | 5.04 | 76.57 | 0.30 | 45.12 | 0.18 | 19.32 | 0.09 | 6.62 | 0.03 | 0.02 | 0.02 |
| Sikkim | 99.24 | 67.30 | 95.89 | 12.52 | 71.11 | 3.60 | 35.62 | 2.77 | 13.71 | 2.74 | 5.46 | 2.74 | 3.36 | 2.74 | 2.62 | 2.62 |
| Tamil Nadu | 99.91 | 45.98 | 98.54 | 14.05 | 82.49 | 3.73 | 57.83 | 1.90 | 33.14 | 1.85 | 16.99 | 1.85 | 7.48 | 1.78 | 2.42 | 0.58 |
| Tripura | 99.98 | 62.29 | 95.97 | 25.27 | 81.56 | 5.42 | 55.96 | 1.05 | 25.94 | 0.78 | 9.40 | 0.78 | 1.47 | 0.40 | 0.40 | 0.11 |
| Uttar P. | 99.57 | 80.25 | 94.09 | 34.97 | 78.98 | 7.66 | 54.33 | 0.75 | 29.26 | 0.65 | 10.81 | 0.65 | 3.45 | 0.54 | 0.39 | 0.29 |
| Uttaranchal | 98.42 | 64.14 | 87.21 | 17.69 | 64.04 | 1.29 | 35.50 | 0.54 | 11.89 | 0.34 | 2.13 | 0.34 | 0.47 | 0.34 | 0.30 | 0.30 |
| West Bengal | 99.59 | 70.28 | 95.94 | 33.20 | 77.66 | 5.04 | 47.52 | 0.67 | 22.08 | 0.62 | 8.20 | 0.59 | 2.11 | 0.46 | 0.64 | 0.38 |

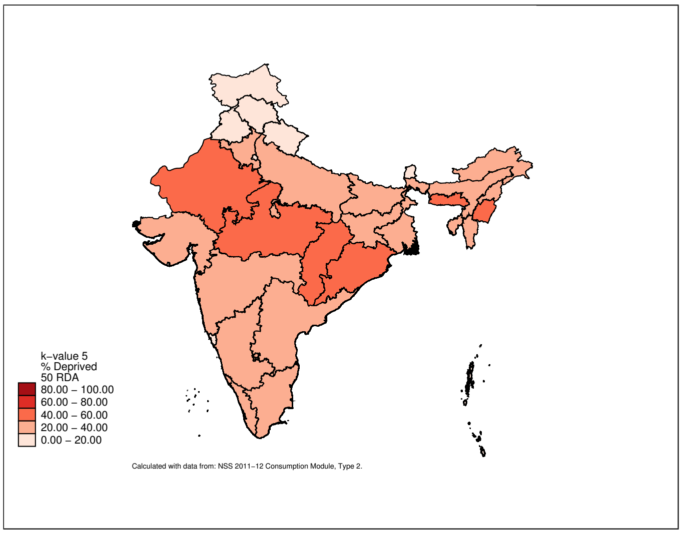
Calculated from NSS Round 68, Consumption Module 2011–12. Applied RDA: 50 per cent of RDA.

too far apart: $H_N$ is just above 30 per cent and $H_D$ is just below 30 per cent. While the two ratios at the national level are not far apart, maps for state variation in $H_N$ and $H_D$, given the two specific $k$-values, reveal a different scenario (Figure 4). $H_N$ for a $k$-value of five is particularly high in the Northern Hindi-speaking belt (Rajasthan, Madhya Pradesh, Chhattisgarh, and Orissa). $H_D$, on the other hand, does not replicate such a pattern entirely as there is more variation across Indian states. For example, Chhattisgarh and Jharkhand are among the most deprived states, the remaining four states identified under $H_N$ as part of the "belt" are not in this group, however. Further, while there does not appear to be much variation across states in Central and Southern India under the $H_N$, there is a stretch identified as much less food deprived under the $H_D$. This stretch reaches from Maharashtra via Karnataka to Tamil Nadu. To sum up, the two frameworks yield highly divergent results. It is apparent that a DDI underestimates food inadequacies to a great extent by just focusing on non-zero food intakes, which is particularly pronounced in regional estimations.

One may conjecture that household-level data are not ideal for either of the two measures. Both measures are ideally applied to individual-level data to account for intra-household allocations. I show, however, that even household-level data can be applied using the NDI framework when "tweaked" for household-level data by summing up individual thresholds at the household-level. Such a scenario is not feasible in the traditional DDI framework when all thresholds are set at zero. Therefore, the NDI has some advantage in this regard. Both the DDI and NDI are ideally suited to capture food groups for a short recall period, for example, two days. For longer periods, its values, especially those of the DDI, are certain to drop drastically, as evident from Table 3.

Both frameworks depend a great deal on the data collected. If these are based on national household consumption surveys, both frameworks will suffer from sampling error. Any measure is bound to suffer from such drawbacks if no census data can be collected. In addition, for the ideal NDI, individual-level data on consumption (in quantity) would be necessary. Given the long list of food items, as, for example, in the latest NSS round, the collection of such data at the individual-level is likely to be very time consuming and might stretch resources of national statistics offices beyond their capacities. Certainly, the fact that individual-level data on just the incidence of eight food groups can be collected in much less time speaks in favor of the DDI. If, however, the data collection is focused on just the eight food groups of interest, the resources of national statistics offices may also be sufficient to collect information on the quantity of consumption items at the individual-level. The latter are then ideally suited for an NDI.

(a) $H_N$ for $k = 5$




(b) $H_D$ for $k = 2$

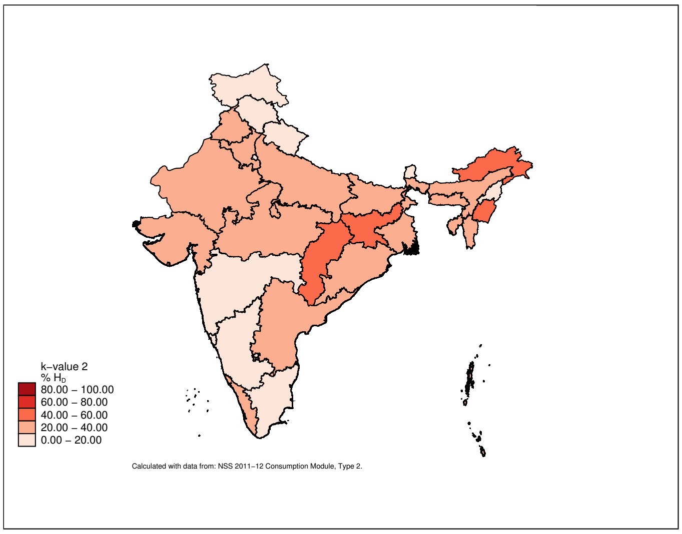



**Figure 4: $H_N$ for $k = 5$ and $H_D$ for $k = 2$, by State**

# 5 Concluding Remarks

This paper presents a new tool to measure dietary diversity: the Nutritional Deprivation Index. Being a counting method, the NDI extends the widely used Dietary Diversity Index and builds on the Alkire-Foster methodology. I show that the NDI can be applied to both individual as well as household-level data from ordinary national sample surveys. The NDI overcomes three major weaknesses of the DDI. First, while the DDI only considers the incidence of the inadequately nourished, the NDI provides both the incidence and the intensity of nutritional deprivation. By doing so, the NDI framework yields the headcount ratio of the inadequately nourished and the average deprivation share of the inadequately nourished. Second, the NDI provides for food group-specific thresholds, which are overlooked in common applications of the DDI. Third, in combination with food group-specific thresholds, the NDI allows for individual-specific thresholds. Since consumption is shown to vary substantially by age, occupation, activity level, and gender among many other factors (Gopalan, 1992; Osmani, 1992; Behrmann, 1992; Deaton and Drèze, 2009; Tilman and Clark, 2015), the NDI feature of allowing for both idiosyncratic and food group-specific thresholds is certainly advantageous and makes the NDI superior to the DDI framework.

In this paper, I demonstrate how the NDI can be applied to ordinary household-level data for rural India. I explain several advantages of the NDI framework, such as regional decomposition and dimensional breakdowns, which provide for useful information. My analyses reveal that the highest incidences of inadequately nourished households are in the Northern states of Rajasthan, Madhya Pradesh, Chhattisgarh, and Orissa. Going beyond an analysis of headcount ratios, these households are deprived in at least five of eight food groups, primarily in the food groups of pulses, leafy vegetables, and fruits. Further, the traditionally most disadvantaged socioeconomic subgroups are the most exposed to inadequate nutrition. These include Scheduled Tribes and Scheduled Castes, the landless, and households with many household members. The results exemplify that the manifold decompositions of the NDI are ideal for targeting purposes. Using this framework, policy makers can, on the one hand, identify inadequately nourished regions and subgroups, while on the other hand identify the most needed food groups. Such a measure can be of great use in low income countries or regions of crises. The rich information gained from the application of the NDI could also inform awareness campaigns designed for wealthier societies, where despite available resources to afford a healthy and diverse diet, many households in higher income countries chose not to do so (Tilman and Clark, 2015).

The outlined technique of an adjusted Alkire-Foster methodology has the potential of being used in other fields of research related to health, nutrition, and health economics. For example, the technique can be easily adopted to measure child nutrition and deficiencies in micro-nutrients in a multidimensional setting. The outlined technique can be adapted to allow for child nutrition-specific weighting schemes, so that nutrients or food groups important during child feeding, e.g. milk and calcium, receive higher weights. Going beyond food groups, one can think of converting food groups into micro-nutrients to measure a more finely tuned measure of nutrition. This may overcome the limitation of some food groups being potential substitutes for other food groups in the NDI framework. While research has established a link between dietary diversity – as based on the DDI – and anthropometric outcomes (e.g. Menon et al., 2015), such a correlation still needs to be established for the likely link between parameters of the NDI and anthropometric outcomes.

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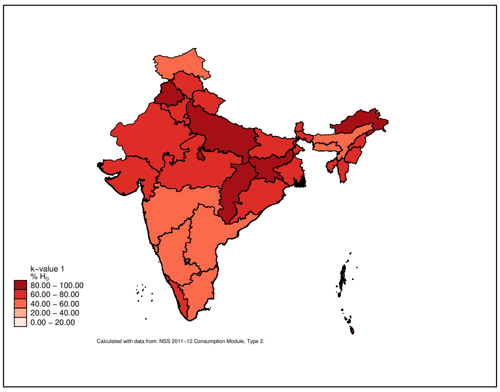
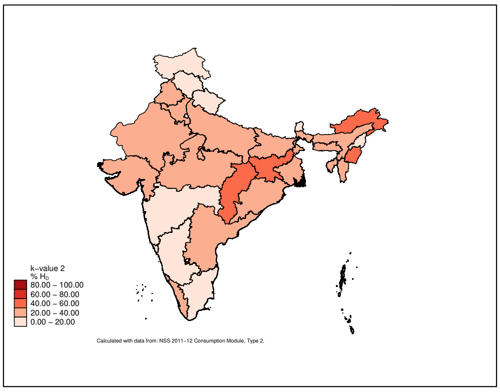
# Appendix

(a) $k = 1$




(b) $k = 2$




(c) $k = 3$

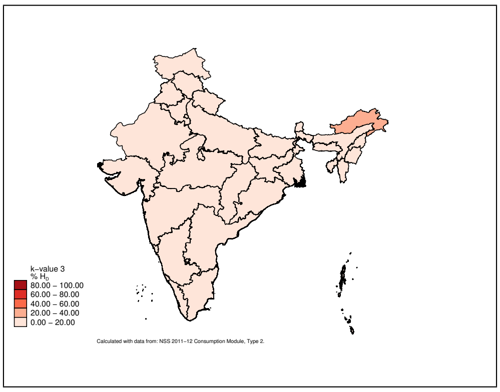



**Figure 5: $H_D$ for $k$-values 1–3, by State**