Rebound effects could offset more than half of avoided food loss and waste

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Abstract

Reducing food loss and waste (FLW) could lessen food systems' environmental impacts and improve food security. However, rebound effects—whereby efficiency improvements cause price decreases and consumption increases—may offset some avoided food FLW. Here, we model rebounds in food consumption under a scenario of costless FLW reduction. We project that consumption rebound could offset 53-71% of avoided FLW. Such rebounds would imply similar percentage reductions in environmental benefits (carbon emissions, land use, water use), and improvements to food security benefits (increased Calorie availability), highlighting a tension between these two objectives. Evidence from energy systems suggests that indirect effects not included in our analysis could further increase rebounds. However, costs for reducing FLW would reduce rebounds. Rebound effects are therefore important to consider in efforts aimed at reducing FLW.

Main

Recent estimates suggest that 14% of food produced for human consumption globally is lost (i.e. damaged or spoiled before reaching retailers or consumers) and 17% is wasted (i.e. spoiled or thrown away by retailers or consumers)[1,2]. Food *loss* occurs on the supply side; food *waste* occurs on the demand side (Fig. 1). Altogether, food loss and waste (FLW) amounts to an average of 527 Calories per person per day[3] and 24% of global food system GHG emissions—6% of total emissions[4]. Although these may be overestimates of the value and extent of FLW[5], and there are also regional and crop-specific differences in FLW[6,7], FLW is still a consistent and substantial inefficiency across food systems.

Consequently, reducing FLW is widely considered a key opportunity to improve environmental sustainability[8] and food security[7,9–11] by increasing food system efficiency. Indeed, Goal 12.3.1 of the United Nations' Sustainable Development Goals (SDGs) aims to "halve per capita food waste at the retail and consumer levels and reduce food losses along production and supply chains, including post-harvest losses"[12]. Many governments[13–15], non-governmental environmental groups[16,17], international organizations[18], industry alliances[19], and private firms[20,21] have begun initiatives to reduce FLW, though the world is still not on track to meet SDG 12[22].

The implied rationale of such initiatives is that less waste or loss would result in less food production, and consequently lessened environmental impacts. However, here we consider the possibility that some avoided FLW might be offset by increased consumption due to lower prices—the 'rebound effect'. Rebound effects (or 'feedback') have been widely studied in energy systems[23–27] and in the context of irrigation[28–30]. Food demand may saturate more quickly than energy demand at high incomes[31], which could dampen rebound effects from avoided FLW in high-income regions. Previous studies have considered rebound effects from avoided FLW[32–38], but they have not been quantified at the global scale. Nonetheless, sensitivities ('elasticities') of food demand to prices have been measured, as we describe below.

The magnitude of the rebound effect is measured as the fraction of reduced FLW offset by increased consumption[39,40]. Similar to previous theoretical models[32], we assume that reducing food loss increases supply (because previously lost food now goes to market), and reducing food waste reduces demand (Fig. 1). If food loss decreases by ΔL, and waste decreases by ΔW, the total savings are ΔW + ΔL. Without a rebound effect, consumption decreases by ΔW (i.e., the market quantity traded, $\Delta T = -\Delta W$), because reducing demand lowers consumption, but increasing supply without a rebound effect lowers prices and does not change consumption (Fig. 1a,b). The total savings lost to rebounds are thus ΔW + ΔT, which is equivalent to the overall change in consumption, ΔC. We measure the rebound effect as the ratio, *R* (Fig. 1c; see also ref. 25 and Supplementary Note 1):

$$R = 100\% * \left(\frac{\Delta \mathrm{W} + \Delta \mathrm{T}}{\Delta \mathrm{W} + \Delta \mathrm{L}}\right) \tag{1}$$

With a 100% rebound effect (*R* = 100%), $\Delta T = \Delta L$; i.e., consumption increases by an amount that not only offsets the demand shift, it also uses up the supply shift.

In the context of energy savings from energy efficiency improvements, a review by Gillingham *et al.*[41] estimated that 5-10% was a typical rebound directly caused by decreased prices and consequent increased demand—the 'direct' rebound effect illustrated in Fig. 1, though others have found direct rebound effects of energy savings to be substantially greater[42]. Gillingham *et al.*[41] also noted three potential indirect rebound effects in the energy context that can further increase the overall rebound. First, consumers saving money due to efficiency improvements might spend some of those savings on other goods and services that use energy, thereby increasing overall energy consumption. Second, lessened consumption in the place of experiencing the energy efficiency gain could drive down fuel prices (e.g., oil) globally, causing increased consumption. Third, higher energy efficiency could stimulate pockets of industrial growth and innovation, which would consume energy. Gillingham *et al.*[41] noted macroeconomic models suggesting the combined rebound effect from all four sources (the direct rebound plus the three forms of indirect rebound) was in the range of 20-60%[43,44]. Some studies suggest economy-wide energy rebound effects might be closer to 100%[45] and sometimes exceeding this[46–49] with a condition known as 'backfire'. However, other studies suggest that energy backfire effects are rare[36,37,38,39]. Energy rebound effects appear to increase in magnitude with the level of aggregation[45,46] and with the number of stages in the supply chain[51]. In general, the greater the flexibility of the economy to adjust production (and consumption) to accommodate energy efficiency gains, the larger the rebound magnitude[46,52]. Magnitudes of rebound effects can also vary substantially according to the type of goods or services involved, the economic and policy context[39,40,53], and the stage of economic development[54].

A small, but growing literature estimates a wide range of rebound effects from avoided FLW[35,36,38], depending on the economic and political context. For example, Chitnis *et al*.[35] find rebound effects from avoided food waste ranging from 66% to 106% in United Kingdom (UK) households. Also in the UK, Meshulam *et al*.[36] find that rebounds offset 80%-95% of GHG emissions, water depletion benefits, and land use benefits from avoided FLW. Our analysis estimates rebound effects from avoided FLW and quantifies their food security benefits at the global level.

Here, we use published income-group- and food-type-specific price elasticities of supply[55] and demand[56] (see sources in Supplementary Tables 1-4) to estimate the direct rebound effects from large reductions in food loss and waste of six different types of food (cereals, fruits & vegetables, meat, milk, oilcrops & pulses, roots & tubers). We use a simple microeconomic model that assumes these elasticities are constant over the relevant quantity domain. In alignment with SDG 12, our model assumes one half of all food loss and waste is avoided globally. Our model represents avoided food loss and waste as horizontal shifts in the supply and demand curves, respectively, whose magnitudes equal the quantities of loss and waste avoided (ΔL and ΔW, respectively; Figs. 1, 2; see *Methods* for full model description). This approach implicitly assumes that avoiding FLW is costless and equivalent across various regions as well as within the food supply chain (we relax this assumption in a sensitivity analysis, below). Similar microeconomic models have been used to assess market dynamics and rebound in the energy sector[57–59], and in theoretical studies of the food sector[32].

Our model (see Supplementary Software 1) calculates the new market equilibrium caused by the horizontal shifts in supply and demand—where the new supply curve meets the new demand curve. The difference between the original and new equilibrium quantities is ΔT (Figs. 1, 2). With linear supply and demand curves, the rebound effect (defined by equation (1)) would depend only on their slopes[60]. With constant elasticities (non-linear supply and demand), the elasticities still almost entirely determine the rebound effect over the ranges of elasticities used in our analysis. Doubling or halving waste-avoided or initial prices in our analysis changes the projected rebound on the order of only 1-2%; and changing initial quantities has almost no effect (see Supplementary Data 5 and Supplementary Software 2. To capture some of the uncertainties, we repeatedly model changes in price and consumption for each food type and region, assessing the full range and combinations of price elasticities, assuming they are drawn from independent distributions approximated from the literature (see *Methods* and Supplementary Tables 1-4).

Results

Fig. 2 shows our modeled supply and demand curves, before and after FLW avoidance, for cereals, fruits and vegetables, and meat, in four SDG-defined regions (Eastern and

South-Eastern Asia, Latin America and the Caribbean, Northern America and Europe, and sub-Saharan Africa). Empirical results for the additional four regions can be found in Supplementary Table 8a-d. Fig. 3 shows the distribution of projections of waste and loss avoided as well as change in the quantity traded (in units of mass: Mt per year), by SDG-defined region, for cereals, fruits and vegetables, and meat (Supplementary Table 8b-d shows these results for all food types). Fig. 4a shows the distribution of projected rebound effects—expressed as a percentage of waste avoided—by food type and World Bank income group. We use income groups instead of SDG-defined regions here because the input data on elasticities—which determine the rebound percentage—exist at this level (Supplementary Tables 1-4). Fig. 4b shows the approximate rebound percentage as function of supply and demand elasticities (colors; assuming stylized initial conditions and ΔL and ΔW values), with the raw published estimates of these elasticities used in our analysis (Supplementary Tables 1-4) shown as points.

We project direct rebound effects ranging from 53-71% (Figs. 2-4). Lower price elasticities of supply and higher (in absolute value) price elasticities of demand translate to larger rebound effects, with slightly more sensitivity to demand elasticity, over the range published elasticities (Fig. 4b). Our projected rebound effects are largest for fruits and vegetables (64-71%; center column in Fig. 2), somewhat less for cereals (58-68%; left column in Fig. 2; Fig. 4a) and meat and dairy (53-61%; right column in Fig. 2; Figs. 4a). Fruits and vegetables have relatively low supply elasticities and high demand elasticities, compared to other food types (Fig. 4b). We project slightly smaller rebound effects in higher-income groups (Fig. 4a), due to relatively high supply elasticities and low demand elasticities (Fig. 4b).

We project the global amount of food loss and waste offset by rebound effects by summing ΔW, ΔL, and our projected ΔT across all regions and food types, and applying equation (1) to these sums. We project that rebound effects offset ~65% of global avoided FLW, resulting in only ~180 Mt saved out of a possible ~516 Mt without rebound effects.

We project that loss avoided—in mass units—is highest in Central and Southern Asia, Eastern and South-Eastern Asia, and Latin America and the Caribbean[1] (Fig. 3). Waste avoided—in mass units—is highest Central and Southern Asia, Eastern and South-Eastern Asia, and sub-Saharan Africa[2]. This does not account for the differences in perishability among food types, particularly fruits and vegetables, which constitute a relatively high fraction of waste in high- and middle-income countries[61]. In contrast, cereals and roots and tubers make up the largest share of waste in low-income countries[61]. We note that the highest waste values being found in low- and middle-income countries reflects the most recent FAO reports[1,2], which updated previous, contrasting findings[61–63] in the food loss and waste literature. Our model assumes a uniform reduction in FLW across all food types by half, to assess the impacts of meeting SDG 12 (but not assessing the SDG's feasibility *per se*).

We also calculate the environmental and food-security impacts of our projected rebounds (Fig. 5a). Using carbon, land, and water impact factors from the 2019 FAO SOFA report[1] (impact / tonne of FLW), we calculate environmental impacts of avoiding FLW, with and without rebound effects (see *Methods*). We project that rebound effects offset 63%, 59%, and 65% of carbon emissions, land use, and water use, respectively. For carbon emissions, this finding is equivalent to reducing FLW-related emissions by only ~0.3 Gt CO_2 eq per year rather than ~0.8 Gt CO_2 eq per year without rebound effects. Supplementary Table 11 provides a detailed comparison of projected environmental impact avoided with and without rebound effects.

We estimate regional changes in calorie, protein, and fat supply from reducing FLW (Fig. 5b) with rebound effects by using the food composition tables. We calculate the fraction of each individual food within a given food type group based on quantity supplied (e.g. the quantity of wheat as a fraction of cereals) and use these fractions to convert the rebound effect quantity into food security impacts. We project that rebound effects of avoided FLW would substantially improve calorie, protein, and fat consumption in most low and middle-income regions, such as sub-Saharan Africa, Oceania (excluding Australia and New Zealand), and Western Asia and Northern Africa. Gains in calorie availability is highest in sub-Saharan Africa (~320 Calories/capita/day) and lowest for Australia, New Zealand, North America, and Europe (~120 Calories/capita/day) (see Supplementary Data 2).

Discussion

Rebound effects of avoided FLW can be direct—avoiding waste lowers prices causing consumption to increase—or indirect, including effects of efficiency on consumer incomes, prices in other markets, and local industry and innovation[41,53]. In the context of energy, studies have typically found direct rebound effects offsetting 5-10% of the energy savings caused by efficiency gains[41] though others are higher[42]. In contrast, we project—based on published supply and demand elasticities—that direct rebound effects could offset half-to-two-thirds of avoided food loss and waste across regions and food types. Our analysis quantifies potential rebound effects of avoided FLW at the global scale, adding to a literature of analyses examined at the national[36,64] and regional[34,65] level. For instance, Salemdeeb *et al.*[64] found a ~60% rebound effect from UK food waste reduction, consistent with our projections.

Rebound effects of avoided FLW could have large environmental costs. For instance, we project that—in a scenario where half of all current FLW is avoided, meeting UN SDG Goal 12.3[12], rebound effects could offset 0.51 Gt CO_2-eq per year (63%) of emissions otherwise saved, equivalent to ~3% of current total food system emissions[66] (Fig 5a). Current official data from FAOSTAT may not encompass the entirety of food losses, thus this may be an underestimate of environmental impacts. However, this finding aligns with recent estimates by Albizzati *et al* (2022)[34] of the offset environmental benefits from rebound effects due to avoided FLW in the European Union.

Conversely, rebound effects of avoiding FLW—i.e., greater food consumption at lower prices—would constitute a benefit to food security. For example, we project that rebound effects from meeting SDG 12.3 would increase calorie availability by more than 300 kcal/person/day in sub-Saharan Africa, which amounts to ~16% of a recommended minimum 2100 Calories per day[67]. Thus, any efforts to suppress rebound effects to improve environmental outcomes could have detrimental effects on food security[65]. This echoes a similar tradeoff with energy rebound, whereby rebound-suppressing policies can harm consumers, especially those experiencing energy poverty[68]. Consequently, the IPCC Special Report on 1.5[69] cautions against rebound-suppressing policies. In contrast, in some rich regions, food overconsumption already contributes to obesity and other public health problems[70]. Rebound in such contexts might not be welfare improving.

Our study only models direct rebound effects. Studies of energy systems have found that indirect rebound effects make total rebound larger than direct rebound (20-60%, compared to 5-10%, according to Gillingham *et al.*[41]). If analogous indirect rebound effects exist in food systems, actual rebounds could be larger than those we project—thus, potentially larger than two-thirds of avoided waste and loss. One study[35] on direct and indirect rebound effects from avoided FLW in the UK found rebounds greater than 100% (i.e. backfire). Larger rebound effects in food systems, could be due to either lower supply or higher demand elasticities, compared to energy systems. Theory from energy systems suggesting that backfire effects should be rare but whether this also applies to FLW merits further study [40,41,50,53].

Nonetheless, the comparison between food and energy rebound effects is imperfect. For instance, energy is used in all economic activities, and thus it makes sense that energy savings in one sector could increase energy use in other sectors. In contrast, avoiding FLW cannot cause food consumption outside of the food system although it could theoretically cause an increase the alternative uses of agricultural products, such as livestock feed, bioenergy, or feedstocks to bio-based materials. Similarly, reducing FLW seems less likely than energy savings to catalyze innovation hubs in other sectors. It does seem plausible, however, that avoided FLW in one region or food type could cause increases in consumption in other regions (*via* decreased global prices) and/or via substitution of other food types (*via* increased demand caused by greater disposable incomes). This may suggest that indirect effects add less to overall rebounds in food systems than energy systems, but this merits further study.

Our analysis makes several important simplifying assumptions. First, we assume that price elasticities are constant (over the relevant quantity domain) and are a reasonable basis for calculating direct rebound effects (*via* supply and demand models). Although studies of energy rebound frequently make these assumptions[71], scholars have noted that they could neglect other important factors, besides prices, influencing consumer behavior, and are difficult to estimate[40]. We use price elasticities of demand from a meta-analysis study including 3495 estimates from 162 countries[56]. The published price elasticity of supply estimates we use[55] are sparse and may be out of date. We were not able to find newer estimates. Supply elasticities may have shifted over time, but we hypothesize that they have not changed substantially, given that food is a staple product. Such a hypothesis warrants a separate future study. Further, as Fig. 4b shows, our projected rebound effects are relatively insensitive over the observed range of elasticities. We also show, in Fig. 6a, that rebound effects with elasticities switching between two values are intermediate to rebound effects produced by constant elasticities at each value. This suggests that non-constant elasticities fluctuating within our observed range might have little effect on our overall findings.

Second, food demand saturation could result in rebounds smaller than we project, though only if demand saturation patterns are not captured in the demand elasticity estimates we use. Demand for food increases less than proportionally as incomes increase[31], and thus is most likely to affect our results in high-income regions. However, an econometric analysis of UK rebound effects from avoided food waste estimated a ~60% rebound effect[64], which is consistent with our results.

Third, we do not consider market interactions across food types. Lower prices of one food type could alter prices of other food types, affecting the dietary choices of consumers. For example, if avoiding FLW decreases cereal prices, producers may divert the more affordable cereals to livestock feed, ultimately influencing consumers to substitute meat for cereals in their shopping baskets. Diversion of crops to feed to make higher-valued (but more resource- and pollution-intensive) meat and dairy products could lead to larger increases in both consumption and the environmental impacts of food production.

Fourth, we do not consider regional and sub-regional differences in how FLW might be avoided or in the nature of market responses (besides those captured in different elasticity estimates). Previous estimates[72] reported that low-income countries struggled more with food loss while high-income countries struggled more with food waste[73]. However, more recent estimates[2] suggest that food waste per capita is remarkably similar across regional income groups. Thus, avoiding FLW in both low- and high-income regions will entail improving supply chain infrastructure as well as changing consumer behavior. It is unclear if or how these differences might affect our modeled rebound. For instance, if avoided waste implies a successful intervention in consumers' behaviors, what effect might that behavioral change have on price elasticities of demand? Even within a single country, differences in consumers' income can be expected to mediate their responses to changes in food prices. Such income elasticities of demand are neglected by our analysis, but have been seen to cause meaningful differences in rebound effects of energy efficiency[74,75].

Finally, we assume that avoiding FLW is costless, but policy and business efforts likely have capital and transactional costs in practice. In that case, rebound effects not only limit the efficacy of such efforts, but increase the costs per unit FLW avoided by those efforts. For example, "pay-as-you-throw" programs charge consumers a fine for food found in their household waste[76]. However, administration of such programs may be costly and difficult, and if fines are set too high, consumers will be incentivized to dispose of waste illegally[76]. In Fig. 6b and 6c, we show that making waste and loss reductions costly lessens rebound effects. Over the range of elasticities we observe, rebound effects reach zero when costs of avoiding waste and loss are approximately one-third to one-half of the initial market price of food.

Food loss and waste comes at high environmental costs globally[1], justifying comparably substantial efforts to avoid FLW and thereby increase the efficiency of food systems. Our results suggest that reducing FLW could face large rebound effects, lessening the environmental benefits of reducing FLW. Policies mitigating rebound effects would have to prevent food prices from decreasing in response to waste-and-loss avoidance. However, artificially increasing food prices could pose a risk to food access and equity concerns particularly in low-income regions. Policy makers interested in reducing environmental impacts of food systems and food security may find our results useful, as they highlight an important tension between these objectives, in the context of reducing FLW. Policies incorporating environmental externalities into food prices could be promising[77], as they theoretically remove economic inefficiencies caused by rebound because any rebound would only occur if it improved social well-being. Developing more holistic approaches to food systems management that consider the complex tradeoffs between addressing the environmental impacts of avoiding FLW and other issues such as food insecurity and obesity will likely be critical.

Methods

Data. We use a variety of published data including: (i) 2019 officially reported production, import, export, stock variation, feed, seed, tourist consumption, loss, processed, other uses (non-food), and residual quantities (tonnes/ year) for six food types (cereals, fruits and vegetables, meat, milk, oilcrops and pulses, and roots and tubers) in eight Sustainable Development Goal (SDG) regions (Australia and New Zealand, Central and Southern Asia, Eastern and South-Eastern Asia, Latin America and the Caribbean, Northern America and Europe, Oceania (excluding Australia and New Zealand), sub-Saharan Africa, and Western Asia and Northern Africa) from the FAOSTAT supply utilization accounts (see Supplementary Data 1). Note that food types are aggregated by using the official FAOSTAT FBS and SUA List, which groups individual foods into food type groups (e.g. wheat flour in cereals). We use 2019 values because these are the most recent official data provided by FAOSTAT (iii) 2019 consumer price food indices in the eight SDG regions from FAOSTAT; (iv) population data for each SDG region from FAOSTAT; (v) most recent aggregate food waste values (kg/capita/year) across SDG regions calculated from the United Nations Environment Program (UNEP) 2021 Food Waste Index (FWI) report. (vi) ranges (low, average, high) of price elasticities of demand from a published meta-analysis by Green *et al.*[56] at the resolution of food types and income groups (high, medium, low) (Supplementary Tables 1-3); (vii) point estimates of price elasticity of supply at the SDG regional level (Supplementary Table 4), and (viii) nutritional composition data from FAOSTAT (see Supplementary Data 2).

Model. We aggregate (see Supplementary Data 1) the above data to calculate supply values for each SDG region and food-type combination (see Supplementary Data 3). Domestic supply quantity ($Supply_{fr}$) for a food type (*f*) in a given SDG region (*r)* is conventionally calculated using equation (2)[78],

$$Supply_{fr} = Production_{fr} + Imports_{fr} - Exports_{fr} - \Delta Stock\ Varation_{fr} \qquad (2),$$

Where $Production_{fr}$ is the quantity in megatonnes (Mt) produced, $Imports_{fr}$ the quantity (Mt) of food imported, $Exports_{fr}$ is the quantity of food exported, and $\Delta Stock\ Varation_{fr}$is the changes in stocks during a particular reference period (e.g. 2019) at all levels between production and retail[79].

Note that domestic supply encompasses all possible uses for a given food type, including feed, seed, tourist consumption, other uses, losses, etc. Thus, to determine the total amount of each food type produced exclusively for human consumption (that is, food supply) in each region, the supply equation must be updated accordingly. We do this by beginning with the assumption underlying the FAOSTAT supply utilization accounts, which is,

$$Supply = \ Utilization \qquad (3a),$$

Which can then be transformed into equation (3b) by applying equation (2) and accounting for different types of utilization, as follows,

$$Production_{fr} + Imports_{fr} - Exports_{fr} - \Delta Stock\ Varation_{fr} = food_{fr} + feed_{fr} + seed_{fr} + loss_{fr} + processed_{fr} + other\ uses_{fr} + \ tourist\ consumption_{fr} + residuals_{fr} \qquad (3b),$$

Where $food_{fr}$ is food supply for human consumption, $feed_{fr}$ is food used for animal feed, $seed_{fr}$ is food used for seed, $loss_{fr}$ is food losses along the supply chain up to (but not including) retail, $processed_{fr}$ accounts for whole foods process for food and non-food uses, $other\ uses_{fr}$ is food use for non-food purposes (e.g essential oils), $tourist\ consumption_{fr}$ is food consumed by tourists, and $residuals_{fr}$ is a variable used to account for discrepancies between supply and utilization. Solving equation (3b) for $food_{fr}$ provides the quantity of supply. For more details on this equation, readers are referred to FAOSTAT's supply utilization accounts.

As mentioned in our *Main* text, food losses and food waste are distinctly and separately defined by the FAO. Food losses occur along the food supply chain including harvest losses to distribution losses. Thus, changes in food loss result in a supply shift. In contrast, food waste consists of food wasted at the retail, food service, and household level, which we assume is not accounted on food supply for human consumption ($food_{fr}$ from equation (3b)). Thus, changes in food waste cause a demand shift.

To demonstrate the effect of supply and demand shifts as a result of reduced food loss and waste, we first generate supply and demand curves for each food type-region combination using the values for supply ($food_{fr}$) calculated using equation (3b) and assuming constant price elasticities (of supply and demand), derived from the following supply and demand equations.

$$Q_s = C_s P_s^{\varepsilon_s} \quad (4a),$$

$$Q_d = C_d P_d^{\varepsilon_d} \quad (4b).$$

Here, Q (Q_S for supply, Q_d for demand) is the quantity of food in Mt; P (P_S for supply, P_d for demand) is price (measured as an index); C_s and C_d are constants; and ε_s and ε_d are the supply and demand elasticities, respectively. We select elasticity values from our generated distributions based on published values (see *Methods* on Approximating uncertainty in rebound effects and Supplementary Tables 1-4). We calculate the constants by plugging the initial equilibrium quantity ($food_{fr}$) and price values from FAOSTAT (Supplementary Tables 5-6) into equations (4a) and (4b) as P and Q, along with the elasticities.

We then shift both the supply and demand curve. First, we multiply our percent loss avoided (50%) by the total losses (in Mt) of a given food type in a particular region (see *Results*) and apply this as a horizontal shift in (i.e. add this quantity to) the supply curve. Note that the $losses_{fr}$ value in equation (3b) does not distinguish between losses of food originally destined for human consumption or other uses. Thus, we assume that the fraction of losses destined for human consumption is equivalent to the fraction of food supply over total domestic supply (see Supplementary Data 1). Next, we multiply our percent waste avoided (50%) by the total waste (in Mt) of a given food type in a particular region (see *Results*) and apply this as a horizonal shift in (i.e. subtract this quantity from) the demand curve. Note that waste quantities are only available by region and thus, we assume that the fraction of waste is equivalent in a given region across all food types. We subtract out quantities of food types not included in this analysis (e.g. vegetable oils, stimulants) from total FLW values in each region before inputting final FLW values into our model.

We then use the *polyxpoly* function in MATLAB (see Supplementary Software 1) to calculate the intersection of the new shifted supply and demand curves to find the new equilibrium price and quantity. The difference between the two equilibrium quantities is the projected change in the market quantity traded (ΔT) caused by the rebound. The rebound effect, as a percentage of FLW avoided, R, is calculated by equation (1).

Approximating uncertainty in rebound effects. To model uncertainty in elasticities, we construct a triangle distribution for demand elasticities in each food type-income group combination—with the min and max set to the ‘low’ and ‘high’ values, and the medium set to the ‘average’ value, from Green *et al.*’s meta-analysis[56]—and we construct a uniform distribution for supply elasticities of each food type, assumed to be a uniform between the range of estimates[55] across regions. This gives us a unique joint distribution of supply and demand elasticities at the resolution of income groups and food types, applied to initial equilibria and waste-avoided scenarios at the resolution of SDG region and food type.

We sample 1000 values from each elasticity distribution for all food- and region-type combinations. We then calculate consumption increase (Mt), waste avoided (Mt), and rebound effects (%) for each combination using an equally-spaced range of percentiles. We model independence of supply and demand elasticities by testing all possible percentile combinations to create a representative sample of the distribution of rebound effects.

Estimating environmental impacts from rebound effects. We use environmental impact factors from the 2019 State of Food and Agriculture report[1] to determine how rebound effects from avoided food loss and waste impact carbon emissions as well as water and land use. Impact factors estimate the relative environmental impact of a single tonne of FLW for different food types and regions. Note that the food categories for impact factors and our six food categories analyzed do not perfectly match. As a result, we include a key for impact factors in Supplementary Table 9. Note, we also create a fifth column of impact factors for Oilcrops and Pulses with the production-weighted average of impact factors of Cereals and Pulses with Roots, Tubers, and Oilbearing Crops. Impact factors can be found in Supplementary Table 10.

We multiply the impact factors for carbon emissions (MT CO_2 eq/tonne of FLW), land use (ha/tonne of FLW), and water use (m^3/FLW) by the average amount in tonnes of total possible FLW avoided and total actual FLW avoided due to rebound effects for each region- and food-type combination. We sum these values across all regions and food types to calculate global estimates (see Supplementary Table 11).

Estimating food security impacts from rebound effects. We use FAOSTAT's food composition tables combined with our data on food supply to calculate regional changes in calorie, protein, and fat consumption as proxy measures of food insecurity. Note that each food type is made of a variety of foods, each with varying nutritional compositions. For example, our cereals category contains more than 50 unique food sub-types, such as wheat, rice, millet, and others. Using our FAOSTAT data, we first calculate the fraction of each food within each food type group based on quantity supplied (e.g. the fraction of the supply in the cereals category that is wheat flour). Next, we multiply those fractions by our projected ΔC for that food type (the change in consumption) and the corresponding nutritional measurement (e.g. kcal/100g) to convert the rebound effect quantity in each SDG region into Calories, protein, and fat availability change. We then divide these values by the regional population and days/year to calculate the change in Calories, protein, and fat availability per person per day in each SDG region for each food type (see Supplementary Data 2).

Data Availability

We used public data from FAOSTAT (https://www.fao.org/faostat/en/), the UNEP Food Waste Index Report database (https://www.unep.org/resources/report/unep-food-waste-index-report-2021), and the 2019 State of Food and Agriculture Report (https://www.fao.org/documents/card/en?details=ca6030en). We also used data from relevant literature as cited in our study (see refs. 55 and 56). All data used in this study are included as supplementary information and are also publicly available at https://github.com/mhegwood/foodwaste.

Code Availability

Data analysis was conducted in Matlab (Version 9.11.0.1809720 (R2021b) Update 1) and Mathematica (Version 11.3). All code used in this study are included as supplementary information and are also publicly available at https://github.com/mhegwood/foodwaste.

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Author Contributions S.J.D. conceived the study. M.H., M.G.B., E.C., and S.J.D. performed the analyses, with support and advice from H.S., P.S. and B.B. on analytical approaches. M.H., M.G.B., and S.J.D. led the writing with input from all co-authors. All co-authors reviewed and commented on the manuscript.

Supplementary Information

The Supplementary Information includes Supplementary Tables 1-11, Supplementary Data 1 (data compilation), Supplementary Data 2 (food security calculations), Supplementary Data 3 (Matlab input data pulled from Supplementary Data 1), Supplementary Data 4 (Model generated results from Supplementary Software 1), Supplementary Data 5 (input data for Figure 4b), Supplementary Note 1 (rebound effect derivation and key assumptions), Supplementary Software 1 (Matlab model code), and Supplementary Software 2 (Mathematica code for Figure 4b).

Competing Interests

The authors declare no competing interests.

Figure Legend/Captions

Figure 1. Conceptual model of rebound effects from shifts in supply and demand. We assume a reduction in food loss results in a supply curve shift **(a)** and a reduction in food waste results in a demand curve shift **(b)** based on the definitions provided by the FAO. **(c)** represents shifts in both supply and demand. The flow chart above provides the intuition for how different quantities move through the food supply chain and impact the rebound effects. See

Supplementary Note 1 for a more detailed derivation and key properties.

Figure 2. Modeled shifts in food price and consumption when waste and loss is avoided. Food type- and region-specific price elasticities of demand and supply correspond to differences in the slopes of demand and supply curves (percentile gradients). When substantial food loss is avoided, food supplies increase, and supply curves shift right. When substantial food waste is avoided, food demand decreases, and demand curves shift left. In turn, the market clearing prices decrease and the horizontal displacement (black arrows) reflects the change in the market quantity traded. Change in production (ΔP) and consumption (ΔC) (at the bottom of each panel) reflect these shifts based on the relationships outlined in Supplementary Note 1. This increase can then be compared to the horizontal distance between the original supply, the “waste avoided”, and “loss avoided” curves to find the rebound effect (percentages in the top center of each panel) as seen in Figure 1c.

Figure 3. Regional differences in change in waste avoided, change in loss avoided, and change in the market quantity traded for three food types. Differences in the quantity of food loss avoided (a, d, g) reflect which regions have the highest absolute loss for the selected food types. Differences in the quantity of food waste avoided (b, e, h) reflect which regions have the highest absolute waste for the selected food types. Differences in the market quantity traded (c, f, i) compound according to relevant price elasticities.

Figure 4. Rebound effects and sensitivity to price elasticities. (**a**) Estimates of rebound effects, by food type and income group. (**b**) Colors indicate the magnitude of rebound as a function of supply and demand elasticities (modeled assuming an initial price of 150, quantity of 100, and waste avoided of 50). Food type- and income-group-specific elasticities from the literature used in our analysis are shown (points) (see Supplementary Tables 2 and 3). Note here that we plot cereals with roots & tubers as a single group for ease of interpretation.

Figure 5. Environmental and food security impacts of rebound effects from avoided *food loss and waste*. (a) Possible emissions avoided without rebounded effects and actual emissions avoided with rebound effects in megatonnes (Mt) of CO_2 equivalents per year on the left-hand y-axis. On the right-hand y axis, the fraction of possible and actual avoided CO_2 equivalents per year as a percentage of total emissions from agriculture. Total emissions from the food system is from Crippa et al (2021) as 18 Gt CO_2 equivalents. We do not include Oceania or Australia and New Zealand due to such small value changes in emissions. **(b)** Total increase in Calories per person per day by food type and SDG region due to rebound effects on the left-hand y axis. On the right-hand y-axis, the fraction of Calories due to rebound effects as a fraction of a recommended minimum of 2100 Calories per person per day from the USDA ERS International Food Security Assessment.

Figure 6. Additional robustness checks regarding cost of avoided *FLW* and non-constant elasticities. (a) Our model assumes constant elasticities. However, we know that elasticities may not be constant and here provide the theory for how non-constant elasticities may affect the resulting rebounds from avoided FLW. **(b)** The model in our main analysis assumes that avoiding food loss and waste is costless. This may not be realistic, especially for supply side shifts. Here we model the projected rebound effect for a range of elasticities where the cost to avoid food losses is an increasing percent of the initial price**.** **(c)** The same as graph (b) except here we

graph change in consumption versus cost of avoided loss as a percent of initial price.

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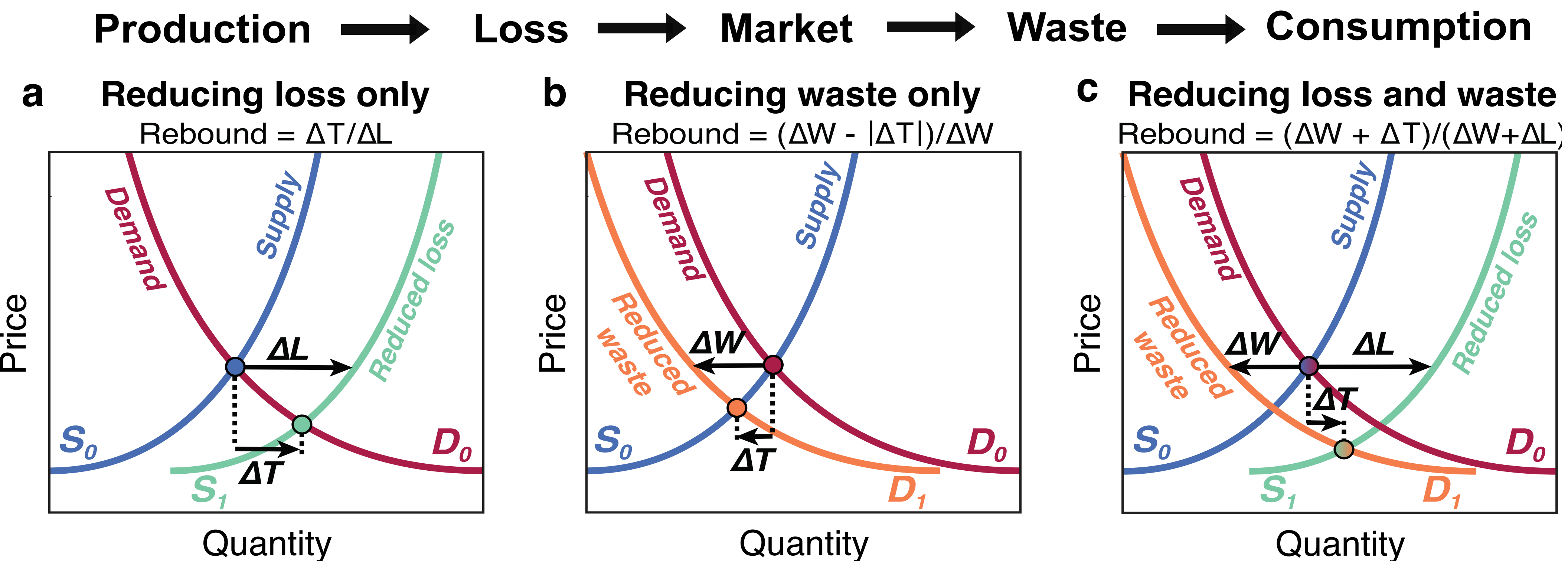
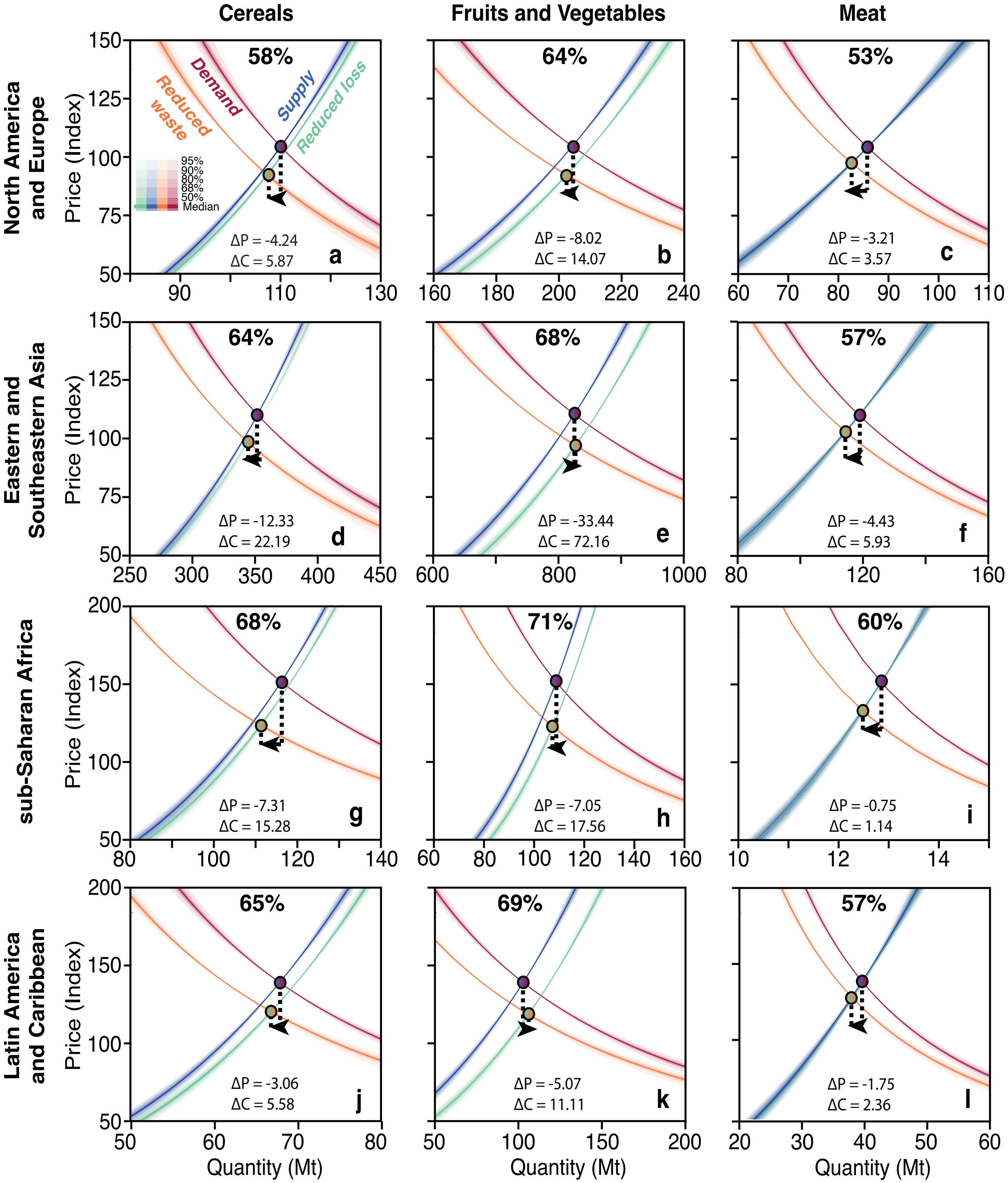

Production
Loss
Market
Waste
Consumption
a
Reducing loss only
Rebound = ΔT/ΔL
Price
Demand
Supply
Reduced loss
ΔL
ΔT
S_0
S_1
D_0
Quantity
b
Reducing waste only
Rebound = (ΔW - |ΔT|)/ΔW
Price
Demand
Supply
Reduced waste
ΔW
ΔT
S_0
D_0
D_1
Quantity
c
Reducing loss and waste
Rebound = (ΔW + ΔT)/(ΔW+ΔL
Price
Demand
Supply
Reduced loss
Reduced waste
ΔW
ΔL
ΔT
S_0
S_1
D_0
D_1
Quantity


Cereals
Fruits and Vegetables
Meat
North America and Europe
Eastern and Southeastern Asia
sub-Saharan Africa
Latin America and Caribbean
Price (Index)
Quantity (Mt)
Demand
Supply
Reduced waste
Reduced loss
95%
90%
80%
68%
50%
Median
58%
ΔP = -4.24
ΔC = 5.87
a
64%
ΔP = -8.02
ΔC = 14.07
b
53%
ΔP = -3.21
ΔC = 3.57
c
64%
ΔP = -12.33
ΔC = 22.19
d
68%
ΔP = -33.44
ΔC = 72.16
e
57%
ΔP = -4.43
ΔC = 5.93
f
68%
ΔP = -7.31
ΔC = 15.28
g
71%
ΔP = -7.05
ΔC = 17.56
h
60%
ΔP = -0.75
ΔC = 1.14
i
65%
ΔP = -3.06
ΔC = 5.58
j
69%
ΔP = -5.07
ΔC = 11.11
k
57%
ΔP = -1.75
ΔC = 2.36
l
150
125
100
75
50
200
90
110
130
160
180
200
220
240
60
70
80
90
100
110
250
300
350
400
450
600
800
1000
80
120
160
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100
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140
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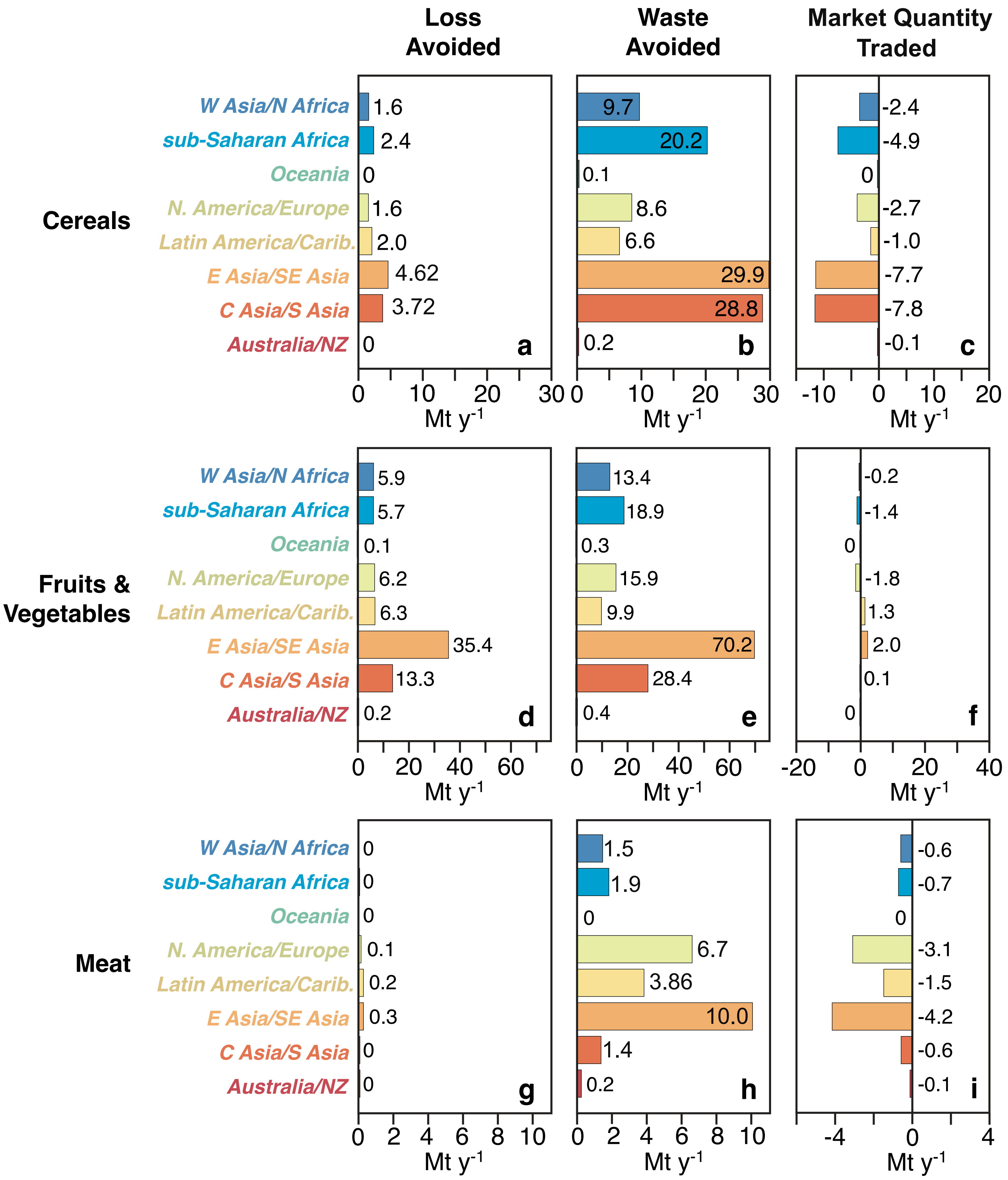
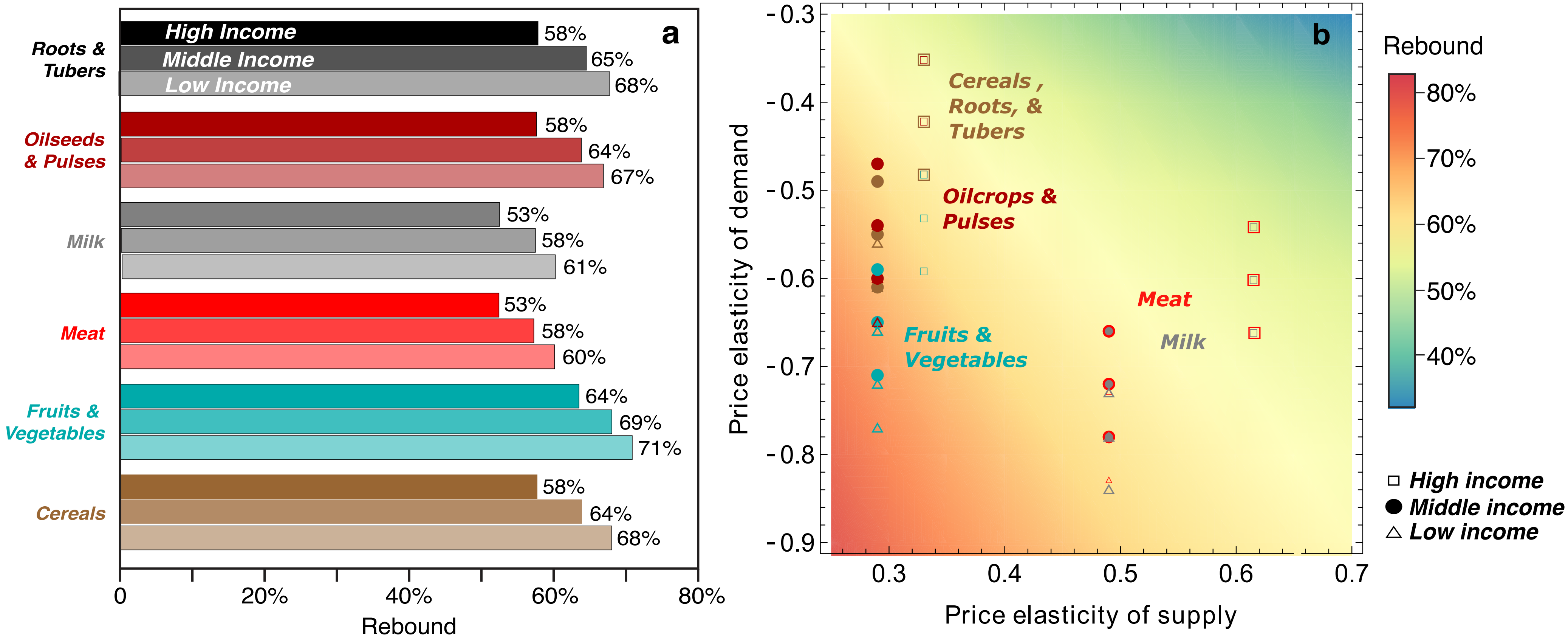
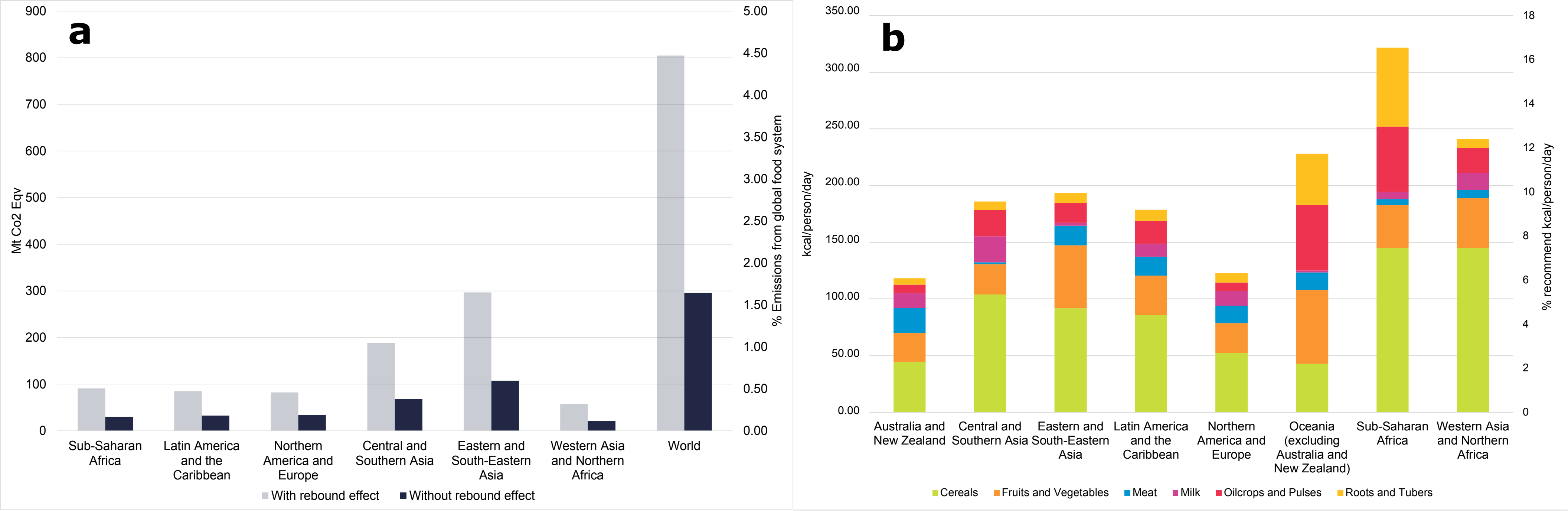
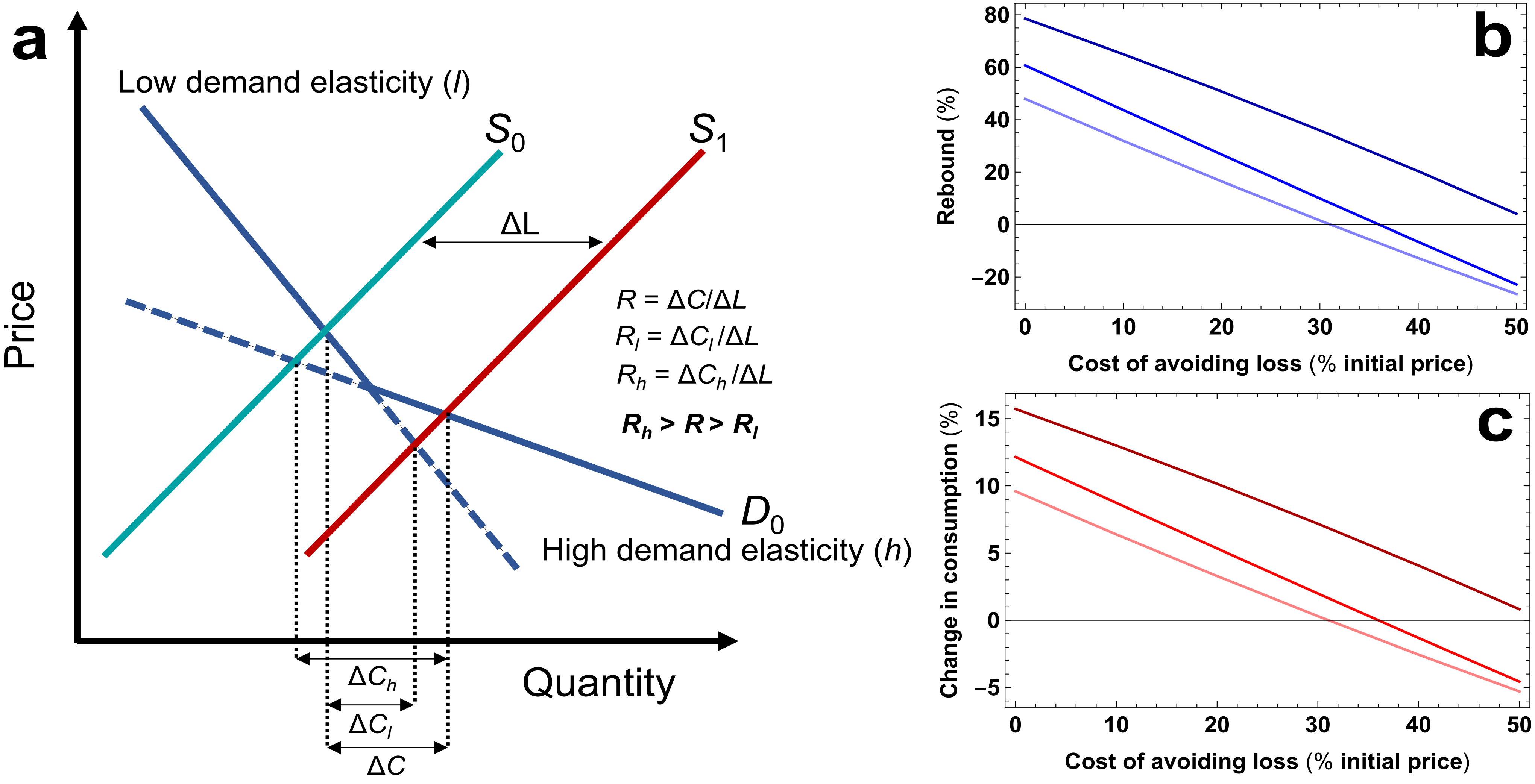

Loss Avoided
Waste Avoided
Market Quantity Traded
Cereals
Fruits & Vegetables
Meat
W Asia/N Africa
sub-Saharan Africa
Oceania
N. America/Europe
Latin America/Carib.
E Asia/SE Asia
C Asia/S Asia
Australia/NZ
1.6
2.4
0
1.6
2.0
4.62
3.72
0
a
9.7
20.2
0.1
8.6
6.6
29.9
28.8
0.2
b
-2.4
-4.9
0
-2.7
-1.0
-7.7
-7.8
-0.1
c
0 10 20 30
0 10 20 30
-10 0 10 20
Mt y-1
5.9
5.7
0.1
6.2
6.3
35.4
13.3
0.2
d
13.4
18.9
0.3
15.9
9.9
70.2
28.4
0.4
e
-0.2
-1.4
0
-1.8
1.3
2.0
0.1
0
f
0 20 40 60
0 20 40 60
-20 0 20 40
0
0
0
0.1
0.2
0.3
0
0
g
1.5
1.9
0
6.7
3.86
10.0
1.4
0.2
h
-0.6
-0.7
0
-3.1
-1.5
-4.2
-0.6
-0.1
i
0 2 4 6 8 10
0 2 4 6 8 10
-4 0 4


a
Roots & Tubers
High Income 58%
Middle Income 65%
Low Income 68%
Oilseeds & Pulses
58%
64%
67%
Milk
53%
58%
61%
Meat
53%
58%
60%
Fruits & Vegetables
64%
69%
71%
Cereals
58%
64%
68%
0
20%
40%
60%
80%
Rebound
b
Cereals , Roots, & Tubers
Oilcrops & Pulses
Meat
Milk
Fruits & Vegetables
Price elasticity of demand
-0.3
-0.4
-0.5
-0.6
-0.7
-0.8
-0.9
Price elasticity of supply
0.3
0.4
0.5
0.6
0.7
Rebound
80%
70%
60%
50%
40%
□ High income
● Middle income
△ Low income


a
Mt Co2 Eqv
% Emissions from global food system
900
800
700
600
500
400
300
200
100
0
5.00
4.50
4.00
3.50
3.00
2.50
2.00
1.50
1.00
0.50
0.00
Sub-Saharan Africa
Latin America and the Caribbean
Northern America and Europe
Central and Southern Asia
Eastern and South-Eastern Asia
Western Asia and Northern Africa
World
With rebound effect
Without rebound effect
b
kcal/person/day
% recommend kcal/person/day
350.00
300.00
250.00
200.00
150.00
100.00
50.00
0.00
18
16
14
12
10
8
6
4
2
0
Australia and New Zealand
Central and Southern Asia
Eastern and South-Eastern Asia
Latin America and the Caribbean
Northern America and Europe
Oceania (excluding Australia and New Zealand)
Sub-Saharan Africa
Western Asia and Northern Africa
Cereals
Fruits and Vegetables
Meat
Milk
Oilcrops and Pulses
Roots and Tubers


a
Low demand elasticity (l)
S_0
S_1
ΔL
$R = \Delta C/\Delta L$
$R_l = \Delta C_l/\Delta L$
$R_h = \Delta C_h/\Delta L$
$R_h > R > R_l$
D_0
High demand elasticity (h)
Price
Quantity
ΔC_h
ΔC_l
ΔC
b
Rebound (%)
80
60
40
20
0
−20
0
10
20
30
40
50
Cost of avoiding loss (% initial price)
c
Change in consumption (%)
15
10
5
0
−5
0
10
20
30
40
50
Cost of avoiding loss (% initial price)