Environmental Impacts Related to Food Consumption of Indonesian Adults

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Summary The challenge for nutrition science is to understand strategies to enable a balance between healthy diets and sustainable food systems. This study was to quantify greenhouse gas (GHG) emission of food consumption related to different dietary preferences among Indonesian adults by body mass index (BMI). Methods: We utilized the existing food consumption survey databases. Dietary and anthropometric information were obtained from Total Diet Study (Studi Diet Total/SDT) in 2014 and Basic Health Research (Riskesdas/RKD) in 2013. The most consumed food items from 14 food groups were selected as representatives of rice, cassava, tofu, long beans, banana, chicken meat, chicken liver, mackerel tuna, chicken egg, condensed milk, palm oil, white sugar, shallot, and ground coffee. The GHGs emission factors were acquired from Thai National Life Cycle Inventory Database. Food weight (gram), energy intake (kcal), and GHGs emission (kgCO2eq) from consumption of these food items were analyzed among BMI groups. Results: Annual GHGs emission by underweight, normal, overweight and obesity group were 794, 827, 801, and 791 kgCO2eq/person, respectively. The highest contributor of GHG was chicken meat, followed by rice and chicken eggs (190, 175, and 123 kgCO2eq/person/y, respectively). Indonesian people in the obesity group consumed higher amount of food (p<0.001) than other groups, however, they emitted lowest GHG emission (p<0.001). Conclusion: This finding suggested that selection of food type plays a critical role on the environment and amount of consumption. Food choices of the population may ultimately result in impacts on environment and have public health consequences.

Key Words food consumption, greenhouse gas emissions, nutritional status, Indonesia

Food sector is one of the major contributor of the global GHG emission. On one hand, food production is necessary to fulfill the nutrition need of the population, on the other hand it has adverse impact on the environment. Food production contributes to around 20–30% of total GHG emission in developed countries, and could be higher in developing countries (1, 2). It is aggravated by dietary trends that is shifting towards westernized diet, which is higher in energy, saturated fats, added sugar and salt, with lower intake of dietary fiber (3–5). The consumption of meat in Indonesia had increased around 11% since 2007, while intakes of vegetable, cereal and tubers had decreased (6, 7). Traditional protein sources made of legumes, such as tofu and tempe, are slowly being replaced with meats. Beef and lamb has been found to emit 250 times more GHG than legumes per gram protein, therefore consuming more meat might be the cause of the problem (8). These dietary shifts, accompanied with population growth, urbanization and sedentary lifestyle, had caused obesity and non-communicable diseases to rise in an alarming rate (9, 10). Therefore, the challenge for nutrition science is to maintain the balance between healthy diets and sustainable food systems.

Understanding dietary patterns that could optimize health outcomes, while minimizing environmental impacts is the key to reduce GHG emission from the food sector. Numerous studies had reported that better nutritional qualities of a diet would cause lower GHG emissions in certain countries (11–14). In Indonesia there are limited studies on environmental impact on the current diet of the population. This paper aims to study the relationship between nutritional status, dietary intake and environmental impact of Indonesian adults based on Total Diet Study (SDT) 2014. The results of this study may be used to recommend a more sustainable eating pattern in Indonesia.

MATERIALS AND METHODS

Population sample and dietary data. This study was based on secondary data from Total Diet Study 2014 (Studi Diet Total/SDT 2014) and Basic Health Research 2013 (Riskesdas/RKD 2013). The two secondary data were cross-sectional health surveys that was conducted by the Ministry of Health of Indonesia representing the country’s population. Participants surveyed in SDT 2014 were selected from 10% among RKD 2013 participants by purposive sampling. RKD 2013 provided

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demographic and anthropometric information (age, gender, weight, height, health status), while SDT 2014 provided dietary data from single 24-h recall (food item, food weight, cooking method). Since the database did not provide nutrient information, we manually inputted energy and protein intake using Indonesian Food Composition Table (Tabel Komposisi Pangan Indonesia/TKPI) (15).

Participants in this study were adults aged 19–55 years old who participated in both surveys. Participants were excluded if: 1) pregnant, 2) had missing data in demographic and/or intake information, and 3) reported energy intake <500 and/or >3,500 kcal, to minimize under- and over-reporters (16). A final of 67,159 participants (30,535 men and 36,624 women) were selected for data analysis in this study (Table 1).

The 24-h dietary recall database contained 17 food groups. However, only 14 were included in this study (cereals, tubers, legumes, vegetables, fruits, meats, organs, fish, eggs, milk, oils and fats, sugar and confectioneries, herbs and seasonings and beverages) and 3 were excluded (water, supplements and composite foods) considering the low contribution to the diet. All food items (n = 988) were aggregated based on the food weight and energy consumed by population and sorted from highest to lowest.

Food items that had the highest contribution to food weight and energy from each food group were selected as the representatives of diet, and was further addressed as “representative food items” in this study. The 14 selected food items were: rice, cassava, tofu, long beans, banana, chicken meat, chicken liver, mackerel tuna, chicken egg, condensed milk, palm oil, white sugar, shallot, and ground coffee.

Estimation of GHG emission from food consumption. GHG emission factors of representative food items were provided by Thai National Life Cycle Inventory (LCI) database compiled by Thailand National Metal and Materials Technology Center (MTEC). The data was a Thailand national-representative collected using Life Cycle Assessment (LCA) method, which complies with ISO 14040 and ISO 14044. The system boundary was “farm-to-gate”, starting from the agricultural process until the product left the farm/factory gate. The environmental impact measured in the database was Global Warming Potential (GWP) represented as carbon dioxide equivalent (kgCO2eq) per kilogram of product.

To get the carbon emission of representative food items in this study, food weight (g) by individual participants was multiplied by the emission factors of each food item. In cases where the emission factor of a representative food was not available in the LCI database, a substitute food item with a similar life cycle was used. Saba banana was substituted with Cavendish banana, chicken liver with chicken meat, and condensed milk with fresh cow milk. Since rice and tofu was not available in the database, emission factors from published literatures were used (17, 18).

To measure the GHG emission from food consumption we used “farm-to-table” as the system boundary, starting from the production of raw materials until the food was consumed by the consumer. The database only provided emission up until factory gate, therefore emissions from post-production stage were estimated. For all food items, we assumed that the emission from transportation was 0.078 kgCO2eq/kg based on a previous study on rice transportation in Thailand (19). The emission from cooking process can be affected by various factors such as cooking method, type of stove, stove efficiency, cooking fuel, cooking time, etc. To simplify the calculation, most frequent cooking methods from SDT 2014 were used to estimate emission from cooking process of each food group. All cooking processes were assumed using medium size stovetop burner (9 MJ/h) with LPG as fuel, and therefore used 0.2 kg of LPG per hour or 0.003 kg per minute (propane contains 45.65 MJ/kg) (20). The method and time required for cooking each food is shown in Table 2.

Data analysis. Participants were classified by nutritional status, using the Body Mass Index (BMI) for “Asian criteria” (underweight <18.5; normal=18.5–22.9; overweight=23–24.9; pre-obese and obese ≥25) (21). All representative food items consumed by the participants were analyzed and quantified for food weight (gram) and energy intake (kcal), and GHG emission (kgCO2eq) and analyzed for statistical differences

### Table 1. Demographic information of participants by BMI group.

|                | Underweight | Normal     | Overweight | Obesity | p     |
|----------------|-------------|------------|------------|---------|-------|
| **N**          | 6,910 (10.3%) | 26,983 (40.2%) | 11,589 (17.3%) | 21,667 (32.3%) | —     |
| **Age (y)**    | 35 (21) | 37 (17) | 40 (15) | 41 (13) | —     |
| **Women%**     | 45.1 | 46.4 | 54.7 | 66.1 | —     |
| **Total energy intake (kcal/d)** | 1580.66 (842.31) | 1574.19 (858.41) | 1577.68 (840.21) | 1561.85 (841.73) | 0.001 |
| **Total food weight (g/d)** | 625.38 (360.37) | 658.15 (370.4) | 672.4 (377.1) | 675.29 (376.64) | 0.001 |
| **Animal-based representative foods (g/d)** | 72.2 (102.15) | 78.2 (113.5) | 75 (116.8) | 77.6 (118.6) | 0.001 |
| **Plant-based representative foods (g/d)** | 277.2 (194.11) | 291.8 (193.05) | 290 (185.33) | 277.4 (182.1) | 0.001 |

* Shown as median±interquartile range.

abc Different superscripts indicates significant difference between groups.
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between groups using Kruskal-Wallis H test in IBM SPSS Statistics for Windows, version 19 (22). The annual GHG emission (kgCO₂eq/y) from each BMI group was calculated for both animal and plant-foods. All analysis results showed as median and interquartile ranges as the data did not qualify for parametric tests.

RESULTS

Representativeness of data

Figure 1 shows the percentage of the representative food items compared to total diet, both in food weight (g) and energy (kcal). The 14 food items that were selected as representatives of the diet contributed to 48% of total food weight and 66% of total kilocalories from the diet.

GHG emission of representative food items

To calculate the GHG emission of the diet, we first calculated the GHG emission from single representative food item by multiplying the weight consumed to their respective emission factors obtained from the Thai National Life Cycle Inventory (LCI) Database. Generally, plant-based generated lower GHG emission compared to animal-based foods. The lowest emission factor was from cassava (0.05 kgCO₂eq/kg and 0.03 kgCO₂eq/1,000 kcal), while the highest was chicken egg (6.32 kgCO₂eq/kg) and chicken liver (39.92 kgCO₂eq/1,000 kcal).

Annual GHG emission of food consumption classified by BMI

The total GHG emission was calculated from GHG emission of food, transportation and cooking. Annual emission per group was calculated by multiplying the total GHG emission by 365. There was a significant difference of annual GHG emissions between BMI groups (H(2)=115.015, p=0.001). Normal and overweight group had significantly higher emission than underweight and obesity group (794, 827, 801, 791 kgCO₂eq/person/y, respectively). Obesity had significantly lower annual emission than all other groups (Table 3).

Animal sources contributed to around 62% of the total emission across all BMI groups, although it was consumed in less amount than plant-based foods. Look-
ing at individual food items, there were significant differences in almost all food items including rice, cassava, long beans, banana, mackerel tuna, chicken egg, condensed milk, palm oil, white sugar, shallots and coffee powder ($p < 0.05$). There were no differences on GHG emission from tofu, chicken meat, and chicken liver.

**DISCUSSION**

This study had shown that there were significant differences of GHG emission in different BMI groups. The result, however, contradicted Author’s hypothesis. People in the obesity groups emitted lowest GHG than other groups despite consuming significantly more amount of food. Although there were no differences in chicken meat and chicken liver consumption, obesity group reportedly consumed less chicken eggs and condensed milk, which had high emission. This could suggest that selection of food type had more impact on GHG emission than the amount consumed. It was consistent with Carlsson-Kanyama and Gonzales study that showed diets similar in caloric content could have significantly different GHG emission depending on the food choices (23). Although some studies suggested that better nutritional qualities leads to lower GHG emission, a few recent studies suggested that the selection of individual food items might have bigger impact. Van de Kamp et al. proposed that adhering to Dutch food based dietary guideline did not always reduce the GHG emission, while replacing meat reduced GHG emission by 34% (24).

In our study, animal-based food items such as chicken meat, chicken eggs and mackerel tuna had highest GHG emission, whereas plant-based foods such as shallots, long beans, and cassava generated lowest GHG emission. An exception was for rice, which is a plant-based food but emitted high GHG because it was consumed in large amount in all groups. Consistent with prior studies, meat and animal products generated more GHG compared to plants in all groups. Although the meat consumption per capita is considered low in Indonesia, it accounted for twice amount of GHG emitted by plant-foods. Reijnders and Soret evaluated the environmental impacts of different protein choices and found that vegetarian diet had relatively low burden (25). Based on the protein content, beef had the highest environmental impact, followed by eggs, chicken, almonds and kidney beans (26). This brings up the importance of choosing plant-based protein sources over meats, which will ultimately lower the GHG emission from diet.

We included 14 food items out of total 988 food items in the database, which represented 48% total food weight and 66% total energy consumed by the population. Previous studies, which included more representative food items had similar percentage of representativeness of diet. Vieux et al., used 391 food items, which had accounted for 71% and 66% of food weight and energy intake in French self-selected diets, while Notarincoca et al., used 17 food items, which contributed to 58% of the food weight in the EU diet (11, 27). To make sure that the study represents the actual diet, future studies could include more food items to be analyzed.

Table 3. Annual GHG emission per person (kgCO$_2$ eq/person/y) by food weight (g).

| Food item          | Underweight | Normal | Overweight | Obesity |
|--------------------|-------------|--------|------------|---------|
| Annual GHG emission per person* (kgCO$_2$ eq/person/y) |             |        |            |         |
| Rice               | 173.13 (129.96) | 181.79 (129.85) | 181.79 (129.85) | 173.13 (138.51) | 0.001 |
| Cassava            | 6.98 (12.68)  | 6.57 (9.86)  | 4.71 (7.68)  | 4.93 (7.46)  | 0.001 |
| Tofu               | 30.60 (33.95) | 31.95 (35.7) | 31.69 (34.78) | 30.64 (33.69) | 0.399 |
| Long beans         | 3.28 (4.37)  | 3.28 (4.37)  | 3.28 (4.48)  | 3.05 (4.3)   | 0.001 |
| Banana             | 19.3 (20.45) | 19.3 (23.73) | 17.56 (19.29) | 19.3 (20.26) | 0.001 |
| Chicken meat       | 181.5 (235.38) | 191 (257.77) | 190.38 (265.71) | 191.85 (264.06) | 0.571 |
| Chicken liver      | 89.43 (62.03) | 93.28 (70.20) | 76.45 (62.07) | 88.51 (84.62) | 0.066 |
| Mackerel tuna      | 79.33 (83.44) | 87.95 (80.62) | 88.93 (82.77) | 82.08 (75.73) | 0.002 |
| Chicken egg        | 124.72 (84.14) | 124.72 (87.58) | 123.88 (94.59) | 118.8 (98.09) | 0.001 |
| Condensed milk     | 15.61 (23.22) | 15.61 (17.17) | 11.70 (19.05) | 7.8 (15.61)  | 0.001 |
| Palm oil           | 14.45 (16.67) | 14.63 (17.04) | 15.15 (16.89) | 14.98 (17.02) | 0.001 |
| White sugar        | 7.61 (8.03)  | 8.45 (8.45)  | 7.48 (7.72)  | 7.04 (6.76)  | 0.001 |
| Shallots           | 0.49 (0.63)  | 0.54 (0.66)  | 0.6 (0.68)   | 0.6 (0.73)   | 0.001 |
| Coffee powder      | 47.78 (43)   | 47.78 (40.07) | 47.78 (38.22) | 47.78 (34.64) | 0.001 |
| Total              | 794.21*      | 826.85b     | 801.34b      | 790.49c      | 0.001 |
| Animal-based***    | 490.59       | 512.56      | 491.34       | 489.04       |         |
| Plant-based***     | 303.62       | 314.29      | 310          | 301.45       |         |

* Shown as median ± interquartile range.
** Differences between groups were tested by Kruskal-Wallis H test and considered significant if $p < 0.05$.
*** Animal based foods were chicken breast, chicken liver, mackerel tuna, chicken eggs, condensed milk. Plant-based foods included rice, cassava, tofu, long beans, banana, palm oil, white sugar, shallots and powdered coffee.
obese people had significantly lower energy intake than other groups. While this might be true, it has been well documented that underreporting is especially common in people with higher BMI and it has been a challenge for epidemiological studies (16). Gibson et al reported that underreporting is very common in low-income countries when using 24-h recall, especially in a large-scale project (28). One way to minimize underreports is by comparing the 24-h interview record with more objective methods such as Double-Labeled Water (DLW), food weighing or Goldberg cut-off (16, 28). Further in this study we compared the reported energy intake to the Goldberg cut-off by calculating a ratio of reported energy intake (EI) to their predicted Basal Metabolic Rate (BMR) (29). The principle of this method is that it is not plausible for a person to perform activities by consuming less than their BMR (29). The result showed that 42.5% of respondents might underreport their energy intake. The obesity group had the lowest EI:BMR ratio, showing that they are most prone to underreporting (data not shown).

In this study we utilized existing food consumption databases from Indonesia and the National Life Cycle Inventory (LCI) Database from Thailand, therefore no data collection was required. Since there were no food GHG emission databases in Indonesia, we used one from Thailand, which had similar food system. Country-specific emission database for Indonesia should be compiled in order to further study the environmental impact with much greater accuracy. Future studies should include more food items to represent the Indonesian diet better, and the study participants should be expanded beyond the adult population. In conclusion, selection of food type plays a critical role on the environment. Food choices of the population may ultimately result in impacts on environment and have public health consequences.

Disclosure of state of COI
No conflicts of interest to be declared.

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