



# Flavour network-based analysis of food pairing: Application to the recipes of the sub-cuisines from Northeast India

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## ABSTRACT

The flavour network-based analysis of food pairing was applied to the sub-cuisines from Northeast India to examine the food pairing behaviour in terms of the co-occurrence of ingredients with the shared flavouring compounds in food recipes. The method applied was based on an existing procedure in computational gastronomy, wherein the preference for positive pairing is attributed to dairy-based ingredients and negative pairing behaviour is attributed primarily to spice based ingredients. Recipe data was subjected to backbone extraction, projection of the recipe-ingredient-compound tri-partite network, and analysis for prevalence and authenticity of ingredients. Further, the average flavour sharing index of the cuisine was determined with the help of the flavour profiles of the ingredients. The extent of deviation for the original cuisine in comparison to a random cuisine was used to determine the degree of bias in the food pairing behaviour, with the sign as the indicator of the nature of pairing. The analysis identified the ingredients responsible to exhibit a positive or negative pairing pattern in the sub-cuisines. The ingredients from the spice category were the most prevalent and have resulted in the negative pairing behaviour in the cuisines. This role of spices in effecting a negative pairing behaviour is in line with the earlier reports for other Indian regional cuisines.

## 1. Introduction

To attain a successful development of innovative food products an excellent understanding of consumers' perceptions, expectations and attitudes is required (Linnemann et al., 2006). The need for a better understanding of the consumers' perception of food innovation is justified by the fact that in certain cases, as a result of 'food neophobia,' consumers are quite likely to reject innovative food products (Barrena and Sánchez, 2013). Although not in the classical domain of food product development, the chefs are leading the domain of food innovation and entrepreneurship in the in-food service development. In the pursuit of effective food innovation, there is an opportunity for the food engineers and food developers to integrate into the gastronomic approach of innovation, considering sustainability, safety, nutrition and improved food use (Aguilera, 2018).

In recent years, data mining and network analysis methods have been applied to characterise and analyse the publicly available large-scale data on food usage and food chemistry. The application of this high-throughput technology has transformed the biological sciences which in most cases rely on experimental data. The advancement of

information technology has led to the accumulation of huge data related to food. Large-scale data analysis, which incorporates machine learning and network analysis, has revolutionised our understanding of food perception and consumption, with implications for our future food choices and habits (Mouritsen et al., 2017). A new research discipline such as computational gastronomy has been introduced by Ahnert (2013). The application of computers in the field of culinary arts has significantly contributed to creating new ingredient pairings which may lie beyond the chef's mental repositories. This system of using machine-generated information in creating of completely new flavour combination which has not been used before is considered to be a culinary application of computational gastronomy (Varshney et al., 2013). The development of data-driven systems has paved a way for food companies and skilled chefs to create new recipes considering the diversity in regional cuisine styles and personal food preferences. However, to create new recipes it is important to determine the degree of mixing of ingredients in each recipe, taking into account the style of regional cuisine and the algorithm developed should be able to replicate the selected regional cuisine style (Kazama et al., 2018).

The science of culinary arts varies from one region to another, the

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**Table 1**  
Regional cuisine statistics.

Regional cuisine	Number of recipes	Number of ingredients	Average number of ingredients per recipe
Assam	319	105	6.725
Arunachal	41	49	4.199
Manipur	38	56	7.148
Meghalaya	34	28	4.428
Mizoram	30	39	4.121
Nagaland	78	38	4.734
Sikkim	52	52	4.708
Tripura	28	37	5.045

difference in the food choice is the result of the differences in flavour preferences. However, there are flavour similarities in regional cuisines that are geographically adjacent to each other (Zhu et al., 2013). The north-eastern part of India is a geographically and culturally significant region. Furthermore, it is referred to as a ‘cultural area’ because it lies outside of, or on the outskirts of, three main academic study regions: East Asia, Southeast Asia and South Asia (de Maaker and Joshi, 2007). The region may be regarded as the north-western borderland of South-east Asia as well as the north-eastern borderland of South Asia (van Schendel, 2002). The rich cultural heritage is derived from the distinct cultures of various ethnic groups. The tastes and flavours of many traditional foods and dishes define each regional cuisine’s culinary identity. The ethnic foods consumed by diverse tribal peoples in North-east India, as well as many other aspects such as food consumption patterns, nutritional content, therapeutic value, and availability, should all be investigated, documented, and analysed (Singh and Singh, 2007). To take advantage of the region’s cultural affinity towards both South Asia and South-East Asia, the region’s culinary tradition has been studied using a modern network theory-based principle.

Our work focussed to provide a scientific validation to the existing trend of ingredient usage patterns in the eight regional cuisines of the Northeastern region of India viz, Assam, Arunachal, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim and Tripura. The work was carried out based

on the available data in food recipes in the form of cookbooks and online repositories. Studies have been reported for the eight regional cuisines of India by Jain et al. (2015) where a negative food pairing behaviour was reported as a common trend. As a result, our study aims to determine whether a uniform trend of negative food pairing behaviour is maintained across the Northeast regional cuisines.

## 2. Materials and methods

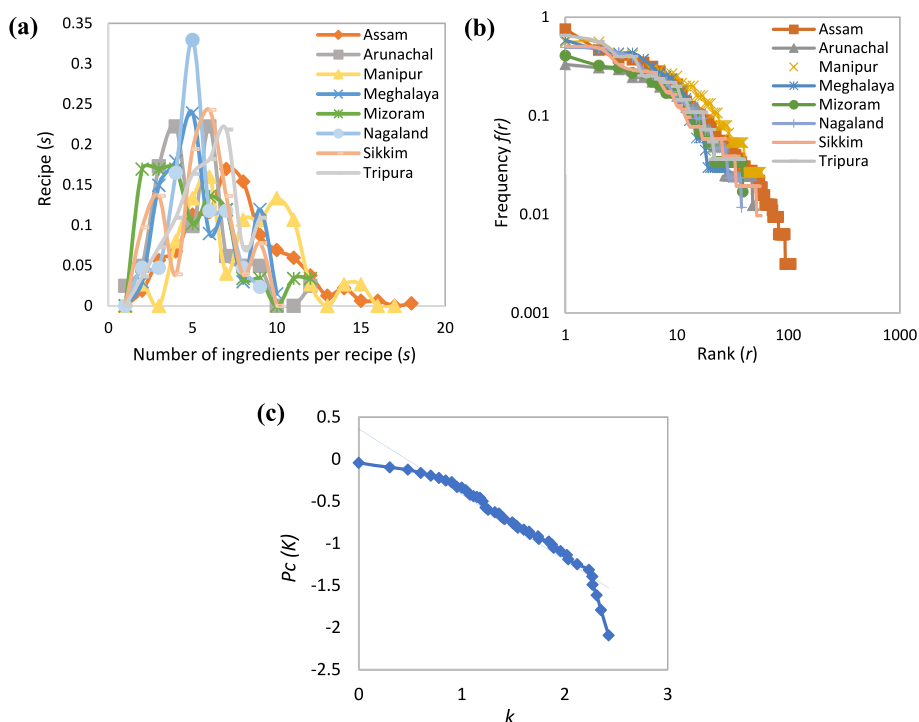
### 2.1. Principle of flavour network theory

#### 2.1.1. Theory

The flavour network is a weighted network that is formed by the projection of a bipartite network. A bipartite network consists of two kinds of nodes (i) ingredients present in the recipes and (ii) ingredient flavour compound of each ingredient known to contribute to the flavour of ingredients. The construction of a flavour network for the regional cuisine was carried out to validate the food pairing hypothesis to examine whether we combine ingredients that share a significant link or we avoid them? The flavour network consists of a node and edges, in our study each node represents the ingredients and the edges/link represent the number of flavour compounds shared amongst the ingredients. Further, to circumvent the high density of the network we carry out a process of backbone extraction for clear visualization of the network. Only the statistically significant edges/links are retained in the network’s extracted backbone (*p*-value 0.04) (Ahn et al., 2011).

#### 2.1.2. Inference

The general theory behind ingredient blending in foods is the flavour pairing theory, which states that ingredients are more likely to blend when they have common flavours. To prove whether or not we should combine ingredients with a strong link in the flavour network, we need data on ingredient combinations that are commonly accepted and liked by people, which can be found in the form of culinary recipes. Flavour pairing was applied as a fundamental algorithm to identify new ingredient pairings in recipes, develop a recipe recommendation system, and



**Fig. 1.** (a) Regional cuisine recipe size distribution (b) Regional cuisine frequency rank distribution (c) Regional cuisine complementary cumulative degree distribution plot.

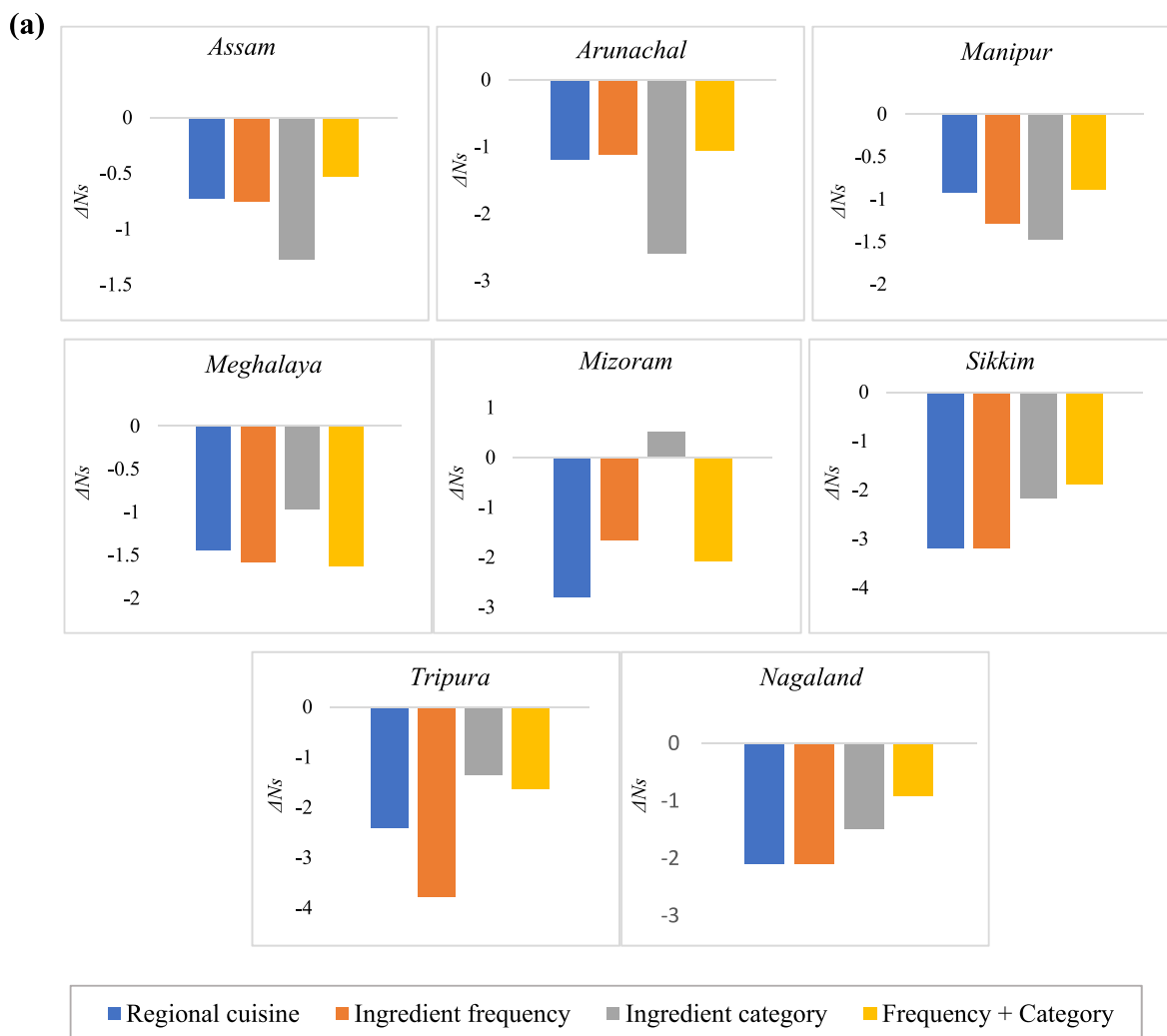


Fig. 2. (a) Statistical significance of  $\Delta N_s$ , which indicates the extent of bias in food pairings of regional cuisines with their random models (b) Regional cuisine rank frequency distribution with its equivalent random mode.

generate new recipes, contributing to the creative domain of culinary arts (Ahn et al., 2011).

## 2.2. Data collection and pre-processing

### 2.2.1. Data collection

This procedure involves gathering recipe data from various sources including internet sources and cookbooks (Jyoti, 2014; Hauzel, 2014; Shridar and Singh, 2014) utilised in most commercial operations. Cookbooks are considered to be an important source in recipe data curation as it provides the required statistical information about cuisines which includes preparation methods, the combination of ingredients and the importance of the foodstuffs (Kinouchi et al., 2008). The majority of the recipes collected are largely traditional recipes that are known to symbolise the region's culinary arts.

### 2.2.2. Pre-processing of data

This procedure involves pre-processing the recipe dataset to obtain an ingredient list. Furthermore, unnecessary phrases and quantifiers are eliminated. In doing so we generate the final recipe dataset consisting of the recipe and its corresponding ingredients. The ingredients were mapped to their flavour profile (volatile compounds present in the ingredient) and categorized into their constituent category. The two major processes involved were,

- Pre-processing of redundant phrases: The ingredients were aliased back to their sources. Ginger paste, for example, was referred to as ginger. Furthermore, spices like garam masala, ginger-garlic paste, and panch phoran seeds were separated into their constituent individual ingredients to preserve a stable ratio of single ingredients.
- Preprocessing in quantifiers: Quantifiers such as '1 cup' or '1 ml' were removed, as were phrases referring to temperature or consistency, such as hot/cold or chopped/shredded.

### 2.3. Ingredients flavour compound data collection

The ingredient flavour compound data was gathered from archived data of Ahn et al. (2011) and Jain et al. (2015). The flavour compound data of those additional ingredients of the NE regional cuisine which are not found in the archived data, such as bamboo shoots, Fermented bamboo shoots, Fermented rice, and Fermented fish were gathered from literature sources (Fu et al., 2002; Garg et al., 2018; Lee et al., 2019; Mohamed et al., 2012).

### 2.4. Statistical analysis

#### 2.4.1. Classification of cuisine

The preliminary statistical investigation was carried out which involves, the analysis of recipe size and frequency rank distribution of the

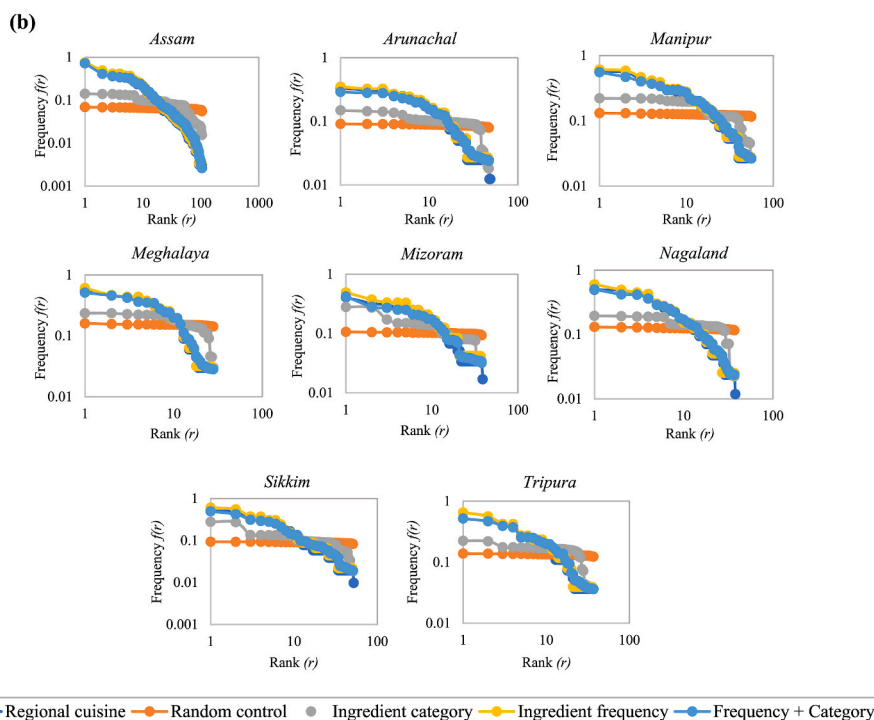


Fig. 2. (continued).

**Table 2**  
List of top 5 authentic ingredients.

Regional cuisine	Authentic ingredients				
Assam	black mustard seed oil	onion	green bell pepper	turmeric	garlic
Arunachal	green bell pepper	ginger	cayenne	black mustard seed oil	pork
Manipur	onion	black mustard seed oil	cayenne	ginger	bay laurel
Meghalaya	onion	green bell pepper	Ginger	black mustard seed oil	pork
Mizoram	black mustard seed oil	rice	Onion	ginger	cayenne
Nagaland	cayenne	garlic	Ginger	green bell pepper	tomato
Sikkim	onion	black mustard seed oil	green bell pepper	cayenne	turmeric
Tripura	green bell pepper	onion	Ginger	garlic	pork

regional cuisine.

- a) *Recipe size:* In a preliminary statistical investigation we determined the size of the recipe for the cuisine. The basic trend of ingredients used by the cuisine was then explored by calculating the average recipe size. The measurements were made to highlight the overall ingredient usage pattern in the cuisine.
- b) *Frequency-rank distribution:* This process is carried out to determine if the ingredients used in the cuisine exhibit a uniform pattern. We assigned a ranking to the ingredient based on their decreasing frequency of use in the cuisine. In addition, we determine the degree distribution for the ingredients which is the probability distribution

$P_I(k)$  to define and test the likelihood of a random ingredient appearing in  $k$  recipes. Further, the complementary cumulative degree distribution  $P_c(k)$  plots were compared to a pure power-law distribution to check if they are similar (Kinouchi et al., 2008).

$$P_c(k) = 1 - \sum_k P_I(k) \tag{1}$$

#### 2.4.2. Flavor sharing behaviour

Flavour sharing analysis is the preliminary process to examine and validate the flavour pairing hypothesis of the regional cuisines. The average number of shared flavour compounds in the recipe having  $s$  number of ingredients  $N_s(R)$  is first calculated (equation (2)), where  $R$  indicates a culinary recipe,  $F_i$  and  $F_j$  represents the set of flavour compounds in ingredients  $i$  and  $j$  in  $R$ . Additional, for cuisine with  $N_c$  recipes we calculate the mean of  $N_s(R)$  to estimate the flavour sharing index  $\bar{N}_s$  as to which degree the flavour pairing exists overall (equation (3)).

$$N_s(R) = \frac{2}{s(s-1)} \sum_{i,j \in R, i \neq j} |F_i \cap F_j| \tag{2}$$

$$\bar{N}_s = \frac{1}{N_c} \sum_R N_s(R) \tag{3}$$

We further validate the shared compound hypothesis, indicative of whether ingredients sharing flavour compounds appear more often in the cuisine. The process involves considering a null hypothesis. A reference model of a randomly constructed recipe is generated from the set of ingredients similar to the overall universe of ingredients considering a probability distribution. To examine the mechanism that contributes to food pairing bias, a set of four random controls was generated from the existing set of recipes. The uniform selection of ingredients provided the first model of random control. The second model was generated by selecting an ingredient while keeping its frequency in mind. The third model was generated by considering the ingredient while keeping the category in mind. The final model was generated by choosing ingredients while keeping the category and frequency in mind. Finally, we compared the difference between  $\bar{N}_s^{Real}$ , degree of the flavour

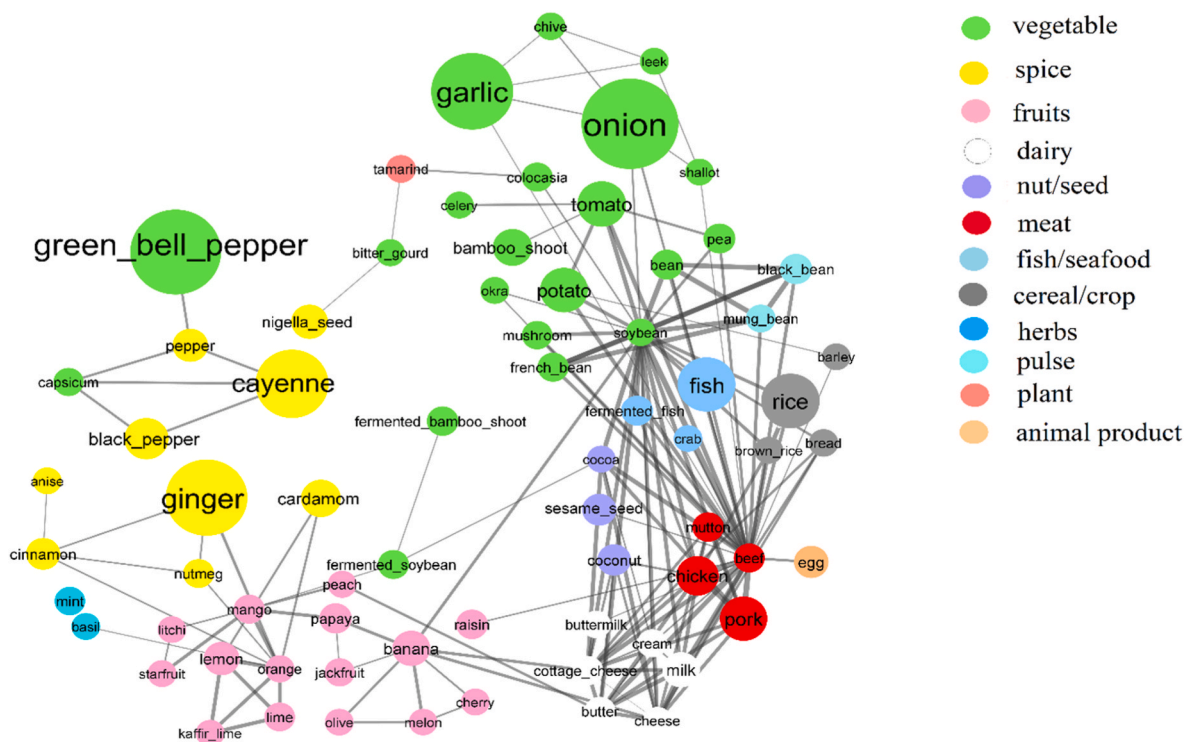


Fig. 3. Flavour network.

pairing of the original cuisine (*Real*) and the  $\bar{N}_s^{Rand}$ , degree of the flavour pairing of randomly constructed cuisine (*Rand*) by calculating  $\Delta N_s$ ,

$$\Delta N_s = \bar{N}_s^{Real} - \bar{N}_s^{Rand} \tag{4}$$

The variation in  $\Delta N_s$  measure, if close to null/zero indicates that there is no significant relationship between the recipe and the flavour compounds. If positive, it indicates that the original recipe has a strong influence over the random recipe where ingredients tend to share more flavour compounds in the recipe validating the shared compound hypothesis. If negative it indicates that the ingredients used in the recipe do not share flavour compounds (Varshney et al., 2013).

#### 2.4.3. Contribution of ingredients

The analysis of ingredient contribution determines the degree of contribution of each ingredient towards the food pairing effect. It can be obtained by calculating each ingredient's contribution  $\chi_i$  to the measure of  $\bar{N}_s$  and analysing it as follows,

$$\chi_i = \bar{N}_s(C) - \bar{N}_s(C^i) \tag{5}$$

here,  $\bar{N}_s(C)$  is the degree of the flavour pairing of a given cuisine *C*, and  $\bar{N}_s(C^i)$  is the degree of the flavour pairing of the cuisine *C* without the ingredient of concern *i*. If an ingredient's contribution is positive, removing the ingredient from the cuisine would cause the  $\bar{N}_s$  measure to decrease. Whereas, if an ingredient's contribution is negative, removing the ingredient from the cuisine would cause the  $\bar{N}_s$  to increase. The differences in the measure of  $\bar{N}_s$  results in determining to which degree it affects the overall food pairing behaviour. This defines the pattern of ingredient combinations in the cuisine, the higher the contribution, the more flavour sharing ingredients are included in the cuisine, and vice versa (Petar, 2019).

#### 2.4.4. Authenticity of ingredients

Every regional cuisine has its specific ingredients that represent the taste palette of the region. Such ingredients are considered to be

uniquely placed in the cuisine which is considered to be authentic. As we explore the authenticity of ingredients across the regional cuisine it helps us to understand the similarities or dissimilarities between the various regional cuisines. We also examine the authenticity of each ingredient ( $P_i^c$ ), ingredients pair ( $P_{ij}^c$ ), and ingredient triplet ( $P_{ijk}^c$ ) based on the frequency with which a particular ingredient appears in a particular cuisine's recipe. Each ingredient's prevalence  $P_i^c$  in a cuisine *c* is defined as,

$$P_i^c = n_c^i / N_c \tag{6}$$

where  $N_c$  is the total number of recipes in the cuisine and  $n_c^i$  is the number of recipes in the cuisine that contain the particular ingredient *i*. The relative prevalence  $P_i^c = P_i^c - (P_i^c)_{C \neq c}$  determines the authenticity of the ingredient *i* which gives the difference between the prevalence of *i* in a particular cuisine *c* and the overall average prevalence of *i* in all other cuisines of each ingredient ( $P_i^c$ ), ingredients pair ( $P_{ij}^c$ ), and ingredient triplet ( $P_{ijk}^c$ ) respectively (Ahn et al., 2011).

### 3. Analysis and findings

#### 3.1. Recipe size statistics and frequency rank distribution

A preliminary study of the eight regional cuisines has been carried out to examine the size of the recipe and the pattern of ingredient usage across the regional cuisine. The statistics of the regional cuisines consisting of the recipe and its ingredients have been listed in Table 1. The regional cuisine of Assam showed a larger average recipe size followed by Manipur, as shown in Fig. 1a.

The statistical characteristic of the cuisine is highlighted by the ingredient frequency rank distribution. As we sorted the items in decreasing usage frequency, the pattern of ingredient distribution across each regional cuisine revealed an invariant pattern, as illustrated in Fig. 1b. Furthermore, we can see that specific ingredient are overused, indicating their popularity in the cuisine. In addition, the

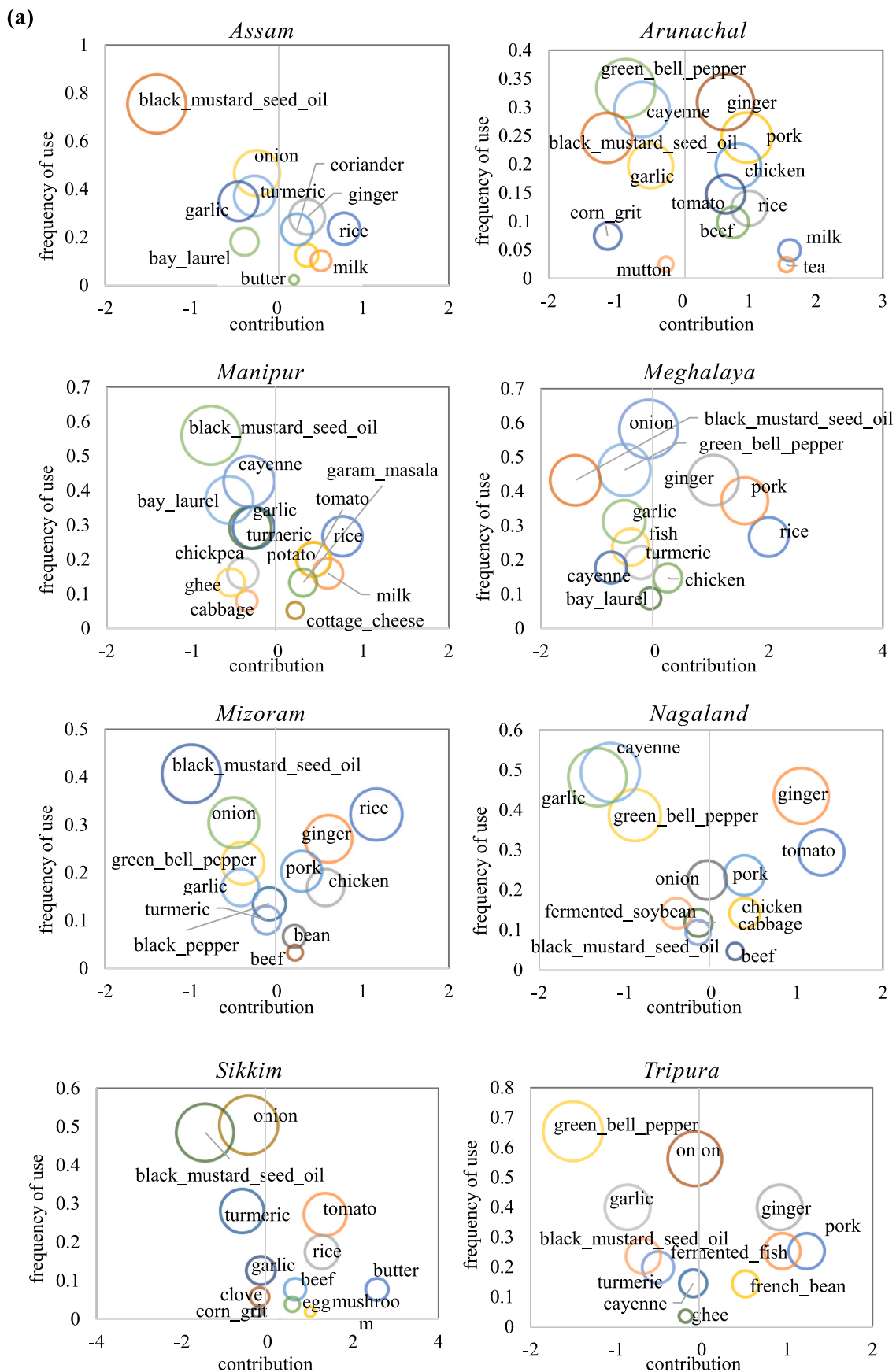


Fig. 4. (a) Ingredient contribution to regional cuisine's flavour pairing pattern vs. frequency of use in the cuisine (b) Change observed in  $\bar{N}_s$  values after removing the least contributing ingredients (c) Change observed in  $\Delta N_s$  values after removing the least contributing ingredients.

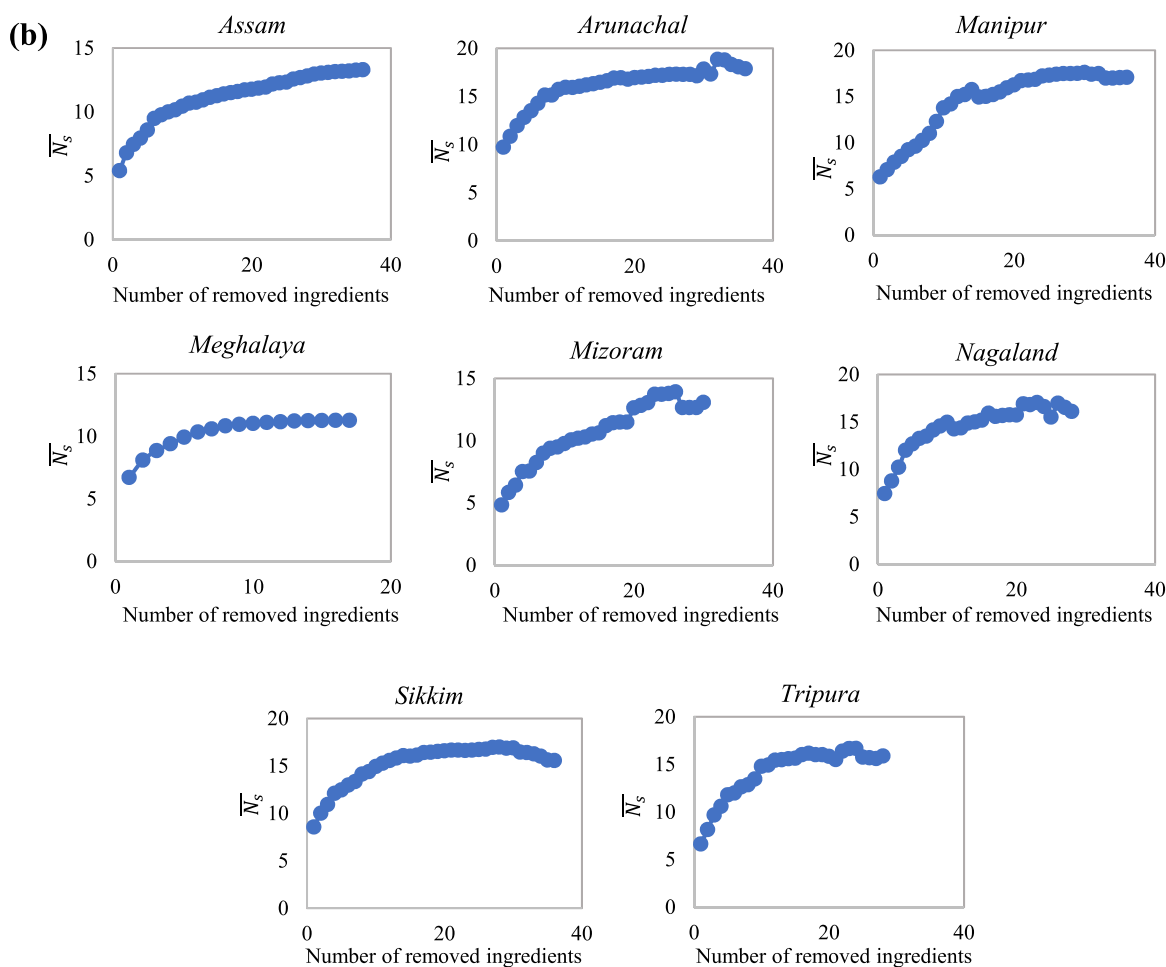


Fig. 4. (continued).

complementary cumulative degree distribution (Fig. 1c) of the ingredients in the cuisine displays a pure power-law with fit proportionate  $k^{-0.77}$  indicating that an ingredient is found in more than  $k$  recipes.

### 3.2. Food pairing

The art of culinary science varies across the regional cuisines as we observe distinct differences in the choice of ingredient usage and ingredient combination which stands unique to the particular region. Fig. 2a illustrates the statistics of the shared compound hypothesis at the regional cuisine recipe level. The extent of bias in the eight regional cuisines viz, Assam, Arunachal, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim and Tripura, when compared with the corresponding randomized cuisine showed uniform negative food pairing behaviour. In comparison, Sikkim showed the most negative food pairing with  $\Delta N_s$  value of  $-3.188$  while, Assam showed the least negative with  $\Delta N_s$  value of  $-0.726$ .

To validate the mechanism underlying the bias in food pairing behaviour the rank distribution of frequency of the regional cuisine was compared to its random model (Fig. 2b). We observed that the pattern created after the frequency composition was fixed was similar to the original cuisine. The pattern exhibited when the category composition was fixed, however, was equivalent to the random control. As a result, the frequency of ingredients can be considered a major indicator of the nature of food pairing behaviour. This behaviour was also recorded in a previous study on Assamese cuisine (Makinei et al., 2021).

The choice of ingredient combination in a recipe strongly determines the factor leading to the bias in food pairing as it depends on the number

of flavours compound each ingredient shares. The majority of the ingredients that made a substantial impact on the food pairing were from the spice category, such as cayenne, bay laurel and turmeric (Table 2). This highlights the prospect for food developers in developing new food products to cater to the preferences of the consumers who have more preferences for spicy flavoured products than for dairy flavoured products. Understanding the nature of ingredient usage in recipes in the cuisines of concern would aid in the development of recipes or products that would assure customer acceptability. Additionally, the ingredients used to create substitutes or supplements for certain lifestyle diseases, which often entail dietary restrictions must possess a balance between flavour, taste, and nutritional properties based on the list of foods that may be consumed (Mitra and Mitra, 2017). Development of healthy food with good sensory qualities is an area of application of the food pairing hypothesis and the findings of this work will facilitate the same for the Northeastern regional cuisines, for taking up as separate research work.

### 3.3. Flavour network

The flavour network is the outcome of backbone extraction, which was carried out to avoid the network's density and for clear visualization. The flavour network of the Northeast regional cuisines is shown in Fig. 3, in the graph, only ingredients with a large number of flavour compounds in common are shown ( $p$ -value 0.04). However, for the overall analysis, the entire network is taken into account. The flavour network of the Northeast regional cuisines showed that the most prevalent ingredient is mostly from the spice and vegetable categories. However, we can observe that the link/edges between ingredients from

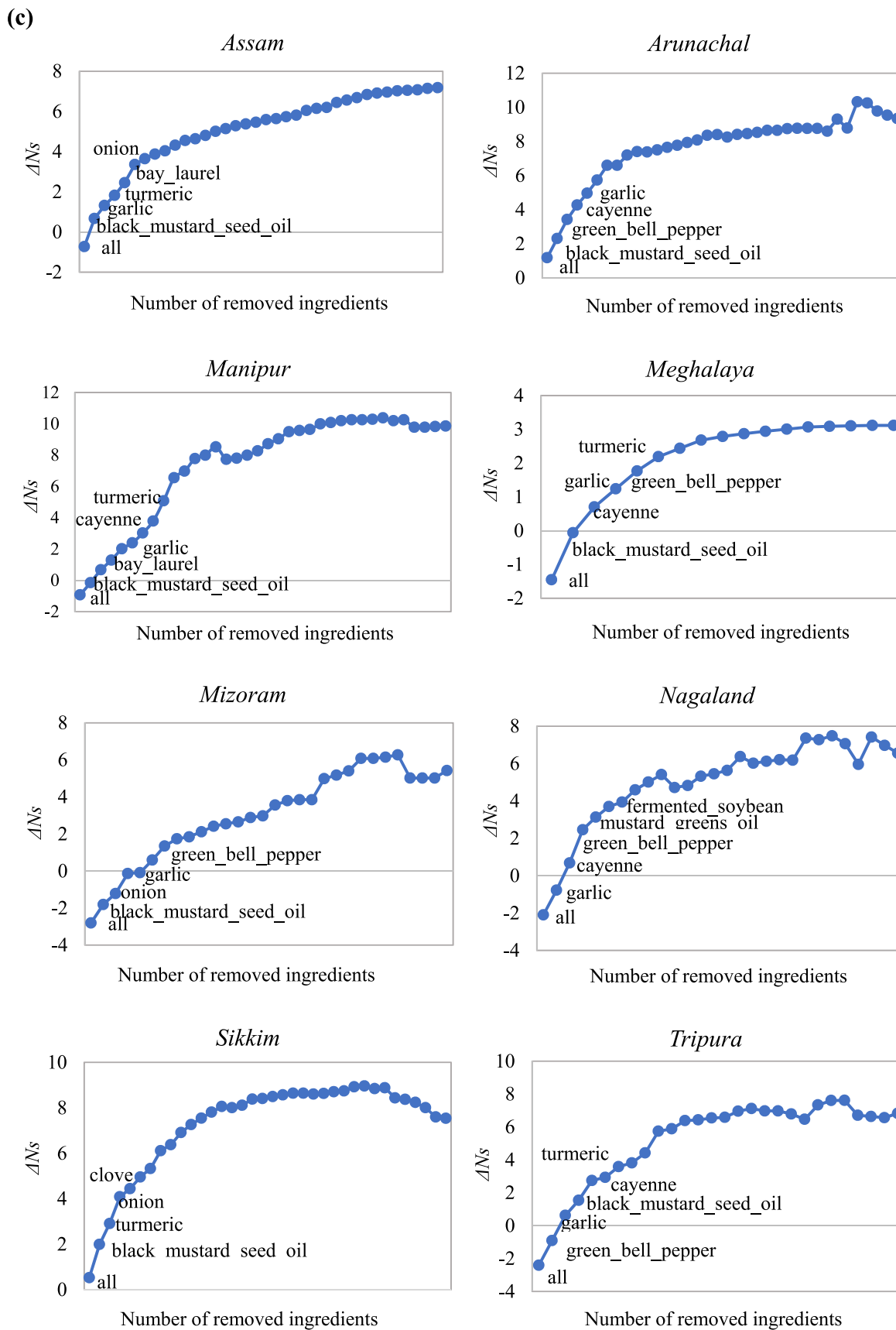


Fig. 4. (continued).



the spice categories are not as significant as compared to other categories such as dairy, cereal/crop and meat. This can be the reason behind the negative food pairing behaviour which has been observed in the majority of the regional cuisines.

### 3.4. Ingredient contribution

We studied the role of each ingredient to understand the mechanism underlying the type of food pairing behaviour and shared compound hypothesis in the regional cuisines if any alteration in the ingredients is to be made. According to our findings, the majority of the ingredients that made a substantial impact on food pairing were from the spice category (Fig. 4a). The change in the average food pairing index  $\bar{N}_s$ , increases as we remove the least contributing ingredients (Fig. 4b) therefore we can conclude that the contribution of the ingredient is negative. In addition, we observed that when we removed those ingredients which significantly contribute to the shared compound effect  $\Delta N_s$ , the original pattern drastically changes even after the removal of one ingredient, changing the food pairing pattern (Fig. 4c). Overall, we observed that spice, both as an individual and as a category, plays an important role in food pairing behaviour.

### 3.5. Ingredient authenticity

The majority of the authentic ingredients in Northeast regional cuisines are found to be from the category of spices such as green bell pepper, ginger, cayenne, bay laurel, garlic and turmeric (Table 2). When compared to ingredients from other categories, spice ingredients are seen to be distributed distinctively in the recipe, which has a substantial effect on the flavour pairing pattern. We can observe that among all the ingredients listed mustard seed oil i.e., an edible oil seems to be widely used in the recipes. This can be seen as one distinct characteristic of the Northeastern regional cuisine as in the other Indian regional cuisines sunflower oil is widely used except in Mughlai cuisine this study has been reported by Jain et al. (2015). In addition, the ingredient usage pattern is almost similar across the Northeastern regional cuisine. Geographical proximity may be a factor in the similarity of authentic ingredients as the Northeast states are close to each other. Zhu et al. (2013) in their findings have also highlighted that geographical distance increases the usage of similar ingredients.

## 4. Conclusion

The study revealed that the ingredients from the spice category were the most common ingredients that made a significant impact on the food pairing behaviour in the food recipes from the Northeastern regional cuisines. Ingredients such as black mustard seed oil, green bell pepper, onion, cayenne, ginger, garlic, rice, turmeric, bay laurel, tomato and pork were listed as the most authentic ingredients across the regional cuisines. In terms of pairing behaviour, the difference comes down to the question of how closely the flavour compounds are shared, i.e., either relatively low or high (negative and positive). Among the ingredients, cayenne, garlic, turmeric, and bay laurel contribute to the negative pairing. At the same time, ingredients such as ginger, tomato, and pork contribute to the positive pairing. Pork meat is identified as one of the most authentic ingredients in the Northeastern regional cuisine which is not the case for other Indian regional cuisines. This, along with the wider use of black mustard seed oil are some of the distinct characteristics of the Northeastern regional cuisine.

### CRedit authorship contribution statement

**L.V. Makinei:** Conceptualization, Methodology, Data curation, Investigation, Writing – original draft. **M.K. Hazarika:** Supervision,

Writing – review & editing.

### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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