The 16S microbiota of Budu, the Malaysian fermented anchovy sauce

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ABSTRACT

Budu is a Malaysian fermented anchovy sauce produced by immersing small fishes into a brine solution for 6 to 18 months. Fermentation of the anchovy sauce is contributed partly by microbial enzymes, but little is known about the microbial community in Budu. Therefore, a better understanding of the Budu microbiome is necessary to better control the quality, consistency and safety of the product. In this study, we collected 60 samples from twenty bottles of Budu produced by seven different manufacturers. We analyzed their microbiota based on V3-V4 16S rRNA amplicon sequencing at the time of opening the bottle as well as 3- and 7-months post-opening. *Tetragenococcus* was the dominant genus in many samples, reaching a maximum proportion of 98.62%, but was found in low abundance, or absent, in other samples. When Budu samples were not dominated by a dominant taxa, we observed a wider genera diversity such as *Staphylococcus*, *Acinetobacter*, *Halanaerobium* and *Bacillus*. While the taxonomic composition was relatively stable across sampling periods, samples from two brands showed a sudden increase in relative abundance of the genus *Chromobacterium* in the 7th month. Based on prediction of metagenome functions, non-*Tetragenococcus*-dominated samples were predicted to have enriched functional pathways related to amino acid metabolism and purine metabolism compared to *Tetragenococcus*-dominated microbiome; these two pathways are fundamental fermented quality and health attributes of fish sauce. Within the non-*Tetragenococcus*-dominated group, contributions towards amino acid metabolism and purine metabolism were biased towards the dominant taxa when species evenness is low, while in samples with higher species evenness, the contributions towards the two pathways were predicted to be evenly distributed between taxa.

Keywords: Microbiome, Fermented food, Fish sauce, *Tetragenococcus,* prediction of metagenome functions

1 INTRODUCTION

Budu is a Malaysian fermented anchovy sauce which is prepared by immersing anchovies in brine solution (salt concentration 21.5 – 25.7 %) containing natural flavor-enhancing ingredients and left to ferment in earthen containers for 6 to 12 months (Rosma et al., 2009). Compared to other Southeast Asian fish sauces such as Nuoc Mam from Vietnam and Nampla from Thailand which are transparent, Budu is turbid and heterogenous (Lopetcharat et al., 2001). Fish sauce such as Budu is as food condiment because of its pleasant umami flavor. It is also nutritious because it is rich in antioxidants, vitamins and fibrin-clotting inhibitors (Shivanne Gowda et al., 2016). However, certain metabolites in Budu might present as a potential health risk. For instance, Budu has a high amount of purine (Li et al., 2019) and histamine (Rosma et al., 2009), metabolites that are associated with gout (Paul and James, 2017) and scombroid poisoning (Tortorella et al., 2014), respectively.

Fish sauce microbes are responsible towards health and gastronomic properties of the fish sauce by altering the metabolite content of the fish sauce. For instance, *Tetragenococcus muriaticus* was known to produce histamine, while *Staphylococcus*, *Bacillus* and *Lactobacillus* were known to express histamine oxidase which can degrade histamine (Shivanne Gowda et al., 2016). Therefore, a better understanding of the Budu microbial community can elevate the Budu organoleptic and health value by harnessing its microbiome. So far, all microbiological studies of Budu to date were done based on culture-based methods. For example, Yuen et al. (2009) discovered bacterial succession takes place in Budu fermentation from *Micrococcus-* to *Staphylococcus arlettae*-dominated community, and uncovered the presence of yeast species such as *Candida glabrata* and *Saccharomyces cerevisiae*. Subsequent microbiological studies on Budu revealed a few other cultivable bacteria such as *Bacillus amyloliquefaciens* FS-05 and *Lactobacillus planatarum* which were able to produce glutamic acid which is associated with the the umami taste (Zaman et al., 2010; Zareian et al., 2012). A recent study on Malaysian fermented foods also displayed the potential of *Bacillus* sp. in producing biosurfactants that inhibit pathogenic bacterial growth (Mohd Isa et al., 2020). While culture-dependent methods are useful in gaining the first insights of role of microbes in Budu fermentation, they are biased towards microbes that can grow optimally under culture conditions. To date, there has yet any culture-independent methods to provide us an overview of the Budu microbial diversity.

In this study, we surveyed the microbial community of 60 samples from twenty bottles of Budu purchased of multiple brands. We investigated their microbial community structure at different sampling periods. We then find association between the microbial composition and diversity found in Budu with its predicted metabolic pathways. Lastly, we explored the use of microbial interaction networks modeled on 16S abundance information.

2 MATERIALS AND METHODS

2.1 Sample collection

Twenty bottles of Budu from different brands were purchased from shops in the state of Kelantan, Malaysia, at five different time points (July 2016, October 2016, November 2016, March 2017 and April 2017). These twenty bottles were sampled at three different periods (24th April 2017, 24th July 2017 and 20th November 2017), amounting a total of 60 samples. The samples were stored at room temperature to emulate typical retail storage condition. The sample metadata is shown in Table 1. Samples were named according to the following format:<brand><bottle number>_<months since last opened>.

2.2 DNA extraction and sequencing

200 µl of the sample was poured into 1.5 ml Eppendorf tubes and centrifuged at 14 800 rpm for 15 minutes to remove the supernatant. The samples were then resuspended in 400 µl of 20 mM Tris-EDTA buffer and added with 100 µm silica beads (OPS Diagnostics LLC, Lebanon, NJ, USA). The samples were later subjected to bead beating using Vortex Genie 2 Mo Bio (Carlsbad, CA, USA) at 3200 rpm for 1 hour. They were later added with 20 ul of 0.5% SDS and 20 ul of 50 mg/ml Proteinase K and incubated at 55°C for 1 hour. The samples were added with 100 ul of saturated potassium chloride solution and were later incubated on ice for 5 minutes. Total DNA was extracted using chloroform-isopropanol precipitation and purified with Agencourt AMPure XP beads (Beckman Coulter, Inc., Indianapolis, IN, USA).

The V3-V4 region of the 16S rRNA gene was amplified using the forward primer 5'-TCGTCGGCAGCGTCAGATGTGTATAAGAGACAGCCTACGGGNGGCWGCAG-3' and reverse primer 5' GTCTCGTGGGCTCGGAGATGTGTATAAGAGACAGGACTACHVGGGTATCTAATCC-3' containing partial Illumina Nextera adapter sequence (Klindworth et al., 2013) following the Illumina 16S Metagenomic Sequencing Library Preparation protocol. To enable multiplexing, 16S amplicons were barcoded using different pairs of index barcodes to prepare DNA libraries. DNA libraries were normalised, pooled, denatured and sequenced on the Illumina MiSeq (Illumina, San Diego, CA, USA) in Monash University Malaysia Genomics Facility, using either 2×250 bp or 2×300 bp run configuration.

2.3 Sequence data analysis, phylogenetic tree construction, taxonomic assignment and generation of feature table

The forward and reverse PCR primer sequences were trimmed off using Cutadapt version 1.16 with default parameters (Martin, 2011). Paired-end sequences were merged using fastq_mergepairs, and quality-filtered using fastq_filter (-fastq_maxee: 1.0, -fastq_minlen: 300) in USearch v10.0.240_i86linux32 (Edgar and Flyvbjerg, 2015). High-quality sequences were then denoised to create amplicon sequence variants (ASVs); the ASV sequences can be obtained from Supplementary File 1. The ASV sequences that were generated were used as reference sequences to create a raw feature table, using UNoise3 in USearch (Edgar, 2016). The raw feature table was further processed by filtering out chloroplast and mitochondrial ASVs (see below for a description on taxonomic assignment) and by rarefying to 6,000 reads per sample for downstream analyses (Supplementary File 3).

Multiple sequence alignment of the ASV sequences was conducted using MAFFT while masking unconserved and highly gapped sites (Katoh and Standley, 2013). A phylogenetic tree was then constructed from aligned ASV sequences and was rooted at midpoint using FastTree version 2.2.10 (Bolyen et al., 2019; Price et al., 2010). 16S V3-V4 Naive-Bayes classifier was trained on V3-V4-trimmed 16S sequences of the SILVA 132 release, using q2-classifier plugin in QIIME 2 (Bokulich et al., 2018; Pedregosa et al., 2011) . The SILVA reference sequences were trimmed using the same primer sequences and parameters for the raw sequencing data. The ASV sequences were then taxonomically assigned using the trained classifier; the taxonomic assignments of all ASV sequences can be found in Supplementary File 2.

2.4 Calculation of alpha and beta diversity indices and comparison of genera distribution between sampling batches

Species richness indices (observed ASVs and Faith PD) as well as species evenness indices (Simpson and Shannon) were calculated using QIIME2 (Bolyen et al., 2019; Hunter, 2007). All calculations of Alpha diversity indices were done at ten iterations per sequencing depth. Wilcoxon paired tests were done to compare species richness between sampling batches, as implemented using DABEST-python library (Ho et al., 2019). Since there is only one bottle for brand F and G, samples from these brands were not included in statistical comparisons of alpha diversity analyses.

Beta diversity was measured based on Bray-Curtis and weighted UniFrac to calculate distances

between microbiota of the samples (Lozupone et al., 2011). ASV- and genus-level relative differential

abundance between sampling batches were done using QIIME2 plugin ANCOM (Mandal et al.,

2015).

2.5 Functional and pathway prediction

Using the normalised feature table as input data, function and pathway prediction pipelines were

conducted using PiCrust2 (Douglas et al., 2020)☐. Briefly, ASVs were phylogenetically placed into a

reference phylogenetic tree using EPA-NG and gappa (Barbera et al., 2019; Czech et al., 2020)☐.

Hidden state prediction to predict 16S copy number was applied using castor R package (Louca and

Doebeli, 2018)☐ to normalise the feature table based on 16S copy number information. This is

followed by prediction of Nearest Sequenced Taxon Index (NSTI) score per ASV. ASVs with NSTI

score which is higher than 2.0 were assumed to not have a representative genome in the reference

phylogenetic tree, thus were filtered out from subsequent analyses. Afterwards, prediction of gene

family abundance was done against the enzyme commission, EC database, followed by prediction of

pathway abundance against METACYC database (Ye and Doak, 2009)☐. Scores of these predictions

were normalised by sequencing depth per sample (6000 reads). Predicted functional table and

predicted pathway table can be obtained from Supplementary Files 4 and 5.

Predicted pathway table was subjected to Bray Curtis distance normalization, followed by

multidimensional scaling (MDS) ordination (ratio transformation) using Ecopy

(https://github.com/Auerilas/ecopy). Samples with high relative abundance of *Tetragenococcus*

formed a distinct cluster which separated from non-*Tetragenococcus* dominated samples. To compare

potential pathways that distinguishes the two groups, post-hoc t-test was applied, adjusted by false

discovery rate Benjamini Hochberg; a predicted pathway with corrected p-value of below $1<10^{-5}$ and

Cohen d effect size of at least 3 is to be considered as significantly different between

Tetragenococcus-dominated group and non-*Tetragenococcus*-dominated group (Terpilowski, 2019;

Vallat, 2018)☐.

2.6 Microbial association network

SPIEC-EASI 0.1.4 was used to predict the microbial association network based on co-abundance (Kurtz et al., 2015). Since SPIEC-EASI applies its own normalization method, the mitochondria and chloroplast ASVs-filtered unrarefied feature table was used as the input table. ASVs were also filtered by prevalence at the minimum occurrence of 30 samples.

Meinshausen-Bühlmann neighborhood selection model was used to model the microbial interaction network at 10,000 replications (Meinshausen and Bühlmann, 2006), and at a variability threshold of 0.05% using StARS (Liu et al., 2010). R igraph package was used for the network visualization and extracting network properties (Csardi and Nepusz, 2006). To find for important nodes in the graph, degree centrality and betweenness centrality were two node centrality measures computed from the predicted network. Degree centrality weighs a node's importance by counting the number of edges linked to the node, while betweenness centrality evaluates the geodesic distances from all node pairs that are passing through the particular node. High degree centrality suggests a role as a keystone species, while high betweenness centrality predicts its importance in maintaining the structure of the interaction network.

3 RESULTS

3.1 The Budu microbiome is inconsistent within the same brand even at high-level taxonomic composition

Firmicutes, Proteobacteria, Halanaerobiaeota, Actinobacteria, and Bacteroidetes were the top five most abundant phyla across all Budu samples (Figure 1A) with an average relative abundance of 60.26%, 22.86%, 10.60%, 3.91%, and 1.91% respectively, while other lesser phyla contributed less than 0.5%. The cumulative relative abundance of the top five most abundant phyla in each sample ranges from 95.75% to 100.00%. The relative abundance of dominant phyla were not statistically different between sampling periods (Wilcoxon paired test $p > 0.4$) , thus the phyla composition was fairly stable across time.

We observed different trends of phyla composition between and within different brands and manufacturing batches. For example, all samples from Brand D were consistently dominated by Firmicutes, making up an average relative abundance of 93% in each sample. On the contrary, some samples displayed uneven phyla distribution within brand. For example, Halanaerobiaeota made up a substantial portion from 18.8% to 48.4% in C1, C3 (except sample C3_0) and C4 samples but was markedly smaller in C2 samples (average = 2.2%). In another instance, a substantial proportion of Proteobacteria and Halanaerobiaeota was found in A2 and A3 samples respectively, which observed in very low proportion in A1 samples. The distinct phyla composition of Budu microbiome was recapitulated in the Principal Coordinates Analysis (PCoA) plot based on Weighted UniFrac distances (Figure 1B). For example, there are three clusters of brand A; each cluster consists of three points correspond to three sampling batches per bottle. This suggests that the microbiome of brand A samples from the same bottle were closely similar and that microbiome of samples of brand A of different bottles were clearly different. This sub-clustering trend was also observed in brand B, providing further evidence that the Budu microbiome observe of bottles of the same brand is inconsistent in some brands.

In weighted-UniFrac PCoA, samples that were dominated by Firmicutes cluster very closely to one side (Figure 1B; red dashed outline). This cluster included samples from multiple brands such as brand D and G. However, in the Bray Curtis distances PCoA, which weighs in only abundance information but not phylogenetic relationship between ASVs, this clustering is not observed. Brand D formed an isolated cluster away from other Firmicutes-dominated samples in Bray Curtis PCoA. This difference between weighted-UniFrac and Bray Curtis clustering indicates that brand D samples contained phylogenetically close but distinct ASVs.

Fourteen genera were found in at least half of the samples (Figure 2). Based on the enormous relative
abundance (average = 38.77%, max. = 98.62%) and prevalence (96.62%), *Tetragenococcus* represents
the most dominant genus of the Budu microbiome. Although it is prevalent and dominant in some
samples, it was also present in low abundances in certain samples like samples from bottle A2 and
samples from brand E. *Halanaerobacterium* is another genus that made up substantial proportion of
some Budu microbiome (max. = 58.15%), despite its lesser prevalence than the *Staphylococcus* and
Acinetobacter. *Tetragenococcus* and *Halanaerobium* are the only two genera that can reach an
abundance of over 50% of reads per sample – this was observed in 21 samples (brands A, B, D and G)
and 3 samples (brand C) respectively.

Despite the lower overall prevalence of *Weissella* (50%), it made over 20% of the genera composition
in four samples - this degree of abundance was not observed in several genera of higher prevalence
such as *Acinetobacter, Pseudomonas, Psychrobacter, Corynebacterium_1, Lentibacillus, Kocuria,*
Brevibacterium, and *Paracoccus*. Meanwhile, there are other prevalent taxa which are present at
lower abundance. For example, the highest abundance of *Comamonas* was at most 1.22 % of reads
per sample, despite being present in half of the samples. This shows that increasing prevalence of
genus in the samples is not predictive of its relative abundance. None of the core genera are 100%
prevalent.

Within *Tetragenococcus*, we detected two different species which are *Tetragenococcus muriaticus*
(ASV1) and *Tetragenococcus halophilus* subsp. halophilus (ASV3, ASV4 and ASV7)
(Supplementary Figure 1). *T. muriaticus* composition was consistently high in brand D, while *T.*
halophilus subsp. halophilus was especially abundant in some bottles of brand A, B and G. We also
observed the co-presence of both *Tetragenococcus* species in some samples such as C1 samples and
samples from brand F. The consistent high abundance of ASV1 in brand D is likely to explain the
sub-cluster formed by brand D samples occurring in the Bray Curtis PCoA. *Halanaerobium*,
Staphylococcus and *Weissella* are the only genera with ASVs above 10% relative abundance.

Bacillus was the most commonly isolated bacterial genus from Budu (Mohd Isa et al., 2020; Zaman et
al., 2010)☐. The abnormally enormous number of *Bacillus* ASVs (Figure 2) is possibly explained by
the historically poor taxonomic demarcation of the *Bacillus* taxonomy (Patel and Gupta, 2020)☐.
Only recently, recent efforts proposed the revision the *Bacillus* taxonomy (Patel and Gupta, 2020)☐.
By maximum likelihood phylogenetic tree of partial V3-V4 16S sequences, *Bacillus* ASVs from Budu
were represented in different clades within the *Bacillus* genus (Supplementary Figure 2). ASV18 was
the most abundant and prevalent *Bacillus* ASV, belonging to the Cereus clade (max. = 7.05%).
However, the bootstrap support values of the tree were low, ranging from 0.34 to 0.75. This indicates
the limited phylogenetic resolution of partial 16S sequence that was also shown previously (Patel and

Gupta, 2020)▯. Some nodes were positioned into a different clade than expected, reflecting the
limitations of 16S sequence as a marker to *Bacillus* evolutionary history, in a few cases. The
resolution of *Bacillus* taxonomy and functional diversity in Budu can be further confirmed in the
future using genomes sequences of more *Bacillus* isolates or metagenome-assembled genomes from
Budu.
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3.2 Comparison of Budu across time reveals minimal differences in
alpha diversity, followed by detectable shifts in relative abundance of a
few genera

Some Budu samples within a brand had greatly different species richness (Figure 3A and B), which
was apparent in brands A and E. This is congruent with the inconsistent phyla composition within a
brand (Figure 1). There were also apparent changes in alpha diversity across sampling batches. After
3 months, increase in observed ASVs and Faith PD were generally observed in most bottles of brand
A, C and E. The alpha diversity indices decreased while a few steadily increased in some of the
bottles between month 3 and month 7. There are also inconsistent shifts in species richness in brand B
samples. The rarefaction plots of observed features and Faith PD indices are shown in Supplementary
Figure 3. Some rarefaction curves did not completely plateau, such as those from brand D and E did
not completely plateue, indicating that certain samples may contain rare taxa which were not sampled
at sequencing depth of 6000 reads.
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When comparing the genera distribution between sampling batches, *Chromobacterium*, *Barnesiella*
and [*Ruminococcus] torques* group displayed significantly differential abundance (W statistic > 0.6x
of total features) and F statistic (> 10), as seen in Figure 3C. The relative abundance of
Chromobacterium was higher at later sampling, reaching above 10% in brand E samples, detected in
lesser abundance in brand D samples, while being virtually absent in other samples (Figure 3D,
Supplementary Figure 4). The relative abundance of *Barnesiella* and *Ruminococcus torques* were
much lower and did not correlate with any common metadata. Relatively minute abundances were
seen in later sampling in only a few samples, suggesting that they were native members of the Budu
microbiome, but at a lower relative abundance. Decreased relative abundance of these genera might
be due to increase in relative abundance of other taxa. Comparison of taxonomic distribution at ASV
level between sampling batches resulted in no significantly differential ASV distribution.

3.3 Comparison between *Tetragenococcus*-dominated and non-*Tetragenococcus*-dominated microbiome in terms of predicted pathways reveal differential enriched predicted pathways, primarily related to amino acid and purine biosynthesis

Based on predicted pathways information, samples dominated by *Tetragenococcus* form a distinct cluster away from non-*Tetragenococcus*-dominated samples (PERMANOVA p-value 0.001, Figure 4A). By looking at pathways that were significantly different between the two groups, it was apparent that a few pathways, such as those involved in cell wall biosynthesis pathways and lactose and galactose degradation I (LACTOSECAT-PWY) were enriched in *Tetragenococcus*-dominated microbiome (Figure 4B). However, a diverse array of predicted pathways were enriched in non-*Tetragenococcus*-dominated microbiome, especially those involved in purine biosynthesis, amino acid metabolism and vitamin/cofactor/carrier biosynthesis. Purine and amino acid biosynthesis are implicated with organoleptic quality of fermented foods. Therefore, we attempted to look within the non-*Tetragenococcus*-dominated microbiome for predicted contributions of individual genus to these two pathways. We did not observe changes in predicted enriched pathways across sampling batches.

Aside from *Tetragenococcus*, *Staphylococcus*, *Halanaerobium*, *Bacillus* and *Weissella*, other prevalent genera did not appear to contribute much towards purine and amino acid biosynthesis, relative to the cumulative contribution of the remaining lesser genera (OTHERS) (Figure 4D). By focusing on the top three most abundant genera per sample regardless of taxonomic prevalence, purine and amino acid biosynthesis in samples of low Shannon index (Figure 4C) were contributed by the dominant genus (Figure 4E). This includes samples without high prevalence genus such as samples from bottle E2 (Figure 4D). This was not observed in samples with high Shannon diversity index. For instance, samples from bottles E1 and E3 which have relatively high Shannon scores possess high percentage of contribution from the remaining genera instead of the top three most abundant genera per sample (Figure 4E).

There are several predicted pathways which are enriched in non-*Tetragenococcus*-dominated samples, such as L-methionine biosynthesis (transsulfuration) (PWY-5347), L-histidine biosynthesis (HISTSYN-PWY), flavin biosynthesis I (bacteria and plants) (RIBOSYN2-PWY) and superpathway of tetrahydrofolate biosynthesis and salvage (FOLSYN-PWY), which nutrients are only to be obtained through diet.

3.4 Microbial abundance interaction network

After prevalence filtering of the ASV to be present in at least 50% of samples, there were a total of 71 nodes in the predicted microbial interaction network (Figure 5A), 73.7% were positive associations, and 26.3% were negative associations. Several isolated sub-clusters formed such as a small cluster consisting of four nodes (ASV4, ASV7, ASV10 and ASV11); all four nodes were assigned as *Tetragenococcus halophilus* subsp. Halophilus. The 16S copy number predicted from these ASVs are just one copy per ASV, which implies that the ASVs possibly belong to closely related *T. halophilus* strains. The isolation of this cluster might imply a lack of interaction between *Tetragenococcus halophilus* subsp. Halophilus with the rest of the Budu inhabitants. The nodes are not fully connected with each other, possibly because of the conditional independence implemented in SPIEC-EASI to prevent spurious links. Positive associations were predicted for edges ASV4-ASV7 and ASV7-ASV11. However, a negative association formed between ASV4 and ASV10.

Several nodes of similar taxonomic assignment were predicted to interact with each other such as that of the *T. halophilus* subsp. Halophilus sub-cluster as well as ASV1-ASV6 (*Tetragenococcus muriaticus*), ASV47-ASV77-ASV228 (*Acinetobacter*), ASV20-ASV28-ASV53 (*Staphylococcus*), ASV216-ASV133 (*Psychrobacter*) and ASV27-ASV66 (*Kocuria*). Co-abundance between these nodes were expected due to 16S copy numbers of slight nucleotide variations originating from the same bacterial genome. There are also patterns of network assortativity, which was most apparent for the *Actinobacteria* nodes surrounding ASV30 which is assigned as *Brevibacterium*. ASV30 formed a number of positive links with *Corynebacterium* nodes which belonged to the Actinobacteria class.

Degree centrality and betweenness centrality were two node centrality measures computed from the predicted interaction network. Majority of the nodes had very low degrees and possessed low betweenness centrality scores. ASV45 (Enterobacteriaceae) boasted the highest degree centrality (degrees = 10) and betweenness centrality (score = 466.72). *Tetragenococcus* nodes have very low node degrees and betweenness. Only one edge that formed between *Tetragenococcus* nodes and non-*Tetragenococcus* nodes (ASV1 *T. muriaticus* with ASV68 *Pseudomonas*).

4 DISCUSSION

Fermented fish sauce is a very popular food condiment in the South East Asian region. The fermentation from raw fish is largely driven by its microbiome because the high salt concentration in fish sauce inhibits the activity of endogenous fish enzymes like cathepsins, but activates halophilic bacterial proteinases (Tungkawachara et al., 2003). Since then, several microbiome-based research were done on fermented fish sauce in Korea, which has revealed insights into the role of the microbiome in industrial fish sauce fermentation as well as fish sauce quality (Jung et al., 2016; Lee et al., 2014). However, current studies on Budu so far are based on culture-based methods which have limited taxonomic breadth; it has not been studied yet to a degree that would enable understanding of the overall microbiome and its potential function. This is needed because its consumption can present as a potential health risk due to its high purine and histamine content (Mohd et al., 2011; Rosma et al., 2009). Due to the rich purine content in anchovies, (2,258.91 mg/kg) (Li et al., 2019), there is a concern that consumption of Budu could present a risk to higher gout incidence in Malaysia (Paul and James, 2017). Also, based on Rosma et al. (2009), seven of twelve Budu samples from twelve different producers contained histamine content exceeding 50 mg/100 g sample, which is the FDA limit for histamine consumption (FDA, 2011). Unchecked consumption of histamine-rich food can lead to scombroid food poisoning, the symptoms which are breathing difficulties and irregular heartbeats (Tortorella et al., 2014; Wilson et al., 2012). By determining the microbial diversity and composition of Budu, we hope to elucidate the relationship between the microbiome in Budu and and Budu quality, which can later translate to enhancement of organoleptic and nutritional value of Budu.

Clear inconsistencies of Budu microbiome were apparent within the same brand in terms of phyla composition, reiterated by the huge distances in PCoA as well as differences in alpha diversity indices. This suggests that most Budu were produced under uncontrolled conditions between production batches which may lead inconsistencies in the microbiome (Jung et al., 2016). This is also a major obstacle to commercial production with uniform, premium quality. From a food production point of view, inconsistent microbial diversity might interpret to different fermentation performances and quality variations. However, it is amusing to see a wider taxonomic diversity of bacteria that can thrive in Budu and potentially contribute to its quality. Future research should include the microbiota composition to predict organoleptic quality of the fish sauce. Our results also highlight the utility of sequencing as a potential tool to assess consistency in fermentation food production.

Tetragenococcus is a tetrad-forming coccus, gram positive halophilic lactic acid bacteria. It was

previously isolated from high-salt fermented foods such as soy sauce, squid liver sauce (Satomi et al.,

1997), dried fish, salted seafood (Kim and Park, 2014), fish sauce (Thongsanit et al., 2002) and

fermented fish paste (Marui et al., 2015). Despite being the genus with the highest average relative

abundance and prevalence, previous studies did not report of its isolation from Budu. Unsuccessful

isolation of *Tetragenococcus* from Budu might be attributed to limited sampling or culturing

conditions unsuitable to *Tetragenococcus*, showing the caveats of culturing-based methods. Despite

its prevalence in numerous fermented food, to the best of our knowledge, *Tetragenococcus* was never

found in the natural environment, neither found in fish gut nor saltern sources (Egerton et al., 2018).

Tetragenococcus was highly abundant in most Budu samples but was very low or absent in other

samples. We also identified two *Tetragenococcus* species which were *T. halophilus* (6 ASVs) and *T.*

muriaticus (2 ASVs) (Kobayashi et al., 2000). Based on 16S copy prediction, *Tetragenococcus* nodes

possess one copy of 16S sequencing. Therefore, the different ASVs found in our samples suggest the

presence of different strains of *Tetragenococcus*, including *T. halophilus* and *T. muriaticus.* The two

species were reported to grow optimally at different pH levels and salt concentrations and utilize

different types of sugar (He et al., 2016; Kobayashi et al., 2004, 2000; Udomsil et al., 2010).

Tetragenococcus muriaticus is known to release histamine and cadaverine, while *Tetragenococcus*

halophilus is known for the ability to reduce histamine and cadaverine formation (Kim et al., 2019;

Zaman et al., 2010). *T. halophilus* was also reported to contribute towards probiotic properties (Kuda

et al., 2014). It is not yet understood how *Tetragenococcus* dominated a microbiome, or if it is

possible to control its abundance – the consequences would include manipulation of the microbiome

to enrich for desirable metabolites or microbial processes.

The Budu microbiome composition was generally consistent post-fermentation. However, it was not

stagnant, as shown by the significant increase of *Chromobacterium* in the last sampling batch in brand

E, followed by brand D. Since *Chromobacterium* was not detected in first and second batches, it is

also possible that the genus was introduced from the surrounding into the samples while sampling

from the previous sampling batches. Brand D and brand E did not exclusively share common

ingredients. The two brands are also different in terms of microbiome composition, therefore we are

unsure of what factors caused the emergence of *Chromobacterium* in the two brands.

Chromobacterium was previously found in environmental samples (Kämpfer et al., 2009; Menezes et

al., 2015) as well as food samples such as vegetables, cheese and seafood samples (Koburger and

May, 1982). Bacteremia-causing *Chromobacterium* species were also reported (Kaufman et al., 1986;

Parajuli et al., 2016). Due to the lack of genomic sequences and analyses of the *Chromobacterium*

species (Santos et al., 2018), future research should address this gap of knowledge and identify the

ecological significance of this genus in fermented food.

The microbiome determines the metabolism taking place in Budu, which was clearly predicted

between *Tetragenococcus*-dominated and non-*Tetragenococcus*-dominated samples. The latter was

predicted to be enriched with biosynthesis of amino acids and purine, which were known to contribute

towards the quality of fermented foods in terms of pleasant organoleptic characteristics. For instance,

umami flavour in food is given by macromolecules which are amino acids such as glutamate and

aspartate as well as purine such as inosinic acid and guanylic acid (Zhao et al., 2019). These

pathways are also implicated with health conditions. For instance, metabolites enriched in Budu such

as histamine and purine compounds are implicated with health conditions such as scromboid

poisoning and gout respectively (Paul and James, 2017; Tortorella et al., 2014). The predicted

functions of the microbiome demonstrates the functional potential of the microbial community but

does not necessarily translate to the activities taking place in the community. To do so, more omics

data are required from genomics (transcriptomics) and also associated metabolomics data.

Unfortunately, these information were not yet within the scope of this current study. Thus, future

studies can focus more on the influence of amino acid and purine biosynthesis on Budu quality while

accounting for the microbial diversity as seen in our samples. A recent study demonstrated that amino

acids and biogenic amines increased in fermented fish sauce after a period of a year post-fermentation

and was also influenced by storage conditions such as temperature (Joung and Min, 2018). Another

study showed that prolonged fermentation of the fish can also lead to conversion of glutamic acid

available in the fish protein into more purine (Tungkawachara et al., 2003). However, we did not

observe changes in predicted enriched pathways across sampling batches.

Microbes exist in communities and interact with each other through mechanisms such as production

of lactic acid, the release of antimicrobials, quorum sensing, and cross-feeding. The ability to broadly

predict such relationships using relative abundance information from 16S sequencing is alluring, thus

attempts on modeling microbial interactions were done in the form of microbial interaction network

(Deng et al., 2012; Faust et al., 2012; Friedman and Alm, 2012; Kurtz et al., 2015). From our

constructed interaction network, we observed small isolated clusters, including a four-nodes cluster

comprising ASV4, ASV7, ASV10 and ASV11, and all the nodes were assigned to *Tetragenococcus*

halophilus subsp. Halophilus. No interactions were predicted between *T. halophilus* nodes with other

taxa. Known interaction of *Tetragenococcus halophilus* was reported in soy sauce fermentation in the

form of antagonism with *Zygosaccharomyces rouxii* which is a yeast (Devanthi et al., 2018). *T.*

muriaticus was another *Tetragenococcus* species that was detected in our study; the ASVs assigned to

T. muriaticus are ASV1 and ASV6 and their nodes are linked in the network. There was only one

non-*Tetragenococcus* node that linked with *Tetragenococcus* node, which was ASV68, assigned as

Pseudomonas. Since the network is based on relative abundance information, the lack of connections

that formed between *Tetragenococcus* nodes and non-*Tetragenococcus* nodes could mean either the

interaction network prediction could not model in situations where ASVs that are highly dominant or

that *Tetragenococcus* form only a few interactions with other taxa. Known interaction of

Tetragenococcus halophilus was reported in soy sauce fermentation in the form of antagonism with

Zygosaccharomyces rouxii which is a yeast (Devanthi et al., 2018). The interpretation of microbial

interaction network and its application in a biological context is still limited. For example, Bacillus is

both abundant and prevalent in our study. However, the high salinity of Budu (>15%) (Mohamed et

al., 2012) was known to inhibit growth of *B. subtilis* of marine origin (Katja et al., 2014). Thus, it

could be that the 16S sequence of *Bacillus* was amplified from spore particles (Fukui et al., 2012).

Research in microbial interaction network is also hampered by the lack of gold standard, thus it is

difficult to disentangle true interactions from strong environmental effect. Budu easily lends itself as a

tractable microbial system which is replicable and manipulable, and it is cheap, making it a potential

gold standard for this benchmark current and future microbial interaction network models (Wolfe,

2018; Wolfe and Dutton, 2015).

468 5 CONCLUSIONS

The microbiome of some brands of Budu are inconsistent, which possibly suggests Budu fermentation

was done under uncontrolled conditions between production batches. With the increasing popularity

of fermented food and the descending sequencing cost, microbiome assessment through DNA

sequencing is now a viable and cost effective method in quality assurance of fermented food. We also

discovered abundant and prevalent genera of Budu, some of which were not previously found in

previous studies on Budu which were based on culturing methods. Albeit not reported in prior culture-

dependent studies on Budu, *Tetragenococcus* was the most abundant genus in our sample collection,

and the two of its species that were detected were *Tetragenococcus muriaticus* and *Tetragenococcus*

halophilus. While *Tetragenococcus* was a common dweller in fermented fish sauce and other

fermented seafood, some of our Budu samples were devoid of the genus. This points out how

Tetragenococcus is well adapted to fermentation environment but also points towards a greater

diversity of bacteria that are as capable as *Tetragenococcus* in fulfilling its role in fermentation. Non-

Tetragenococcus dominated samples were predicted to be enriched with metabolic pathways

associated with amino acid biosynthesis and purine biosynthesis, macromolecules that were attributed

to organoleptic properties as well as nutrition. This opens up towards exploration of a wider array of

microbes as a candidate starter culture of Budu to improve Budu quality and safety. We also detected

Chromobacterium as the only genera that was significantly increased in the last sampling batch,

though its ecological role and its potential source was not yet clear. We also attempted to model the

microbial interaction using 16S abundance data, although its interpretation is still quite limited.

6 DATA ACCESS

All FastQ raw data can be accessed through SRA accession SRP193353, or through NCBI BioProject under BioProject ID: PRJNA534025. Supplementary files are accessible through the Mendeley Dataset http://dx.doi.org/10.17632/6jhvcgh6fm.1

7 CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationship that could be perceived as a potential conflict of interest.

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10 CRediT AUTHOR STATEMENT

Muhammad Zarul Hanifah: Data curation; Formal analysis; Investigation; Methodology; Resources; Visualization; Roles/Writing - original draft

Han Ming Gan: Conceptualization; Funding acquisition; Methodology; Project administration; Resources; Supervision; Writing - review & editing

11 Figure AND TABLE CAPTIONS

** All Figures are to be treated as coloured.

Table 1: Sample metadata of Budu from seven different brands

Figure 1: A. Relative abundance of the top five most abundant phyla in each bottle across sampling

time. B. Principal Coordinates Analysis (PCoA) plots, based on Weighted UniFrac and Bray Curtis

distances. Point shapes were assigned by sample batch. Point colour were by either brand, or Simpson

alpha diversity index. Circular perimeter marks a cluster that was dominated by Firmicutes (> 60%

relative abundance).

Figure 2: Plots indicating the prevalence of prevalent genera (at least 50% prevalence, > 0.01%

abundance per sample), it's maximum abundance for each ASV assigned to the corresponding genus

and and it's relative abundance. The bracketed numbers beside the maximum abundance per ASV

boxplots indicate the number of ASVs assigned to the genus.

Supplementary Figure 1: Prevalence and abundance per sample for dominant ASVs (ASVs displaying

maximum abundance of >10% in at least one sample)

Supplementary Figure 2: Maximum likelihood phylogenetic tree of representative *Bacillus* sequences

from SILVA and RDP databases together with ASVs assigned as *Bacillus*. Bar plots represent

prevalence (blue, max. = 73.33 %) and maximum relative abundance of ASV (green, max. = 7.05%).

ASV18 was the most abundant and prevalent *Bacillus* ASV. Leaf nodes are colored according to Patel

and Gupta (Patel and Gupta, 2020)□ *Bacillus* clade designation. The phylogenetic tree was rooted to

Geobacillus stereothermophilus as outgroup.

Figure 3: Trajectory of Observed ASVs (A) and Faith Phylogenetic Diversity (B) across sampling

periods, and the comparison of alpha diversity measures at 3rd and 7th month sampling against control

range (0th Month), C) Dot plot of W statistic computed by ANCOM against F-stat of each genera, D)

Relative abundance of *Chromobacterium*, *Barnesiella* and *[Ruminococcus] torques* group across

sampling periods

Supplementary Figure 3: Alpha rarefaction curves based on observed ASVs and Faith Phylogenetic

Diversity, faceted by brand and sampling period. The interquartile ranges are shown. Circles indicate

outlier alpha diversity calculations

Supplementary Figure 4: *Relative abundance of Chromobacterium, Barnesiella and [Ruminococcus]*

torques group across sampling periods per sample

Figure 4: A) Multidimensional scaling plot based on overall predicted pathways for each samples.

Sample are coloured based on relative abundance of *Tetragenococcus,* B) Heatmap of differential

pathways between *Tetragenococcus*-dominated and non-*Tetragenococcus*-dominated samples based

on normalised METACYC score. Pathways labels are based on shortened pathway labels from the

Metacyc database, C) Shannon index, sorted by value. Only non-*Tetragenococcus*-dominated samples

are shown, D) Heatmap of pooled contribution towards predicted organoleptic pathway per genus of

prevalence >= 50% per sample. Only non-*Tetragenococcus*-dominated samples are shown, E) Pooled

contribution towards predicted organoleptic pathway of top three most abundant genus per sample.

Only non-*Tetragenococcus*-dominated samples are shown.

Figure 5: A) Predicted interaction network based on Meinshausen-Bühlmann neighborhood selection

model. Nodes represent ASVs, coloured based on class taxonomic assignment, and node size was

given based on relative abundance, scaled logarithmically. Green edges indicate positive interaction,

while red edges indicate negative. To shorten the node label, the letters "ASV" was removed from the

node label, B) Distribution of degree distribution, C) Distribution of degree betweenness scores

12 SUPPLEMENTARY MATERIAL CAPTIONS

Supplementary File 1: ASV sequences in fasta format

Supplementary File 2: Taxonomic assignment table of individual ASVs using q2-classifier

Supplementary File 3: Observation table of all samples after filtering out the ASVs of non-microbial,

rarefied at 6000 reads per sample

Supplementary File 4: Predicted functional table based on EC. The table is stratified by ASV

Supplementary File 5: Predicted pathway table based on Metacyc database. The table is stratified by

ASV

13 REFERENCES

Barbera, P., Kozlov, A.M., Czech, L., Morel, B., Darriba, D., Flouri, T., Stamatakis, A., 2019. EPA-ng: Massively Parallel Evolutionary Placement of Genetic Sequences. Syst. Biol. https://doi.org/10.1093/sysbio/syy054

Bokulich, N.A., Kaehler, B.D., Rideout, J.R., Dillon, M., Bolyen, E., Knight, R., Huttley, G.A., Gregory Caporaso, J., 2018. Optimizing taxonomic classification of marker-gene amplicon sequences with QIIME 2's q2-feature-classifier plugin. Microbiome. https://doi.org/10.1186/s40168-018-0470-z

Bolyen, E., Rideout, J.R., Dillon, M.R., Bokulich, N.A., Abnet, C.C., Al-Ghalith, G.A., Alexander, H., Alm, E.J., Arumugam, M., Asnicar, F., Bai, Y., Bisanz, J.E., Bittinger, K., Brejnrod, A., Brislawn, C.J., Brown, C.T., Callahan, B.J., Caraballo-Rodríguez, A.M., Chase, J., Cope, E.K., Da Silva, R., Diener, C., Dorrestein, P.C., Douglas, G.M., Durall, D.M., Duvallet, C., Edwardson, C.F., Ernst, M., Estaki, M., Fouquier, J., Gauglitz, J.M., Gibbons, S.M., Gibson, D.L., Gonzalez, A., Gorlick, K., Guo, J., Hillmann, B., Holmes, S., Holste, H., Huttenhower, C., Huttley, G.A., Janssen, S., Jarmusch, A.K., Jiang, L., Kaehler, B.D., Kang, K. Bin, Keefe, C.R., Keim, P., Kelley, S.T., Knights, D., Koester, I., Kosciolek, T., Kreps, J., Langille, M.G.I., Lee, J., Ley, R., Liu, Y.X., Loftfield, E., Lozupone, C., Maher, M., Marotz, C., Martin, B.D., McDonald, D., McIver, L.J., Melnik, A. V., Metcalf, J.L., Morgan, S.C., Morton, J.T., Naimey, A.T., Navas-Molina, J.A., Nothias, L.F., Orchanian, S.B., Pearson, T., Peoples, S.L., Petras, D., Preuss, M.L., Pruesse, E., Rasmussen, L.B., Rivers, A., Robeson, M.S., Rosenthal, P., Segata, N., Shaffer, M., Shiffer, A., Sinha, R., Song, S.J., Spear, J.R., Swafford, A.D., Thompson, L.R., Torres, P.J., Trinh, P., Tripathi, A., Turnbaugh, P.J., Ul-Hasan, S., van der Hooft, J.J.J., Vargas, F., Vázquez-Baeza, Y., Vogtmann, E., von Hippel, M., Walters, W., Wan, Y., Wang, M., Warren, J., Weber, K.C., Williamson, C.H.D., Willis, A.D., Xu, Z.Z., Zaneveld, J.R., Zhang, Y., Zhu, Q., Knight, R., Caporaso, J.G., 2019. Reproducible, interactive, scalable and extensible microbiome data science using QIIME 2. Nat. Biotechnol. https://doi.org/10.1038/s41587-019-0209-9

Csardi, G., Nepusz, T., 2006. The igraph software package for complex network research. InterJournal Complex Syst.

Czech, L., Barbera, P., Stamatakis, A., 2020. Genesis and Gappa: Processing, analyzing and visualizing phylogenetic (placement) data. Bioinformatics. https://doi.org/10.1093/bioinformatics/btaa070

Deng, Y., Jiang, Y.H., Yang, Y., He, Z., Luo, F., Zhou, J., 2012. Molecular ecological network analyses. BMC Bioinformatics. https://doi.org/10.1186/1471-2105-13-113

Devanthi, P.V.P., Linforth, R., Onyeaka, H., Gkatzionis, K., 2018. Effects of co-inoculation and sequential inoculation of Tetragenococcus halophilus and Zygosaccharomyces

rouxii on soy sauce fermentation. Food Chem.
https://doi.org/10.1016/j.foodchem.2017.07.094

Douglas, G.M., Maffei, V.J., Zaneveld, J.R., Yurgel, S.N., Brown, J.R., Taylor, C.M.,
Huttenhower, C., Langille, M.G.I., 2020. PICRUSt2 for prediction of metagenome
functions. Nat. Biotechnol. https://doi.org/10.1038/s41587-020-0548-6

Edgar, R., 2016. UNOISE2: improved error-correction for Illumina 16S and ITS amplicon
sequencing. bioRxiv. https://doi.org/10.1101/081257

Edgar, R.C., Flyvbjerg, H., 2015. Error filtering, pair assembly and error correction for next-
generation sequencing reads. Bioinformatics.
https://doi.org/10.1093/bioinformatics/btv401

Egerton, S., Culloty, S., Whooley, J., Stanton, C., Ross, R.P., 2018. The gut microbiota of
marine fish. Front. Microbiol. https://doi.org/10.3389/fmicb.2018.00873

Faust, K., Sathirapongsasuti, J.F., Izard, J., Segata, N., Gevers, D., Raes, J., Huttenhower, C.,
2012. Microbial co-occurrence relationships in the Human Microbiome. PLoS Comput.
Biol. https://doi.org/10.1371/journal.pcbi.1002606

FDA, 2011. Fish and fishery products hazards and controls guidance. US Department of
Health and Human Services Food and Drug Administration ….

Friedman, J., Alm, E.J., 2012. Inferring Correlation Networks from Genomic Survey Data.
PLoS Comput. Biol. https://doi.org/10.1371/journal.pcbi.1002687

Fukui, Y., Yoshida, M., Shozen, K. ichi, Funatsu, Y., Takano, T., Oikawa, H., Yano, Y.,
Satomi, M., 2012. Bacterial communities in fish sauce mash using culture-dependent
and -independent methods. J. Gen. Appl. Microbiol. https://doi.org/10.2323/jgam.58.273

He, G., Wu, C., Huang, J., Zhou, R., 2016. Acid tolerance response of Tetragenococcus
halophilus: A combined physiological and proteomic analysis. Process Biochem.
https://doi.org/10.1016/j.procbio.2015.11.035

Ho, J., Tumkaya, T., Aryal, S., Choi, H., Claridge-Chang, A., 2019. Moving beyond P values:
data analysis with estimation graphics. Nat. Methods. https://doi.org/10.1038/s41592-
019-0470-3

Hunter, J.D., 2007. Matplotlib: A 2D graphics environment. Comput. Sci. Eng.
https://doi.org/10.1109/MCSE.2007.55

Joung, B.C., Min, J.G., 2018. Changes in Postfermentation Quality during the Distribution
Process of Anchovy (Engraulis japonicus) Fish Sauce. J. Food Prot. 81, 969–976.
https://doi.org/10.4315/0362-028X.JFP-17-348

Jung, J.Y., Lee, H.J., Chun, B.H., Jeon, C.O., 2016. Effects of temperature on bacterial
communities and metabolites during fermentation of Myeolchi-Aekjeot, a traditional

644   Korean fermented anchovy sauce. PLoS One.

645   https://doi.org/10.1371/journal.pone.0151351

646 Kämpfer, P., Busse, H.J., Scholz, H.C., 2009. Chromobacterium piscinae sp. nov. and

647   Chromobacterium pseudoviolaceum sp. nov., from environmental samples. Int. J. Syst.

648   Evol. Microbiol. https://doi.org/10.1099/ijs.0.008888-0

649 Katja, N., Peter, S., Yong-Qing, L., Ralf, M., 2014. High Salinity Alters the Germination

650   Behavior of Bacillus subtilis Spores with Nutrient and Nonnutrient Germinants. Appl.

651   Environ. Microbiol. 80, 1314–1321. https://doi.org/10.1128/AEM.03293-13

652 Katoh, K., Standley, D.M., 2013. MAFFT multiple sequence alignment software version 7:

653   Improvements in performance and usability. Mol. Biol. Evol.

654   https://doi.org/10.1093/molbev/mst010

655 Kaufman, S.C., Ceraso, D., Schugurensky, A., 1986. First case report from Argentina of fatal

656   septicemia caused by Chromobacterium violaceum. J. Clin. Microbiol.

657   https://doi.org/10.1128/jcm.23.5.956-958.1986

658 Kim, K.H., Lee, S.H., Chun, B.H., Jeong, S.E., Jeon, C.O., 2019. Tetragenococcus halophilus

659   MJ4 as a starter culture for repressing biogenic amine (cadaverine) formation during

660   saeu-jeot (salted shrimp) fermentation. Food Microbiol.

661   https://doi.org/10.1016/j.fm.2019.02.017

662 Kim, M.S., Park, E.J., 2014. Bacterial Communities of Traditional Salted and Fermented

663   Seafoods from Jeju Island of Korea Using 16S rRNA Gene Clone Library Analysis. J.

664   Food Sci. https://doi.org/10.1111/1750-3841.12431

665 Klindworth, A., Pruesse, E., Schweer, T., Peplies, J., Quast, C., Horn, M., Glöckner, F.O.,

666   2013. Evaluation of general 16S ribosomal RNA gene PCR primers for classical and

667   next-generation sequencing-based diversity studies. Nucleic Acids Res.

668   https://doi.org/10.1093/nar/gks808

669 Kobayashi, T., Kajiwara, M., Wahyuni, M., Hamada-Sato, N., Imada, C., Watanabe, E.,

670   2004. Effect of culture conditions on lactic acid production of Tetragenococcus species.

671   J. Appl. Microbiol. https://doi.org/10.1111/j.1365-2672.2004.02267.x

672 Kobayashi, T., Kimura, B., Fujii, T., 2000. Differentiation of Tetragenococcus populations

673   occurring in products and manufacturing processes of puffer fish ovaries fermented with

674   rice-bran. Int. J. Food Microbiol. https://doi.org/10.1016/S0168-1605(00)00214-2

675 Koburger, J.A., May, S.O., 1982. Isolation of Chromobacterium spp. from foods, soil, and

676   water. Appl. Environ. Microbiol. https://doi.org/10.1128/aem.44.6.1463-1465.1982

677 Kuda, T., Izawa, Y., Yoshida, S., Koyanagi, T., Takahashi, H., Kimura, B., 2014. Rapid

678   identification of Tetragenococcus halophilus and Tetragenococcus muriaticus, important

679   species in the production of salted and fermented foods, by matrix-assisted laser

desorption ionization-time of flight mass spectrometry (MALDI-TOF MS). Food
Control. https://doi.org/10.1016/j.foodcont.2013.07.039

Kurtz, Z.D., Müller, C.L., Miraldi, E.R., Littman, D.R., Blaser, M.J., Bonneau, R.A., 2015.
Sparse and Compositionally Robust Inference of Microbial Ecological Networks. PLoS
Comput. Biol. https://doi.org/10.1371/journal.pcbi.1004226

Lee, S.H., Jung, J.Y., Jeon, C.O., 2014. Effects of temperature on microbial succession and
metabolite change during saeu-jeot fermentation. Food Microbiol.
https://doi.org/10.1016/j.fm.2013.08.004

Li, T., Ren, L., Wang, D., Song, M., Li, Q., Li, J., 2019. Optimization of extraction
conditions and determination of purine content in marine fish during boiling. PeerJ.
https://doi.org/10.7717/peerj.6690

Liu, H., Roeder, K., Wasserman, L., 2010. Stability approach to regularization selection
(StARS) for high dimensional graphical models, in: Advances in Neural Information
Processing Systems 23: 24th Annual Conference on Neural Information Processing
Systems 2010, NIPS 2010.

Lopetcharat, K., Choi, Y.J., Park, J.W., Daeschel, M.A., 2001. Fish sauce products and
manufacturing: A review. Food Rev. Int. https://doi.org/10.1081/FRI-100000515

Louca, S., Doebeli, M., 2018. Efficient comparative phylogenetics on large trees.
Bioinformatics. https://doi.org/10.1093/bioinformatics/btx701

Lozupone, C., Lladser, M.E., Knights, D., Stombaugh, J., Knight, R., 2011. UniFrac: An
effective distance metric for microbial community comparison. ISME J.
https://doi.org/10.1038/ismej.2010.133

Mandal, S., Van Treuren, W., White, R.A., Eggesbø, M., Knight, R., Peddada, S.D., 2015.
Analysis of composition of microbiomes: a novel method for studying microbial
composition. Microb. Ecol. Heal. Dis. https://doi.org/10.3402/mehd.v26.27663

Marui, J., Boulom, S., Panthavee, W., Momma, M., Kusumoto, K.-I., Nakahara, K., Saito,
M., 2015. Culture-independent bacterial community analysis of the salty-fermented fish
paste products of Thailand and Laos. Biosci. Microbiota, Food Heal. 34, 45–52.
https://doi.org/10.12938/bmfh.2014-018

Meinshausen, N., Bühlmann, P., 2006. High-dimensional graphs and variable selection with
the Lasso. Ann. Stat. https://doi.org/10.1214/009053606000000281

Menezes, C.B.A., Tonin, M.F., Corrêa, D.B.A., Parma, M., de Melo, I.S., Zucchi, T.D.,
Destéfano, S.A.L., Fantinatti-Garboggini, F., 2015. Chromobacterium amazonense sp.
nov. isolated from water samples from the Rio Negro, Amazon, Brazil. Antonie van
Leeuwenhoek, Int. J. Gen. Mol. Microbiol. https://doi.org/10.1007/s10482-015-0397-3

Mohamed, H.N., Man, Y.C., Mustafa, S., Manap, Y.A., 2012. Tentative identification of
volatile flavor compounds in commercial budu, a malaysian fish sauce, using GC-MS.
Molecules. https://doi.org/10.3390/molecules17055062

Mohd, A., Das Gupta, E., Loh, Y.L., Gandhi, C., D'Souza, B., Gun, S.C., 2011. Clinical
characteristics of gout: A hospital case series. Malaysian Fam. Physician.

Mohd Isa, M.H., Shamsudin, N.H., Al-Shorgani, N.K.N., Alsharjabi, F.A., Kalil, M.S., 2020.
Evaluation of antibacterial potential of biosurfactant produced by surfactin-producing
Bacillus isolated from selected Malaysian fermented foods. Food Biotechnol.
https://doi.org/10.1080/08905436.2019.1710843

Parajuli, N.P., Bhetwal, A., Ghimire, S., Maharjan, A., Shakya, S., Satyal, D., Pandit, R.,
Khanal, P.R., 2016. Bacteremia caused by a rare pathogen – Chromobacterium
violaceum: A case report from Nepal. Int. J. Gen. Med.
https://doi.org/10.2147/IJGM.S125183

Patel, S., Gupta, R.S., 2020. A phylogenomic and comparative genomic framework for
resolving the polyphyly of the genus bacillus: Proposal for six new genera of bacillus
species, peribacillus gen. nov., cytobacillus gen. nov., mesobacillus gen. nov.,
neobacillus gen. nov., metabacillu. Int. J. Syst. Evol. Microbiol.
https://doi.org/10.1099/ijsem.0.003775

Paul, B.J., James, R., 2017. Gout: an Asia-Pacific update. Int. J. Rheum. Dis.
https://doi.org/10.1111/1756-185X.13103

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M.,
Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D.,
Brucher, M., Perrot, M., Duchesnay, É., 2011. Scikit-learn: Machine learning in Python.
J. Mach. Learn. Res.

Price, M.N., Dehal, P.S., Arkin, A.P., 2010. FastTree 2 - Approximately maximum-likelihood
trees for large alignments. PLoS One. https://doi.org/10.1371/journal.pone.0009490

Rosma, A., Afiza, T.S., Nadiah, W.A.W., Liong, M.T., Gulam, R.R.A., 2009.
Microbiological, histamine and 3-MCPD contents of Malaysian unprocessed "budu."
Int. Food Res. J.

Santos, A.B., Costa, P.S., Do Carmo, A.O., Da Rocha Fernandes, G., Scholte, L.L.S., Ruiz,
J., Kalapothakis, E., Chartone-Souza, E., Nascimento, A.M.A., 2018. Insights into the
Genome Sequence of Chromobacterium amazonense Isolated from a Tropical
Freshwater Lake. Int. J. Genomics. https://doi.org/10.1155/2018/1062716

Satomi, M., Kimura, B., Mizoi, M., Sato, T., Fujii, T., 1997. Tetragenococcus muriaticus sp.
nov., a new moderately halophilic lactic acid bacterium isolated from fermented squid
liver sauce. Int. J. Syst. Bacteriol. https://doi.org/10.1099/00207713-47-3-832

Shivanne Gowda, S.G., Narayan, B., Gopal, S., 2016. Bacteriological properties and health-
related biochemical components of fermented fish sauce: An overview. Food Rev. Int.
32, 203–229. https://doi.org/10.1080/87559129.2015.1057844

Terpilowski, M., 2019. scikit-posthocs: Pairwise multiple comparison tests in Python. J.
Open Source Softw. https://doi.org/10.21105/joss.01169

Thongsanit, J., Tanasupawat, S., Keeratipibul, S., Jatikavanich, S., 2002. Characterization
and Identification of Tetragenococcus halophilus and Tetragenococcus muriaticus
Strains from Fish Sauce (Nam-pla). Japanese J. Lact. Acid Bact.
https://doi.org/10.4109/jslab1997.13.46

Tortorella, V., Masciari, P., Pezzi, M., Mola, A., Tiburzi, S.P., Zinzi, M.C., Scozzafava, A.,
Verre, M., 2014. Histamine Poisoning from Ingestion of Fish or Scombroid Syndrome.
Case Rep. Emerg. Med. https://doi.org/10.1155/2014/482531

Tungkawachara, S., Park, J.W., Choi, Y.J., 2003. Biochemical properties and consumer
acceptance of Pacific whiting fish sauce. J. Food Sci. https://doi.org/10.1111/j.1365-
2621.2003.tb08255.x

Udomsil, N., Rodtong, S., Tanasupawat, S., Yongsawatdigul, J., 2010. Proteinase-producing
halophilic lactic acid bacteria isolated from fish sauce fermentation and their ability to
produce volatile compounds. Int. J. Food Microbiol.
https://doi.org/10.1016/j.ijfoodmicro.2010.05.016

Vallat, R., 2018. Pingouin: statistics in Python. J. Open Source Softw.
https://doi.org/10.21105/joss.01026

Wilson, B.J., Musto, R.J., Ghali, W.A., 2012. A case of histamine fish poisoning in a young
atopic woman. J. Gen. Intern. Med. https://doi.org/10.1007/s11606-012-1996-6

Wolfe, B.E., 2018. Using Cultivated Microbial Communities To Dissect Microbiome
Assembly: Challenges, Limitations, and the Path Ahead. mSystems.
https://doi.org/10.1128/msystems.00161-17

Wolfe, B.E., Dutton, R.J., 2015. Fermented foods as experimentally tractable microbial
ecosystems. Cell. https://doi.org/10.1016/j.cell.2015.02.034

Ye, Y., Doak, T.G., 2009. A parsimony approach to biological pathway
reconstruction/inference for genomes and metagenomes. PLoS Comput. Biol.
https://doi.org/10.1371/journal.pcbi.1000465

Yuen, S.K., Yee, C.F., Anton, A., 2009. Microbiological characterization of budu, an
indigenous Malaysian fish sauce. Borneo Sci.

Zaman, M.Z., Bakar, F.A., Selamat, J., Bakar, J., 2010. Occurrence of biogenic amines and
amines degrading bacteria in fish sauce. Czech J. Food Sci.
https://doi.org/10.17221/312/2009-cjfs

Zareian, M., Ebrahimpour, A., Bakar, F.A., Mohamed, A.K.S., Forghani, B., Ab-Kadir,
M.S.B., Saari, N., 2012. A glutamic acid-producing lactic acid bacteria isolated from
malaysian fermented foods. Int. J. Mol. Sci. https://doi.org/10.3390/ijms13055482

Zhao, Y., Zhang, M., Devahastin, S., Liu, Y., 2019. Progresses on processing methods of
umami substances: A review. Trends Food Sci. Technol. 93, 125–135.
https://doi.org/https://doi.org/10.1016/j.tifs.2019.09.012
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A Microbial interaction network of Budu ASVs

Bacterial class

- ● c__Actinobacteria
- ● c__Alphaproteobacteria
- ● c__Bacilli
- ● c__Bacteroidia
- ● c__Clostridia
- ● c__Gammaproteobacteria
- ● c__Halanaerobiia

log(Relative abundance x 100)

- 0.5
- 1
- 2
- 4
- 5
- 6
- 7

B Degree distribution

C Node betweenness score distribution

Prevalence(%)

Heatmap of
ASV relative abundance(%)

ASV1
s__Tetragenococcus_muriaticus

ASV3
g__Halanaerobium

ASV4
s__Tetragenococcus_halophilus_subsp._halophilus

ASV14
g__Staphylococcus

ASV10
s__Tetragenococcus_halophilus_subsp._halophilus

ASV7
s__Tetragenococcus_halophilus_subsp._halophilus

ASV9
g__Weissella

ASV20
g__Staphylococcus

ASV6
s__Tetragenococcus_muriaticus

ASV11
s__Tetragenococcus_halophilus_subsp._halophilus

Highest max. relative abundance: 73.3%

Highest prevalence: 7.05%

ASV	Jeotgali
Alcalophilus	Niacini
Cereus	Simplex
Fastidiosus	Subtilis
Firmus	

Relative abundance of significant genera, split by week, per bottle