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## Reviewers' Comments:

### Reviewer #1:

#### Remarks to the Author:

This study aims to assess temporal effects (diurnal, seasonal, lifelong) on the wild meerkat gut microbiome in terms of alpha diversity, beta diversity, and bacterial load. The study presents an impressive sample set spanning many individuals across several decades, assesses a wide variety of biological and environmental variables on gut microbiome variation, and concludes with interesting findings that diurnal factors exert stronger influences on the microbiome than seasonal or lifelong impacts, which has not been shown in a wild system. The study is well-written but would benefit from several additions, both statistical and discussion based. Larger changes are listed first followed by smaller changes for each section.

#### Larger changes

- Only one metric for alpha and beta diversity each are presented to assess the impact of temporal, biological, and environmental variables on the gut microbiome. It is more typical to present multiple metrics. Is there are a reason why only these were chosen? I think it would be especially important to include a second metric for beta diversity. Only weighted UniFrac was used which is based on relative abundance of ASVs. However, there appear to be large differences in ASV richness across groups, and thus a metric assessing presence/absence of ASVs may be beneficial as the authors mention they are only explaining a small amount of overall variation (line 156).
- As sample storage method can have significant impacts on microbial communities, I appreciate the inclusion of data aggregated by storage method in figures S5-6. However, the authors mention in the methods section that trends were largely the same across storage groups and thus, storage should not have impacted results (line 504). However, especially in figures S5 C and F the trends for freeze dried vs frozen samples look almost opposite one another. I think there should be some mention of this caveat in the results or discussion.
- Some additional interpretation of the main study results is needed in the discussion. For example, is there any speculation as to what biological mechanism may drive daily oscillations in gut microbiome load/diversity based on light/dark cycles? Clostridium seemed to be a central driver of several results—what might be the significance of this group and why might it have been so plastic? Different trends for ASV richness and bacterial loads were discussed on the basis of seasonality in the discussion (paragraph starting line 300). However, these differences also appeared on a diurnal scale which wasn't discussed. Why might these trends be different (e.g. is bacterial load driven by one dominant ASV that reduced richness?)
- There appeared to be little sampling during the mid-day period (e.g. Figs 2b, 4a). Why was this and how might this impact results? This should be discussed a bit.

#### Smaller changes

##### Introduction

- Line 51: There seems to be a typo here. May-September is listed as both summer and winter months
- Line 57: Different storage methods should be added here, as not all samples were frozen afterwards?

##### Results

- Line 98: change "genera" to "genus"
- Line 159: Was this 62% of the 34% of overall variation explained above? Or 62% of overall variation?
- Line 183: this header indicates results regarding clostridium, but I don't think there is any mention of clostridium in this section? Consider rephrasing
- Line 202: please explain in a bit more detail how genera were identified as core. In most cases, they are taxa present in a certain number of samples. Is that what is meant by 80% prevalence here, or does this refer to relative abundance of the taxa? Is the N here the number of genera or number of samples? A list of the taxa somewhere would be helpful

- Lines 206-211: a supplemental table may be helpful to show exactly which genera were influenced by which variables, unless they are all listed in figure 6? Maybe that figure should be cited here.
- Line 227: Were only the genera listed as core used for this analysis?

#### Methods

- Line 360: some additional information is needed about this storage experiment. How were the samples handled after collection? Were the samples split into storage treatments from single individuals or different individuals were used for each type? etc.
- Line 363: what statistical methods were used to compare beta and alpha diversity between these groups?
- Line 392: what version of QIIME2 was used?
- Line 397: change "that" to "than"
- Line 421: what units was weight measured in?
- Overall for beta and alpha diversity metrics, was rarefaction used to standardize sequencing depth?
- Line 518: why was MDS used as opposed to NMDS which appears to be more common for these analyses?

#### Figures/Tables

- Fig 2a is really difficult to glean information from due to the number of samples and microbial taxa. It may help to distill the number of taxa displayed to smaller number (e.g. top 5-10 most abundant)
- Fig2 d-e: what cutoffs were used to delineate groups (e.g. what hours were used for morning/afternoon and months for wet/dry season). This is explained for age but not these two.
- Fig 2 legend: change GAM to GAMM?
- Figure 3a: it is unclear to me what joint vs. independent represent. This should be explained in more detail in the text or legend.
- Table S3 caption: change "statics" to "statistics"?

#### Reviewer #2:

##### Remarks to the Author:

Risley et al. extensively document microbiome variation in wild meerkats, isolating dynamics associated with circadian rhythms, seasonality, and host demography. The authors leverage an extensive sample and metadata set to answer questions previously untackled in microbiome analyses, and they use appropriate mixed effects models to do so. The paper provides a unique perspective on gut microbiome dynamics in a wild population and is a significant contribution to the field.

I have identified four larger issues that should be addressed before publication however and also provide a list of smaller concerns.

##### Larger Issues:

**Model choice**—The authors do a laudable job of describing their GAMM fitting in the methods, but their use of hierarchical variance partitioning models is much less well motivated. The R package used is not specified nor are the validation tests. Moreover, the authors fail to explain (i) why the hierarchical variance partitioning model approach was used to analyze the biological predictors of the first four major principal components of the MDS ordination and (ii) why it wasn't used for analyses of biological predictor role for other dependent variables. Furthermore, why analyze biological fit on 4 MDS axes rather than just modeling fit of overall dissimilarity with PERMANOVA?

**Abundance patterns**— The fact that all but one major genera exhibit the same diurnal shifts despite being associated with different biological and environmental variables is confusing to me. To what extent may these just be reflecting the overall trend in load? The strong effect of sequencing depth for all genera except *Geodermatophilus* seems to indicate this may be at play. Are similar shifts observed when analyzing relative abundance? (I'm not advocating including relative abundance analyses in the published paper, just using them as a tool to better understand

why absolute abundance patterns appear as they do.)

The extreme response exhibited by *Clostridium* may in part reflect the fact that it has much higher (2-5x) 16S copy number than the other genera analyzed (for which genomes are available and copy number estimates are published in rrnDB). While the authors note in the methods that the internal standard technique directly assesses copy number but generally reflects absolute abundance trends, they don't discuss how large differences in copy number will impact their interpretation.

Diurnal time series—For totally understandable methodological/behavioral reasons, the authors were unable to sample evenly across the course of the day. However, they fit their models across the entire day even though between ~5 and ~10 hours after sunrise their sampling is very sparse. The confidence intervals are somewhat larger there, but I'm not sure you should be fitting through at all. Certainly more discussion of this limitation is necessary.

It's unclear to me as a non-meerkat specialist how frequently an individual defecates so whether there could potentially be samples in the middle of the day if one had access to burrows or even at multiple times during the day for one host. It is hard to tell from Figure 1 whether there are individuals who were ever sampled multiple times on the same day even during the two dense sampling campaigns. If there are, would it be possible to provide supplemental figures plotting their observed richness or load over such a day? This would be especially helpful for estimating how representative the overall fit is for individuals given that there is such variance at any given time of sampling.

Dominant genera—The specification of "dominant genera" for the enterotype analyses (Figure 3) needs to be better defined in the results and the methods. Is it just the most abundant genus? Why aren't these the genera of focus for the core genera analyses if they are what distinguishes between communities?

At the very least the color schemes should be consistent between 3b and 4e-h so the reader can more easily tie them together.

Smaller Concerns:

-line 39 It is unclear what the definition of "biological systems" is in this context. Do you mean non-microbiome host physiological programs?

-line 47-50 What are animals doing when they aren't foraging?

-line 65 Specify you mean the abundance of each of the 15 genera, not the 15 together.

-line 68 What kind of models?

-lines 98, 99 Specify if 60% and 30% are means and provide standard deviation or confidence intervals for the summary statistic.

-The presentation of the GAMM model fits is a bit hard to follow in the text (e.g. lines 106-116; 144-156). Is there a way to report statistical significance for relevant variables in the text rather than just directing to a supplementary table?

-line 469-470 You're testing underlying mechanism not necessarily "identifying" them since you don't have all possible relevant mechanistic variables included in your analyses.

-line 509-512 What would've been evidence for more than marginal overfitting? Isn't a 1/4 drop in variance explained a lot?

-line 522-528 You could analyze with `adonis2` function in `vegan`, rather than `adonis` function, to capitalize on a marginal sums of squares approach (`by="margin"`) and thus not be subject to the same sequential effects.

Figures

-Please provide supplementary figures with histograms of your sample set. For example, what is the frequency of samples for time of day (maybe hourly bins), months, and age? And what is the

frequency of samples for time of day by age groups (underlying the figure 5 analysis)? It's not possible to back this out of Figure 1 or the highly dense observed data plots (like 2b-d), but such information is useful for understanding how robust the patterns are.

-I find figure 2a really hard to parse, especially since the x-axis is not plotted as a continuous axis. Either fewer families need to be plotted and/or averages for ordinal time points need to be plotted. The current version could be included in the supplement if you think it is necessary, but it is too busy to read as is. Also, 2A should not be cited after the sentence "The most abundant genera across samples was *Clostridium sensu stricto* 1, an anaerobe that made up 30% of reads, and which was more abundant in the morning than the afternoon and evening" since there are no genera results in it.

-"Dominant genera" needs to be defined in the legend of Figure 3. Is "other" any other genera or a group of non-specified but not exhaustive genera?

-Figure 4d x and y axes should match, the axes should not have decimal places in the superscript, and the blue line should be defined (is it a fit line or 1:1)?

-Why are 4h-j not also on a log scale?

-Can you provide the overall load oscillations for each age group in Figure 5? If differences in overall abundance are underlying much of the genera oscillations (see "Abundance Patterns" above) we'd expect to see a similar overall abundance curve for each age group. But if the overall signal varies while the genera patterns are consistent, that supports the idea that genera behave somewhat independently.

-Figure 6 in general is an excellent way of summarizing some very complex model results. It would be helpful though to have a legend on the plot specifying what dot size indicates.

Reviewer #3:

Remarks to the Author:

The manuscript titled "Diurnal oscillations in gut microbiome load and composition eclipse seasonal and lifetime dynamics in wild meerkats, *Suricata suricatta*" aims to quantify and compare the meerkat gut microbiome across diurnal, seasonal, and lifetime cycles.

The general approach of the study was to characterize the bacterial load and structure of the meerkat gut microbiome using 1027 samples collected in the Kalahari across 20 years of morning and evening behavioral observations of individually known meerkats. Longitudinal sampling was available for 168 meerkats. The gut microbiome was characterized via 16S rRNA gene sequencing. Bacterial load was estimated by scaling reads to internal standards (commercially available) that were introduced prior to DNA extraction. Alpha and beta analyses were performed.

The key finding of the study was that most common bacterial genera exhibited diurnal oscillations in bacterial load. These oscillations were driven by changes to *Clostridium sensu stricto* 1, and were better explained by light-dark cycles than foraging schedule. Diurnal cycling of the microbiome did not decay with age.

The conclusion of the study was that diurnal oscillations shape gut microbiome load and structure in wild meerkats.

Comments/Concerns

This is a high-quality and well written study addressing circadian rhythms of the gut microbiome in a wild population across 20 years of intensive sampling and behavioral observation. The breadth, scope, and detail of the metadata available for the samples is impressive. Commendably, the authors provide all code in an Rmarkdown file. Extraction and PCR negative controls were included on all sequencing runs.

I initially had two concerns, however, both are ultimately addressed in the study.

1) The first potential concern was that fecal samples collected prior to 2008 were frozen at -80°C, while those collected after 2008 were freeze-dried and stored at room temperature. However, the study includes an analysis showing that biological variation exceeds technical variation potentially introduced by these differences in storage method.

2) The second potential concern was that bacterial load was estimated using ZymoBIOMICS Spike-in Controls. I have never seen this approach for quantifying bacterial load and was instead expecting quantitative real-time PCR. However, after reading the product literature and related manuscripts, I appreciate the approach. As noted below, I would however recommend that the approach be described in greater detail in the Methods, as it is novel.

I therefore have only minor suggestions.

Minor comments/edits:

Additional proof-reading is recommended prior to publication (e.g., plural/singular).

Abstract

N/A

Introduction

It would be valuable to present what is known of the mongoose gut microbiome from prior studies in the Introduction. At present, there is no indication that mongoose gut microbiome has been characterized at all. If it has not, make this clear.

Materials and Methods

Line 379 – Did the kit extract all genomic DNA, including that of the host, or only of the bacteria?

Lines 388-390 – Were the DNA extractions also performed in a randomized manner?

Line 393 – What parameters were used for the DADA2 pipeline? They were not included in the Rmarkdown report.

Line 402 – What functions/parameters were used for Decontam? They were not included in the Rmarkdown report.

Line 408 – By what manner were these ASVs identified as laboratory contaminants? Given their rarity, they would not affect any study outcomes, but given the careful methodology used in the study, stating these criteria would benefit others in conducting similar studies.

Line 413 – Please explain how samples were scaled to *Allobacillus*. This is a new technique, which warrants further explanation.

Lines 424-426 – Explain how weights were collected in a near daily manner, or include a reference to prior descriptions of the process.

Results

Figure 2 – There are two “d” panels in the figure.

Discussion & Conclusions

A section on the strengths and limitations of the study would be valuable.

Other

It appears that Ben Dantzer’s name is misspelled in the Acknowledgements, unless that is not who is being referred to.

Kevin R. Theis

## RESPONSE TO REVIEWERS

### Summary of changes for reviewers

We would like to thank the three reviewers for taking the time to review the manuscript and for their constructive criticism. We have taken all suggestions on board in our revised paper and believe the manuscript is now considerably improved. As requested, we have made major alterations to our paper. Because some of the points brought up by reviewers as ‘discussion points’ lead us to add more data and reanalyse the data more vigorously, there has been some analytical changes that warrant an overall summary of the changes to the manuscript:

1. All reviewers thought there should be more discussion and context. We have expanded the introduction to include two paragraphs on what we know about the temporal processes we are interested in, specifically circadian rhythms and development and senescence of the gut microbiome. We have also expanded the discussion to more fully interpret our results, as well as a paragraph on the methodological limitations.
2. One reviewer requested additional diversity metrics be added to the analysis – we have added these. We added Shannon diversity as another measure of alpha diversity, and Unweighted Unifrac as an additional, unweighted, measure of beta diversity.
3. Two reviewers were concerned about the lack of data in the middle of the day and how this affected models. We agree that this situation was not ideal, so we sequenced 80 more samples that were collected during the middle of day (between 12-4pm), or very early in the morning (~6am) or late in the day (~8pm). This does not close the noon gap, but it narrows the gap from about 5 hours to 3 hours. We also go into more detail on the new sensitivity analyses we apply (random sub-sampling across the day) and why this gap does not effects estimates from other parts of the day.
4. Because we did another sequencing run, we also took this opportunity to do a small technical replication test, since as reviewer 3 brought up, the use of spike-ins/internal references is still a relatively novel method, and there is little information on how reliable it is. Sample ID counted for 90% of variation in estimated bacterial load, and therefore technical variation was 10% (technical variation of alpha and beta diversity was much lower at ~1-2%). This is relatively high, but still good enough to work with and identify biological trends. All reviewers brought up the reliability of the methods, therefore to be completely transparent we have now added a ‘methods validation’ section at the start of the results, which tackles the effect of storage on the microbiome, and the technical variation. Readers now do not need to dig into the methods to find this information.
5. Two reviewers wanted more discussion on the effect of frozen/freezefried samples on results. Possibly the largest change in terms of the interpretation of our results comes from the fact we now only consider an association robust if it exhibits the same significant trends both in freezedried and frozen samples. We believe this makes the results and conclusions much clearer, because it weeds out any weak associations that are significant just because of the large sample size. During this process, we realised that our models containing all the mechanistic variables (the ‘full models’) shouldn’t have the non-linear terms included, because these correlate substantially with some of the fixed terms in the model, and the resulting associations were not robust when we split the

43 dataset by storage. Our largest analytic change, therefore, is to rerun these models (that  
44 include all the climate/biological variables) without temporal non-linear terms, whilst  
45 thoroughly taking into account co-correlation. For example, we now only consider one  
46 foraging variable instead of two due to correlation issues, and also test for the effect of  
47 co-correlation between climate variables. This has altered our interpretations of the  
48 mechanisms, with temperature-constrained foraging patterns becoming much more  
49 important, which we believe makes sense with what we know of the gut microbiome. We  
50 emphasize though that the extra data and reanalysis does not alter our overall conclusions.

51 6. Focus genera: There was some confusion about the selection of genera modelled and the  
52 colour scheme of figures, since different genera were presented in different analyses  
53 using different colours. To be more consistent, we have tested for temporal dynamics  
54 across a larger suite of genera, but still focused in on the 16 most important. These 16  
55 genera have the same colour scheme across all figures, and we more fully justify their  
56 inclusion.

57 7. Lastly, we have slightly reorganised the results section, based on a new set of four clear  
58 aims that we added at the end of the introduction. For example, we now focus on the  
59 mechanistic effects in one section, whilst previously this was spread out over the  
60 manuscript.

61 We have responded to each comment in detail below. We have highlighted revisions in our  
62 revised manuscript by colouring new or changed in sections in blue.

63

64 **Reviewer #1 (Remarks to the Author):**

65

66 This study aims to assess temporal effects (diurnal, seasonal, lifelong) on the wild meerkat  
67 gut microbiome in terms of alpha diversity, beta diversity, and bacterial load. The study  
68 presents an impressive sample set spanning many individuals across several decades, assesses  
69 a wide variety of biological and environmental variables on gut microbiome variation, and  
70 concludes with interesting findings that diurnal factors exert stronger influences on the  
71 microbiome than seasonal or lifelong impacts, which has not been shown in a wild system.  
72 The study is well-written but would benefit from several additions, both statistical and  
73 discussion based. Larger changes are listed first followed by smaller changes for each  
74 section.

75 Thank you for this positive assessment for our work.

76

77 Larger changes

78 - Only one metric for alpha and beta diversity each are presented to assess the impact of  
79 temporal, biological, and environmental variables on the gut microbiome. It is more typical to  
80 present multiple metrics. Is there are a reason why only these were chosen? I think it would  
81 be especially important to include a second metric for beta diversity. Only weighted UniFrac  
82 was used which is based on relative abundance of ASVs. However, there appear to be large  
83 differences in ASV richness across groups, and thus a metric assessing presence/absence of

84 ASVs may be beneficial as the authors mention they are only explaining a small amount of  
85 overall variation (line 156).

86 In response we have now added Shannon diversity and Unweighted Unifrac to analyses. We  
87 agree it is the norm for wildlife microbiome studies to present more than one diversity metric,  
88 and our decision to present just one metric of alpha and beta diversity was based on space  
89 alone, since we present rather a lot of information.

90 We have outlined the results of these analyses in the results section (L168-170), and methods  
91 section (L 570), and included summary stats for them in Figure 5. In summary, Shannon  
92 diversity only shows very weak temporal trends, yet unweighted Unifrac shows similar  
93 patterns to Weighted Unifrac.

94  
95 - As sample storage method can have significant impacts on microbial communities, I  
96 appreciate the inclusion of data aggregated by storage method in figures S5-6. However, the  
97 authors mention in the methods section that trends were largely the same across storage  
98 groups and thus, storage should not have impacted results (line 504). However, especially in  
99 figures S5 C and F the trends for freeze dried vs frozen samples look almost opposite one  
100 another. I think there should be some mention of this caveat in the results or discussion.

101 As outlined in point 5 of the summary above, we now only consider associations robust if  
102 they hold up both for frozen and freeze-dried samples, even if the association is significant  
103 overall. This is because many associations can be significant if the sample size is high, yet do  
104 not necessarily represent meaningful relationships. The associations that were inconsistent  
105 across frozen and freeze-dried samples (e.g. bacterial load as brought up by the reviewer) were  
106 those that tended to be weak overall, and therefore prone to being inconsistent. We now  
107 present all trends split by storage (Figs S3, S6, S7, and S8), and colour associations by how  
108 robust they are in Figure 5. In Figure 5, it is clear that strong associations are almost always  
109 robust across the two storage types, whilst weak associations tend not to be robust. We state  
110 more clearly now when presenting each result about whether we consider it robust or not.  
111 For example, we have altered the bacterial load results to:

112 L145: “Mean bacterial load underwent the largest shifts across the day, in comparison to  
113 seasonal and lifetime scales, which were both much weaker (Hours after sunrise:  $F = 54.4$ ,  $p$   
114  $< 0.0001$ ; Month:  $F = 1.1$ ,  $p = 0.007$ ; Age:  $F = 9.1$ ,  $p = 0.003$ ; model  $R^2 = 0.47$ ; Table S2).  
115 Bacterial load tended to be highest early in the morning (Fig. 2a), and fluctuated only weakly  
116 with season (Fig. 2b) and age (Fig. 2c). Whilst seasonal and lifetime shifts in bacterial load  
117 were weak but significant across the full dataset, they were not replicable across both frozen  
118 and freeze-dried samples (Fig S3a).”

119  
120 - Some additional interpretation of the main study results is needed in the discussion. For  
121 example, is there any speculation as to what biological mechanism may drive daily  
122 oscillations in gut microbiome load/diversity based on light/dark cycles?

123 Given our new analysis of the mechanisms, we believe temperature-constrained foraging  
124 schedules are at least partly to explain for diurnal oscillations. However, we wanted to  
125 quantify how much variation could be attributed to foraging schedules, and how much was  
126 explained solely by time of day (which suggests regulation by light-dark cycles and host  
127 circadian rhythms). We therefore partition this variation in Figure 5c. The results are in line  
128 with findings from mouse studies, which show both feeding schedule and light-dark cycles  
129 govern microbial oscillations. Nevertheless, we suspect diurnal oscillations in this species  
130 might be stronger than usual, due to arid conditions which are characterized by large  
131 temperature differentials across the day, and which strongly shape foraging schedules. We  
132 have now expanded our discussion on these points (L320-393, four paragraphs that cover  
133 interpretation of diurnal, seasonal, and lifetime dynamics).

134 *Clostridium* seemed to be a central driver of several results—what might be the significance  
135 of this group and why might it have been so plastic?

136 *Clostridium* has been implicated in a number of lab mouse studies on microbial circadian  
137 rhythms (which we now outline in the introduction in L41-53). Therefore, we know already  
138 that this genus is highly dynamic, especially over the daily time scales. Whilst we can only  
139 speculate on its function, *Clostridium sporogenes* is known to generate metabolites that  
140 mediate host metabolism and immunity, therefore we believe something similar might be  
141 going on here. Moreover, gut conditions may also play a role: *Clostridium* is strictly  
142 anaerobic, whilst at least one taxa that increases in the afternoon (*Cellulomonas*) is strictly  
143 aerobic. Therefore, there is evidence that there is a change in oxygen levels over the day that  
144 is likely to maintain diurnal oscillations. We now touch on this in our discussion in L332-  
145 343.

146 “An additional mechanism maintaining diurnal oscillations may be niche modification over  
147 the day, with the spike in bacterial abundance in the morning, for instance, causing changes  
148 to gut pH and aerobic conditions<sup>33</sup>. This shift in gut environment may generate favourable  
149 conditions for *Raoultibacter* and *Cellulomonas*, and suppress *Clostridium* even during periods  
150 of afternoon foraging. A shift in gut oxygen levels over the day is supported by the fact that  
151 *Clostridium* is strictly anaerobic, whilst *Cellulomonas* is aerobic. Whilst we can only  
152 speculate on the function of these microbial diurnal oscillations, *Cellulomonas* degrades  
153 chitin<sup>35</sup>, a key feature of arthropod exoskeletons, therefore increases in this genus in the  
154 afternoon therefore facilitate the breakdown of arthropods and other non-soluble fibres such  
155 as cellulose. Moreover, previous research has shown that *Clostridium* species generate  
156 metabolites that alter host metabolism and immunity<sup>34</sup>, suggesting that the dawn spike in this  
157 genus may be key to mediating meerkat circadian function.”

158

159 Different trends for ASV richness and bacterial loads were discussed on the basis of  
160 seasonality in the discussion (paragraph starting line 300). However, these differences also  
161 appeared on a diurnal scale which wasn't discussed. Why might these trends be different (e.g.  
162 is bacterial load driven by one dominant ASV that reduced richness?)

163 We believe so. This pattern is likely in part due to the spike in Clostridium pushing  
164 abundance of rare taxa down beyond our detection level. This is supported by the fact that  
165 Shannon diversity doesn't really change across the day, showing that the lower observed  
166 richness in the morning is generated by the drop in rare taxa. We now specifically state this in  
167 the results when reporting on Shannon diversity (L 166). However, a peak in alpha diversity  
168 at noon has also been shown in humans, suggesting at least part of the peak in ASV richness  
169 at noon is due to feeding and not necessarily just a statistical effect.

170 We have acknowledged this negative relationship in the results (L159), yet unfortunately we  
171 do not have the space to discuss this relationship in detail given we have already expanded  
172 our discussion greatly and have hit the word limit. Temporal dynamics in alpha diversity are  
173 really weak, and also our models of alpha diversity also have quite low explanatory power.  
174 As such, we do not focus that heavily on this aspect of the results. Nevertheless, we do now  
175 compare our results to a study on humans (which didn't account for bacterial load) to show  
176 that this pattern is likely not an artefact:

177 L314: "Our findings are in line with those from laboratory mice and humans, which also  
178 report spikes in bacterial load when mice become active at dusk<sup>6,18</sup>, and a peak in alpha  
179 diversity at noon in humans<sup>7</sup>."

180

181 - There appeared to be little sampling during the mid-day period (e.g. Figs 2b, 4a). Why was  
182 this and how might this impact results? This should be discussed a bit.

183 We agree that this situation was not ideal. The reason for the gap is because both meerkats  
184 and humans are not active during the middle of the day, although in winter it is very possible  
185 that meerkats are active but just not monitored (there is now evidence for this from  
186 unpublished accelerometer data). As outlined in point 3 in the summary above, we have  
187 added 80 more samples to try and cover this gap, which does not close it completely but does  
188 narrow the midday gap from 5 hours to 3 hours. We also carry out a sensitivity analysis by  
189 randomly subsampling samples equally across the day, which shows similar results  
190 (presented in Figs S10 and S11). In addition, the smoothing function we use (cubic regression  
191 splines), only fit smoothing knots where there are data (opposed to distributing the knots  
192 equally), so that gaps in the data do not produce spurious trends. We have added this  
193 information in the methods:

194 L543: "Cubic regression splines calculate smoothing knots based on data density (rather than  
195 distributing them equally along a gradient), and therefore periods of missing data, e.g. during  
196 the middle of the day, do not contain knots nor generate erratic trends."

197 We also outline our sensitivity analysis for unequal sampling distribution in the methods:

198 L556: "because samples were collected unequally across the day, with few samples in the  
199 middle of the day, we randomly subsampled 20 samples per hour interval (minus two hours at  
200 noon that had fewer than 20 samples and were therefore excluded) and reran models on the  
201 reduced dataset, and found results were robust to sampling distribution (Fig. S10a)."

202

203 Smaller changes

204

## 205 Introduction

206 - Line 51: There seems to be a typo here. May-September is listed as both summer and winter  
207 months

208 Thanks – fixed (L87)

209 “The Kalahari region is also highly seasonal, with the climate marked by high temperatures  
210 and sporadic rainfall during the wet summer (October to April), and dry winters (May to  
211 September; Fig. 1c) being cool with almost no rainfall.”

212

213 - Line 57: Different storage methods should be added here, as not all samples were frozen  
214 afterwards?

215 As outlined above in the summary of changes, we have brought the effect of storage up so  
216 that it is the first section of the results (L114). We have added this information to the  
217 introduction as requested (L99):

218 “For long-term storage, samples prior to 2008 were mostly frozen at -80c (n = 461), or, after  
219 2008, freeze-dried and kept at room temperature (n = 648; Fig. S1a).”

220

## 221 Results

222 - Line 98: change “genera” to “genus”.

223 This paragraph has been deleted, and replaced with a methods validation section.

224

225 - Line 159: Was this 62% of the 34% of overall variation explained above? Or 62% of overall  
226 variation?

227 62% of overall variation. However, we have taken out this paragraph since the contribution of  
228 each axis is marked in the figures (Figures 2 and 3).

229

230 - Line 183: this header indicates results regarding clostridium, but I don't think there is any  
231 mention of clostridium in this section? Consider rephrasing

232 Thanks. We have now restructured the results section, and taken out Clostridium in the  
233 headings.

234

235 - Line 202: please explain in a bit more detail how genera were identified as core. In most  
236 cases, they are taxa present in a certain number of samples. Is that what is meant by 80%  
237 prevalence here, or does this refer to relative abundance of the taxa? Is the N here the number  
238 of genera or number of samples? A list of the taxa somewhere would be helpful.

239 Thanks for highlighting this. We agree this was not clear, and in retrospect, we believe we  
240 should have expanded our analyses to include more taxa. We still do focus on 16 genera,

241 which we call ‘focus genera’ instead of ‘core taxa’. In the previous manuscript, we did limit  
242 our analyses to the most prevalent taxa (> 80% prevalence across samples) because a) they  
243 are the most common and therefore contributing the most to composition (confusingly, these  
244 taxa do make up around 80% relative abundance too, although we did not report this before);  
245 and b) it is much easier to model prevalent taxa to avoid zero inflation. Rare taxa (ie low  
246 prevalence taxa) are very challenging to model.

247 However, this strategy does risk missing important associations with rarer taxa. For example,  
248 we were particularly interested in identifying juvenile-associated genera, or genera which  
249 increases in the afternoon. Yet we cannot present GAMM models for a hundred or more  
250 genera, this is overwhelming for the reader and not very focused. We therefore compromise:  
251 we present non-parametric differential abundance analyses for all genera with over 15%  
252 prevalence (Fig. S4). This provides a broad summary of which and how many genera are  
253 undergoing temporal changes. However, we still focus on the most common genera for more  
254 in depth analysis (n = 12), and use the differential abundance analysis to select four additional  
255 (but rarer) genera that are showing notable changes to run GAMMs on.

256 We now explain this in more detail in the manuscript:

257 L203: “We first performed simple differential abundance non-parametric tests across all  
258 genera with over 15% prevalence across samples (n = 117) to identify genera that were  
259 differentially abundant in the morning compared to afternoon, in the dry season compared to  
260 the wet season, young meerkats versus adults, and adult meerkats versus old meerkats (Fig.  
261 S4). Almost all genera were significantly associated with time of day (Fig. S4a), suggesting  
262 that diurnal oscillations are widespread across gut microbiome members. Only a few genera  
263 significantly differed between dry and wet seasons (Fig. S4b). A small number of genera  
264 were differentially abundant in adults compared to young meerkats (Fig. S4c), whilst none  
265 were differentially abundant in old meerkats compared to adults (Fig. S4d).

266 We next focused on 16 notable genera in order to model their temporal dynamics using  
267 GAMMs whilst controlling for potentially confounding methodological variables. We  
268 focused on the most prevalent and abundant genera (n = 12) which all had at least 60%  
269 prevalence across samples and together accounted for 75% relative abundance. However, we  
270 used the results from the differential abundance analysis to select four additional rarer genera  
271 that exhibited notable trends for additional analysis, including *Raoultibacter* (43%  
272 prevalence), and *Callulomonas* (38% prevalence). We also include a particularly rare genus,  
273 *Eubacterium* (18% prevalence), which was only present in young individuals.”

274 - Lines 206-211: a supplemental table may be helpful to show exactly which genera were  
275 influenced by which variables, unless they are all listed in figure 6? Maybe that figure should  
276 be cited here.

277 All associations are now visualised in Figure 5 (which was previously figure 6). Our updated  
278 figure summarises all effect sizes (and whether they are robust to methodology or not). This  
279 figure is now split into effect sizes of temporal variables (Fig. 5a; ie just the strength of their  
280 temporal dynamics across the three temporal scales) and effect size for mechanistic variables  
281 (ie which underlying mechanisms best explain temporal dynamics; Fig. 5b). Note that we

282 have altered this figure to also include diversity metrics, and – for clarity - it no longer  
283 visualises the effects of individual methodological variables. We decided to remove  
284 methodological variables because 1) they just don't fit; and 2) due to rather large effect sizes  
285 they tend to distort the x-axis scale, making it very hard to see effect sizes of the biological  
286 variables we are interested in. Instead, we visualise the proportion of variation explained by  
287 methodological variables in Fig. 5c, where we have partitioned model  $R^2$  into temporal,  
288 mechanistic, and methodological variation. This figure now acts as an overall summary of all  
289 models presented in the manuscript.

290

291 - Line 227: Were only the genera listed as core used for this analysis?

292 As outlined in detail above, we now no longer limit the analysis to only core taxa.

293

294 Methods

295 - Line 360: some additional information is needed about this storage experiment. How were  
296 the samples handled after collection? Were the samples split into storage treatments from  
297 single individuals or different individuals were used for each type? etc.

298 Each sample represent a different individual (1 sample per meerkat). As with samples from  
299 wild meerkats, meerkat's were observed defaecating, the sample collected, and immediately  
300 frozen. Samples were frozen immediately after collection We have clarified this in the  
301 methods:

302 L660- 671: "Whilst the effects of storage can be accounted for statistically, we wanted to  
303 confirm experimentally that the two storage methods used here do not overly affect bacterial  
304 composition. We experimentally tested the effect of freezing versus freeze-drying on overall  
305 bacterial community composition by collecting fresh faecal samples from nine different  
306 captive meerkats housed at the University of Zurich. Faecal samples were frozen immediately  
307 on collection. A subsample of the sample was then freeze-dried, whilst another subsample  
308 remained frozen at  $-80^{\circ}\text{C}$  for one week. DNA was extracted and processed following the  
309 same protocols as described above, with the exception that an internal standard was not added  
310 to samples. To analyse the effect on storage on these samples, samples were normalised by  
311 rarefaction and we performed a marginal PERMANOVA on a Weighted Unifrac distance  
312 matrix, including sample ID and storage as terms."

313

314 - Line 363: what statistical methods were used to compare beta and alpha diversity between  
315 these groups?

316 This is outlined above.

317

318 - Line 392: what version of QIIME2 was used?

319 We used version 2020.2. This has been added in L470.

320

321 - Line 397: change “that” to “than”

322 Thanks, corrected.

323

324 - Line 421: what units was weight measured in?

325 Meerkats are weighed in grams. This has been added, but due to space limitations, this part of  
326 the methods has been moved to the supplementary materials (see Supplementary methods  
327 S1).

328

329 - Overall for beta and alpha diversity metrics, was rarefaction used to standardize sequencing  
330 depth?

331 All analyses were carried out on normalised data (scaling to the internal standard) and  
332 controlling for sequencing depth and other methodological variables in the various models (  
333 for both alpha and beta diversity). Since beta diversity results are based on relative  
334 abundances, rarefying the counts actually makes no difference to results (we tested this). We  
335 now make it clearer that all analyses are conducted on scaled reads (L496, L570, L590).

336

337 - Line 518: why was MDS used as opposed to NMDS which appears to be more common for  
338 these analyses?

339 In my experience, one has difficulty converging NMDS ordinations with any large microbial  
340 dataset due to the huge amount of variation. Convergence is usually possible with small  
341 datasets. In our case, NMDS ordinations did not converge, and we did not want to filter the  
342 dataset too heavily. Even with unconverged NMDS ordinations, the effects looked similar to  
343 those presented, yet we did not want to present unconverged models. We have justified our  
344 use of MDS ordination on L590.

345

346 Figures/Tables

347 - Fig 2a is really difficult to glean information from due to the number of samples and  
348 microbial taxa. It may help to distill the number of taxa displayed to smaller number (e.g. top  
349 5-10 most abundant)

350 We have revised this barplot to represent every half an hour period (suggested by reviewer 2),  
351 and moved it to figure 3. We still retain 16 genera because this then keeps the colour scheme  
352 consistent across plots.

353

354 - Fig2 d-e: what cutoffs were used to delineate groups (e.g. what hours were used for  
355 morning/afternoon and months for wet/dry season). This is explained for age but not these  
356 two.

357 Thanks for pointing out this omission. We use the ‘noon gap’ in the data as a cutoff  
358 threshold for morning/afternoon (</> 7 hours after sunrise), since this is more biologically

359 meaningful than 12pm as it represents when meerkats finish their morning bout of foraging.  
360 We have stated these thresholds in more detail in the methods (L608-612), as well as the  
361 legend of Figure 2.

362 L608: “We therefore ran a differential abundance analysis on all genera with over 15%  
363 prevalence to assess any differences in taxa between morning (< 7 hours after sunrise; n =  
364 743) and afternoon (>7 hours after sunrise; n = 366), dry (May-September; n = 418) and wet  
365 seasons (October-April; n = 691), and young (<1 year; n = 385) and old (> 5 years; n = 97)  
366 meerkats.”

367

368 - Fig 2 legend: change GAM to GAMM?

369 Thanks, fixed.

370

371 - Figure 3a: it is unclear to me what joint vs. independent represent. This should be explained  
372 in more detail in the text or legend.

373 In this version we have excluded this hierarchical partitioning analysis. This is because  
374 another reviewer also queried this analysis, and we realised after careful consideration that it  
375 merely duplicates the models we generated to add arrows to our ordination plot. To add the  
376 arrows to our ordination plot in Figure 3b and c, we apply `vegan::envfit()`, which uses linear  
377 models (with permutations) to model variables onto ordination axes. This is essentially the  
378 same as hierarchical partition analysis, except that the latter also divides variation into  
379 independent variation and shared variation (variation explained by multiple variables). Since  
380 shared variation was low and not an issue, we have decided to keep things simple and report  
381 the stats from the `envfit()` analysis, which match the arrows on the ordination.

382

383 - Table S3 caption: change “statics” to “statistics”?

384 Thanks, fixed.

385

386

387 **Reviewer #2 (Remarks to the Author):**

388

389 Risley et al. extensively document microbiome variation in wild meerkats, isolating dynamics  
390 associated with circadian rhythms, seasonality, and host demography. The authors leverage  
391 an extensive sample and metadata set to answer questions previously untackled in  
392 microbiome analyses, and they use appropriate mixed effects models to do so. The paper  
393 provides a unique perspective on gut microbiome dynamics in a wild population and is a  
394 significant contribution to the field.

395 Thank you for this positive assessment!

396

397 I have identified four larger issues that should be addressed before publication however and  
398 also provide a list of smaller concerns.

399

400 Larger Issues:

401 Model choice—The authors do a laudable job of describing their GAMM fitting in the  
402 methods, but their use of hierarchical variance partitioning models is much less well  
403 motivated. The R package used is not specified nor are the validation tests. Moreover, the  
404 authors fail to explain (i) why the hierarchical variance partitioning model approach was used  
405 to analyze the biological predictors of the first four major principal components of the MDS  
406 ordination and (ii) why it wasn't used for analyses of biological predictor role for other  
407 dependent variables. Furthermore, why analyze biological fit on 4 MDS axes rather than just  
408 modeling fit of overall dissimilarity with PERMANOVA?

409 As mentioned in a response to Reviewer 1, we have now removed the hierarchical  
410 partitioning analysis because it is simply not necessary and does more to confuse the matter  
411 (see comment starting L346 of this document). Our motivation for using the hierarchical  
412 partitioning analysis was that we wanted to show the predictors of each ordination axis  
413 independently, given that each axis represents a different suite of taxa and the first four axes  
414 make up a disproportionate amount of the variation. E.g. axis 1 largely represents Clostridium  
415 on one side and Bacillaceae on the other end, whilst axis 2 largely represents Bacteroides.  
416 Most of the diurnal temporal dynamics appears to be driven these taxa, and we wanted to  
417 emphasize this with the hierarchical partitioning analysis. The use of PERMANOVA alone  
418 suggests that diurnal effects are rather weak (although it should be noted that effect sizes are  
419 large, but R<sup>2</sup> is weak), when in fact the effect sizes are really rather large when considering  
420 the first two axes of ordination.

421 Instead of hierarchical partitioning analysis, we now simply report the results of the envfit()  
422 models, which map variables onto an ordination using linear models. We have added more  
423 details on these models in the methods.

424 L595: “We statistically tested for differences in centroids across axes 1 and 2 (Fig. 3b) and 3  
425 and 4 (Fig. 3c) by using the *vegan::envfit* function, controlling for methodological variables,  
426 and with 999 permutations. The *envfit* function uses linear model permutations to map  
427 variables onto an ordination.”

428

429 Abundance patterns— The fact that all but one major genera exhibit the same diurnal shifts  
430 despite being associated with different biological and environmental variables is confusing to  
431 me. To what extent may these just be reflecting the overall trend in load? The strong effect of  
432 sequencing depth for all genera except Geodermatophilus seems to indicate this may be at  
433 play. Are similar shifts observed when analyzing relative abundance? (I'm not advocating  
434 including relative abundance analyses in the published paper, just using them as a tool to  
435 better understand why absolute abundance patterns appear as they do.)

436 Thanks for bringing this up. Previously we only tested genera with over 80% prevalence  
437 (since these were the most abundant and also the most reliable to model). However, in our  
438 new analysis we have checked all taxa with over 15% prevalence using simple non-  
439 parametric differential abundance analysis (which we visualise in Fig. S4). Whilst most still  
440 underwent the same patterns, we did find a few genera which do the opposite and increase in

441 the afternoon. Because these are biologically interesting, we have included these in our list of  
442 focus genera. See comment starting L239 in this document for more explanation on the 16  
443 genera we model in our revised analysis.

444 I hope that our new results, which show that there is a number of genera that do the opposite  
445 pattern and increases in the afternoon, satisfies your concern that this might be an analytical  
446 artefact or just a consequence of bacterial load.

447

448 The extreme response exhibited by *Clostridium* may in part reflect the fact that it has much  
449 higher (2-5x) 16S copy number than the other genera analyzed (for which genomes are  
450 available and copy number estimates are published in rrnDB). While the authors note in the  
451 methods that the internal standard technique directly assesses copy number but generally  
452 reflects absolute abundance trends, they don't discuss how large differences in copy number  
453 will impact their interpretation.

454 Thanks for this resource. In response, we have discussed this as a caveat in the last paragraph  
455 in the discussion (L394-414), where we also bring up other methodological limitations.

456 “Our study combined extensive longitudinal data and microbiome load quantification to  
457 advance our understanding of temporal dynamics in gut microbiomes. Nevertheless, it faces  
458 some study design and methodological limitations that may affect interpretations. Notably,  
459 the use of internal standards is likely prone to high technical variation, since it is challenging  
460 to accurately standardize sample weight, and subsequent technical variation can be inflated  
461 by PCR bias<sup>45</sup>. Our technical replication analysis confirmed that technical variation was  
462 higher for estimates of bacterial load (10%) than measures of alpha and beta diversity (~2%).  
463 Whilst this variation is non-negligible, sample ID still accounted for 90% of variation and  
464 therefore the identification of true biological associations is possible, especially with large  
465 sample sizes. We also minimise the risk of further PCR bias by controlling for sequencing  
466 depth in all analyses<sup>45</sup>. A perhaps more serious concern is that variation in 16S rRNA gene  
467 copy number biases bacterial load estimates due to differences in the number copies between  
468 bacterial species. To date there is no consensus about how to control for 16S copy number in  
469 amplicon data<sup>46</sup>, and bacterial genomes can contain between one and 21 gene copies<sup>47,48</sup>. As  
470 such, our estimated abundances are almost certainly over-estimates. *Clostridium* species  
471 predictably have high copy numbers (~10 copies), therefore at least part of the large spike in  
472 *Clostridium*, and reflected in bacterial load, may be an artefact of high copy number.  
473 Nevertheless, we are interested in estimating relative changes in abundance over time within  
474 communities, rather than comparing abundances amongst taxonomically different  
475 communities. Therefore, whilst the rates of change over time are not comparable between  
476 different taxa, the overall direction of change for each taxa is reliable.”

477

478 It does seem that the *Clostridium* genus has an average 16S copy number of around 10  
479 (compared to average of 5, I believe), and it seems that this copy number is generally quite  
480 consistent across strains. This definitely could explain the very large peak in the morning.  
481 Whilst the overall trend for *Clostridium* should be reliable, it is true that one cannot compare

482 the degree of change over time between species, and this is why we don't include analyses  
483 such as ecological networks, which can be very biased by differences in copy number.

484 Because we merge ASVs by genus, and it conceivable that different ASVs represent different  
485 strains with different copy numbers, we additionally checked that all *Clostridium* ASVs (~7  
486 ASVs) were behaving in the same way, and they all exhibited very similar dynamics (not  
487 presented). This supports our decision to merge ASVs by genus, even though the different  
488 ASVs may have different copy numbers.

489  
490 Diurnal time series—For totally understandable methodological/behavioral reasons, the  
491 authors were unable to sample evenly across the course of the day. However, they fit their  
492 models across the entire day even though between ~5 and ~10 hours after sunrise their  
493 sampling is very sparse. The confidence intervals are somewhat larger there, but I'm not sure  
494 you should be fitting through at all. Certainly more discussion of this limitation is necessary.

495 As outlined in the summary above, we have added 80 more samples to the dataset to try and  
496 close this gap a little. This gap is now around 2-3 hours, opposed to 5 hours. Whilst still not  
497 ideal, with analytical precautions and sensitivity analyses we believe GAMMs are still  
498 appropriate, with a clear acknowledgement that there is uncertainty around the middle of day.  
499 Firstly, the cubic regression splines we fit only place smoothing knots where there is enough  
500 data so that small sample sizes don't generate erratic trends. Therefore, in places of low data  
501 (including, for example, in very old meerkats where less data is available), the model makes  
502 no assumptions about what is going on but basically just fits a linear trend between periods of  
503 dense data. Given the constraints on the GAMM smooths (cubic regression splines, plus  
504 correlation error distributions, which both limit how 'wobbly' the line can be), it would take  
505 quite aberrant data during this 2 hour period to change the shape of the trend.

506 As well as adding extra data, we also run random sampling across the day to check whether  
507 uneven sample size distribution (apart from 2 hours in the middle of the day where there was  
508 less than 40 samples) alters results. It doesn't, and we present this in the supplementary  
509 material (Fig S10 and S11). Therefore, we acknowledge that uncertainty is high during the  
510 middle of day, but provide evidence that this gap does not affect estimates for the rest of the  
511 day.

512 In response, we have added the following lines:

513 L147: (results) "Bacterial load tended to be highest early in the morning and lowest  
514 approximately 10 hours after sunrise (Fig. 2a), although it should be noted there is  
515 considerably uncertainly regarding estimates for the middle of the day when sampling is  
516 sparse."

517 L543 (methods): "Cubic regression splines calculate smoothing knots based on data density  
518 (rather than distributing them equally along a gradient), and therefore periods of missing data,  
519 e.g. during the middle of the day, do not contain knots nor generate erratic trends."

520 L556 (methods): "because samples were collected unequally across the day, with few  
521 samples in the middle of the day, we randomly subsampled 20 samples per hour interval

522 (minus two hours at noon that had fewer than 20 samples and were therefore excluded) and  
523 reran models on the reduced dataset, and found results were robust to sampling distribution  
524 (Fig. S10a).”

525

526 It’s unclear to me as a non-meerkat specialist how frequently an individual defecates so  
527 whether there could potentially be samples in the middle of the day if one had access to  
528 burrows or even at multiple times during the day for one host. It is hard to tell from Figure 1  
529 whether there are individuals who were ever sampled multiple times on the same day even  
530 during the two dense sampling campaigns. If there are, would it be possible to provide  
531 supplemental figures plotting their observed richness or load over such a day? This would be  
532 especially helpful for estimating how representative the overall fit is for individuals given  
533 that there is such variance at any given time of sampling.

534 Unfortunately we do not sample the same individual on the same day. The closest samples for  
535 individuals are about a month or two apart, since our aim was to sample meerkats rather  
536 evenly throughout their lives. In this system, there appears to be very little ‘individual’ effect,  
537 although samples collected close together (~ within a few months) are more similar than  
538 samples collected further apart (> a year). This individual stability (and predictors of  
539 stability) is actually the subject of our next paper on this dataset, therefore this is in part why  
540 we do not focus much here on individual effects. The effect of ID as a random effect in all  
541 the models we present is almost always not significant (with the exception of alpha diversity,  
542 where there is some small effect of ID). There is an effect of ID on beta dissimilarity ( $r^2 =$   
543 20%), but the effect size is very small (ie, individual centroids are very close together).  
544 Therefore, whilst individual effects are probably much larger over the short term, over the  
545 long term (years), individual effects are very weak. This is line with the recent Grieniesen et  
546 al. paper (Science, 2021) on baboon microbiomes over long time frames.

547

548 Dominant genera—The specification of “dominant genera” for the enterotype analyses  
549 (Figure 3) needs to be better defined in the results and the methods. Is it just the most  
550 abundant genus? Why aren’t these the genera of focus for the core genera analyses if they are  
551 what distinguishes between communities? At the very least the color schemes should be  
552 consistent between 3b and 4e-h so the reader can more easily tie them together.

553 The dominant genus is indeed just the most abundant genus in each sample. We now simply  
554 say that points are coloured and grouped “by the most abundant genus in each sample”  
555 (legend Fig. 3). These genera were included in the list of ‘core’ genera in the previous  
556 version. However, to increase clarity the same 16 focus genera are now the same colours  
557 across all figures.

558

559 Smaller Concerns:

560 -line 39 It is unclear what the definition of “biological systems” is in this context. Do you  
561 mean non-microbiome host physiological programs?

562 Yes. We have clarified this to ‘host physiological circadian rhythms’ (L62).  
563  
564 -line 47-50 What are animals doing when they aren’t foraging?  
565 Resting, playing, moving, etc. They often move very far from their burrows to forage,  
566 therefore they spend quite a lot of time on the move. In the summer, they don’t spend lot of  
567 time foraging (just v early and v late in the day) and this is confirmed by unpublished  
568 accelerometer data.

569  
570 -line 65 Specify you mean the abundance of each of the 15 genera, not the 15 together.

571 We have revised this aim to “To identify which genera exhibit predictable dynamics at each  
572 scale” (L108).  
573  
574 -line 68 What kind of models?  
575 This section has now been removed. We now explain model structure at the point where we  
576 present the results of the model in question, rather than try and summarise our models at the  
577 end of the introduction.

578  
579 -lines 98, 99 Specify if 60% and 30% are means and provide standard deviation or confidence  
580 intervals for the summary statistic.

581 We have now replaced this section with the results of our investigation on storage methods  
582 and the technical replication analysis, which we believe is more pertinent and important than  
583 a summary of relative abundances.  
584  
585 -The presentation of the GAMM model fits is a bit hard to follow in the text (e.g. lines 106-  
586 116; 144-156). Is there a way to report statistical significance for relevant variables in the text  
587 rather than just directing to a supplementary table?

588 We now add all relevant statistics within the text, as well as in the supplementary table.  
589  
590 -line 469-470 You’re testing underlying mechanism not necessarily “identifying” them since  
591 you don’t have all possible relevant mechanistic variables included in your analyses.

592 Noted, we have altered this terminology across the manuscript.

593  
594 -line 509-512 What would’ve been evidence for more than marginal overfitting? Isn’t a ¼  
595 drop in variance explained a lot?

596 Good question. We performed a one sample t-test (we only present this in the R markdown  
597 report) to test the R2 from our model and 100 train/test models and it was significantly  
598 different. We have altered this in the text:

599 L581: “Finally, we validated the model by splitting the dataset into training and test sets 100  
600 times. The model explained on average 24% of variation in the untrained data (in comparison  
601 to the 29% reported), indicating model predictions were likely over-fitted and true  
602 explanatory power was closer to ~24%.”

603

604 -line 522-528 You could analyze with adonis2 function in vegan, rather than adonis function,  
605 to capitalize on a marginal sums of squares approach (by=”margin”) and thus not be subject  
606 to the same sequential effects.

607 We have now done this. The PERMANOVA results are the marginal effects. The  
608 PERMANOVA results are outlined in Table S4.

609

610 Figures

611 -Please provide supplementary figures with histograms of your sample set. For example, what  
612 is the frequency of samples for time of day (maybe hourly bins), months, and age? And what  
613 is the frequency of samples for time of day by age groups (underlying the figure 5 analysis)?  
614 It’s not possible to back this out of Figure 1 or the highly dense observed data plots (like 2b-  
615 d), but such information is useful for understanding how robust the patterns are.

616 We have added the histograms of each temporal scale in Figure 1e. These were previously  
617 just in the R markdown report. We have also added histograms to the top of Figure 6 (which  
618 was figure 5 – diurnal oscillations by age group).

619

620 -I find figure 2a really hard to parse, especially since the x-axis is not plotted as a continuous  
621 axis. Either fewer families need to be plotted and/or averages for ordinal time points need to  
622 be plotted. The current version could be included in the supplement if you think it is  
623 necessary, but it is too busy to read as is. Also, 2A should not be cited after the sentence “The  
624 most abundant genera across samples was Clostridium sensu stricto 1, an anaerobe that made  
625 up 30% of reads, and which was more abundant in the morning than the afternoon and  
626 evening” since there are no genera results in it.

627 We have now altered this figure to represent mean composition per half hour interval (Figure  
628 3a below). We have also removed the paragraph you refer to here (which previously just  
629 summarised overall composition).

630

631

632

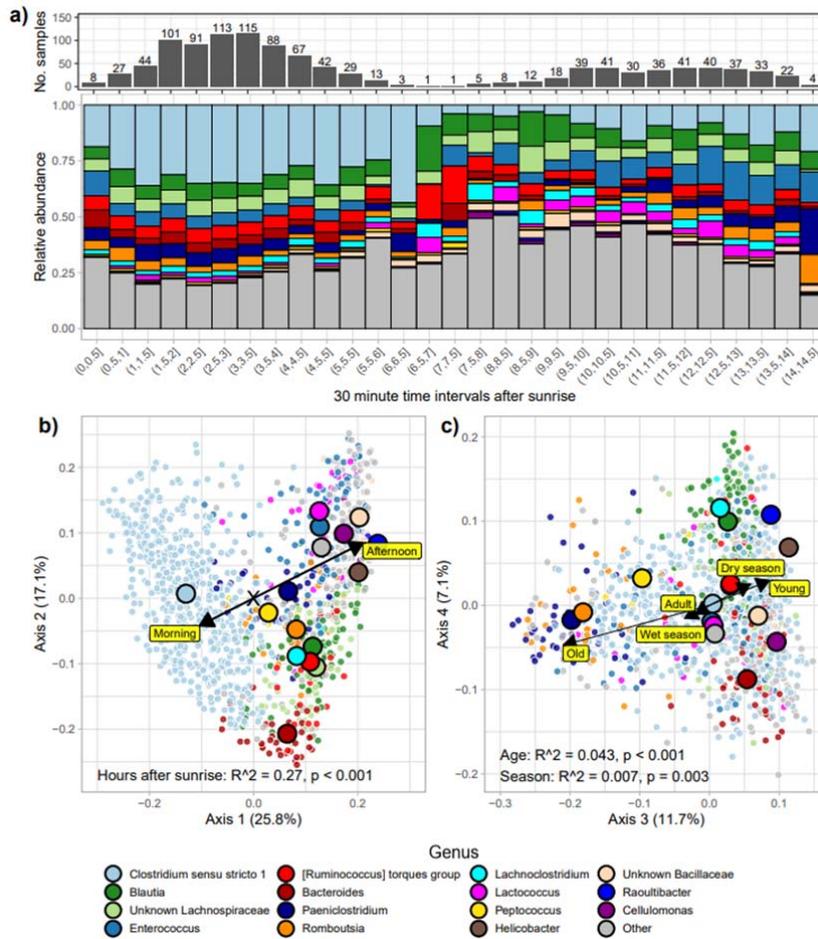
633

634

635

636

637 New figure 3:



638

639

640

641 -“Dominant genera” needs to be defined in the legend of Figure 3. Is “other” any other genera  
 642 or a group of non-specified but not exhaustive genera?

643 We have clarified that dominant means the most abundant genus per sample. “Other” means  
 644 that sample was dominated by a genus not listed in the colour key. We have clarified these  
 645 points in the legend.

646

647 -Figure 4d x and y axes should match, the axes should not have decimal places in the  
 648 superscript, and the blue line should be defined (is it a fit line or 1:1)?

649 We have removed this figure in this version, to save space, since we believe it is not essential.

650

651 -Why are 4h-j not also on a log scale?

652 We have now visualised this figure on the log scale (Fig. 4b).

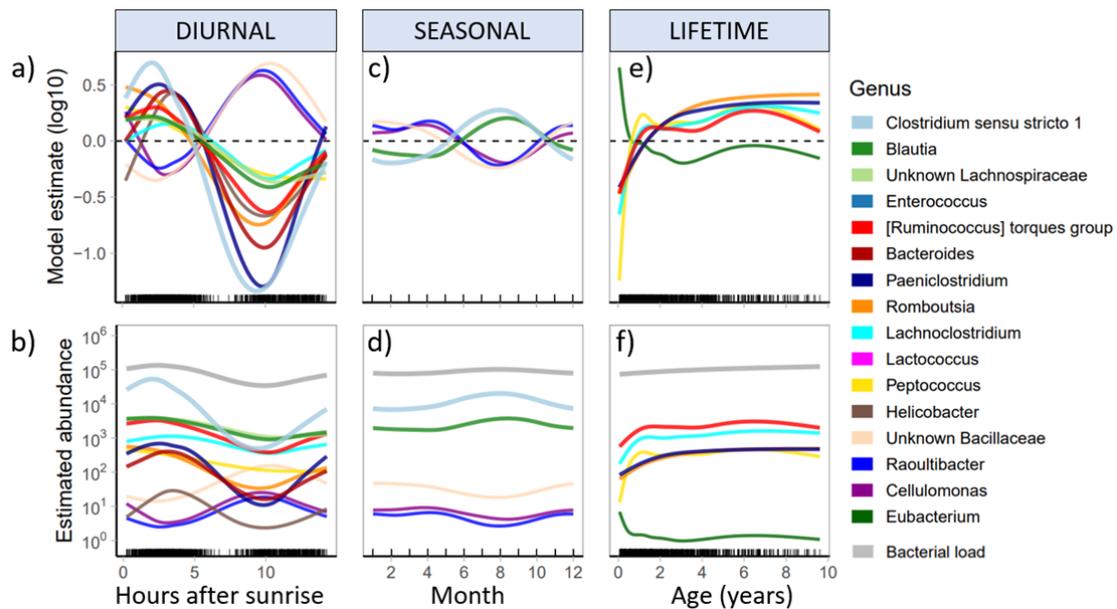
653

654 -Can you provide the overall load oscillations for each age group in Figure 5? If differences

655 in overall abundance are underlying much of the genera oscillations (see “Abundance  
 656 Patterns” above) we’d expect to see a similar overall abundance curve for each age group.  
 657 But if the overall signal varies while the genera patterns are consistent, that supports the idea  
 658 that genera behave somewhat independently.

659 We have added bacterial load to Figure 4b (see below). We do not believe that bacterial load  
 660 is independent of these taxa dynamics, since by definition bacterial load is the sum off all  
 661 taxa. However, in the revised figure below, you can see that genera are demonstrating  
 662 different dynamics, providing some evidence that these are somewhat independent of  
 663 bacterial load.

664 New figure 4:



665

666

667 -Figure 6 in general is an excellent way of summarizing some very complex model results. It  
 668 would be helpful though to have a legend on the plot specifying what dot size indicates.

669 Thank you. We have actually now expanded this figure to include diversity measures,  
 670 visualized effect sizes on the same axis (so that it is easier to compare effect sizes), and  
 671 distinguished between robust and non-robust effects (ie, effects that show the same trends  
 672 across frozen and freeze-dried samples).

673

674

675 **Reviewer #3 (Remarks to the Author):**

676

677 The manuscript titled “Diurnal oscillations in gut microbiome load and composition eclipse  
 678 seasonal and lifetime dynamics in wild meerkats, *Suricata suricatta*” aims to quantify and  
 679 compare the meerkat gut microbiome across diurnal, seasonal, and lifetime cycles.

680

681 The general approach of the study was to characterize the bacterial load and structure of the  
682 meerkat gut microbiome using 1027 samples collected in the Kalahari across 20 years of  
683 morning and evening behavioral observations of individually known meerkats. Longitudinal  
684 sampling was available for 168 meerkats. The gut microbiome was characterized via 16S  
685 rRNA gene sequencing. Bacterial load was estimated by scaling reads to internal standards  
686 (commercially available) that were introduced prior to DNA extraction. Alpha and beta  
687 analyses were performed.

688

689 The key finding of the study was that most common bacterial genera exhibited diurnal  
690 oscillations in bacterial load. These oscillations were driven by changes to *Clostridium sensu*  
691 *stricto* 1, and were better explained by light-dark cycles than foraging schedule. Diurnal  
692 cycling of the microbiome did not decay with age.

693

694 The conclusion of the study was that diurnal oscillations shape gut microbiome load and  
695 structure in wild meerkats.

696

697 Comments/Concerns

698 This is a high-quality and well written study addressing circadian rhythms of the gut  
699 microbiome in a wild population across 20 years of intensive sampling and behavioral  
700 observation. The breadth, scope, and detail of the metadata available for the samples is  
701 impressive. Commendably, the authors provide all code in an Rmarkdown file. Extraction  
702 and PCR negative controls were included on all sequencing runs.

703 [Thank you for this positive assessment of our study.](#)

704

705 I initially had two concerns, however, both are ultimately addressed in the study.

706 1) The first potential concern was that fecal samples collected prior to 2008 were frozen at -  
707 80°C, while those collected after 2008 were freeze-dried and stored at room temperature.  
708 However, the study includes an analysis showing that biological variation exceeds technical  
709 variation potentially introduced by these differences in storage method.

710

711 2) The second potential concern was that bacterial load was estimated using ZymoBIOMICS  
712 Spike-in Controls. I have never seen this approach for quantifying bacterial load and was  
713 instead expecting quantitative real-time PCR. However, after reading the product literature  
714 and related manuscripts, I appreciate the approach. As noted below, I would however  
715 recommend that the approach be described in greater detail in the Methods, as it is novel.

716

717 I therefore have only minor suggestions.

718

719 Minor comments/edits:

720 Additional proof-reading is recommended prior to publication (e.g., plural/singular).

721 [We have hopefully done a more thorough job of proof reading in this version, and had a](#)  
722 [couple of colleagues read through it too.](#)

723

724 Abstract

725 N/A

726

727 Introduction

728 It would be valuable to present what is known of the mongoose gut microbiome from prior  
729 studies in the Introduction. At present, there is no indication that mongoose gut microbiome  
730 has been characterized at all. If it has not, make this clear.

731 Thank you for this suggestion. The meerkat gut microbiome has not been characterised  
732 previously, but this comment did lead to a more thorough review of papers on mongoose  
733 microbiomes which lead to some interesting comparisons which we bring up in the  
734 discussion. Notably, there is one study on the Egyptian mongoose gut microbiome that  
735 looked at differences between juveniles and adults.

736 We did attempt to add this information (ie overview of the previous literature on mongoose  
737 microbiomes) into the introduction, yet despite this we could not find a place to insert this  
738 information that did not disrupt the flow of the paper. Our manuscript is on temporal  
739 dynamics of the meerkat microbiome rather than the characterization of the mongoose gut  
740 microbiome, and we do not believe that outlining findings from the Egyptian mongoose is  
741 necessarily relevant. We have substantially increased the length of the introduction and  
742 discussion, and added additional analyses, and at this point we are at the maximum word  
743 limit. Any inclusion of previous studies on mongooses would require an explanation and  
744 justification on why this is relevant to our study, which took the word count over the limit.

745 Nevertheless, we do outline some results from the one available study on the Egyptian  
746 Mongoose in the discussion, since this study did a analysis of age (juvenile/adult) on the gut  
747 microbiome and identified one Genus (*Eubacterium*) which was more abundant in juveniles,  
748 which matched our results. However, this is also the case of humans, suggesting that this  
749 process is not necessarily limited to mongooses.

750 L362: “We also identify some genera that change over juvenile development, including a  
751 decrease in *Eubacterium* over the first year of life. This genus was also more abundant in  
752 juveniles in the Egyptian mongoose<sup>38</sup>, and is associated with the transitional state between  
753 the infant and adult gut microbiota in humans<sup>11,39,40</sup>. Therefore, *Eubacterium* likely represents  
754 the weaning period, when young meerkats transition from a milk-based to an arthropod diet.”

755

756 Materials and Methods

757 Line 379 – Did the kit extract all genomic DNA, including that of the host, or only of the  
758 bacteria?

759 Presumably some DNA of the host was extracted, but likely not very much. Since it would  
760 not have been amplified, we did not test for nor detect host DNA.

761

762 Lines 388-390 – Were the DNA extractions also performed in a randomized manner?

763 DNA extractions were carried out in the order of sequencing, since samples were randomised  
764 after subsampling. We have added this information in L467.

765

766 Line 393 – What parameters were used for the DADA2 pipeline? They were not included in  
767 the Rmarkdown report.

768 We have added parameter information on L472.

769 “All sequence reads were processed using QIIME2 version 2020.2<sup>54</sup>. Sequences were  
770 merged, quality filtered, and chimera filtered using the DADA2 pipeline<sup>29</sup> to generate  
771 amplicon sequence variants (ASVs)<sup>29,55</sup>. Primers were trimmed and reads were truncated at  
772 244 (forward) and 235 (reverse) base pairs.”

773

774 Line 402 – What functions/parameters were used for Decontam? They were not included in  
775 the Rmarkdown report.

776 We used the *isContaminant* function using the ‘prevalence’ method. We have added this  
777 information in (L481).

778

779 Line 408 – By what manner were these ASVs identified as laboratory contaminants? Given  
780 their rarity, they would not affect any study outcomes, but given the careful methodology  
781 used in the study, stating these criteria would benefit others in conducting similar studies.

782 We also used the *decontam* package for this, using the negative controls. This has been  
783 clarified in L487.

784

785 Line 413 – Please explain how samples were scaled to *Allobacillus*. This is a new technique,  
786 which warrants further explanation.

787 We have added at L493:

788 “The sample scaling factor was generated by multiplying the mean read count of *Allobacillus*  
789 by its read count in each sample, and sample reads were then multiplied by the sample  
790 scaling factor to normalise the dataset”.

791

792 Lines 424-426 – Explain how weights were collected in a near daily manner, or include a  
793 reference to prior descriptions of the process.

794 Individual meerkats are weighed daily by enticing them onto electronic scales using crumbs  
795 of hard-boiled egg. We have added this information in the relevant section on how we  
796 calculated body condition, which we have had to move to supplementary materials due to  
797 word limit constraints.

798

799 Results

800 Figure 2 – There are two “d” panels in the figure.

801 Yes I realised this after submitting! The figures have been modified but they are now  
802 labelled correctly.

803

#### 804 Discussion & Conclusions

805 A section on the strengths and limitations of the study would be valuable.

806 We have expanded the introduction and the discussion substantially. We have added a  
807 paragraph on the most important limitations at the end of the discussion, which we believe  
808 are the technical variation for bacterial load, and 16S copy number. Whilst unequal sampling  
809 distribution is also an unavailable limitation, we have gone to lengths in the methods to show  
810 that this does not affect overall conclusions.

811

812 L394: “Our study combined extensive longitudinal data and microbiome load quantification  
813 to advance our understanding of temporal dynamics in gut microbiomes. Nevertheless, it  
814 faces some study design and methodological limitations that may affect interpretations.  
815 Notably, the use of internal standards is likely prone to high technical variation, since it is  
816 challenging to accurately standardize sample weight, and subsequent technical variation can  
817 be inflated by PCR bias<sup>45</sup>. Our technical replication analysis confirmed that technical  
818 variation was higher for estimates of bacterial load (10%) than measures of alpha and beta  
819 diversity (~2%). Whilst this variation is non-negligible, sample ID still accounted for 90% of  
820 variation and therefore the identification of true biological associations is possible, especially  
821 with large sample sizes. We also minimise the risk of further PCR bias by controlling for  
822 sequencing depth in all analyses<sup>45</sup>. A perhaps more serious concern is that variation in 16S  
823 rRNA gene copy number biases bacterial load estimates due to differences in the number  
824 copies between bacterial species. To date there is no consensus about how to control for 16S  
825 copy number in amplicon data<sup>46</sup>, and bacterial genomes can contain between one and 21  
826 gene copies<sup>47,48</sup>. As such, our estimated abundances are almost certainly over-estimates.  
827 *Clostridium* species predictably have high copy numbers (~10 copies), therefore at least part  
828 of the large spike in *Clostridium*, and reflected in bacterial load, may be an artefact of high  
829 copy number. Nevertheless, we are interested in estimating relative changes in abundance  
830 over time within communities, rather than comparing abundances amongst taxonomically  
831 different communities. Therefore, whilst the rates of change over time are not comparable  
832 between different taxa, the overall direction of change for each taxa is reliable. “

833

#### 834 Other

835 It appears that Ben Dantzer’s name is misspelled in the Acknowledgements, unless that is not  
836 who is being referred to.

837 Thanks, corrected.

838

839 Kevin R. Theis

Reviewers' Comments:

Reviewer #1:

Remarks to the Author:

I have reviewed the author's response to reviewers and the revised manuscript and feel that all my previous comments and concerns were successfully addressed. Therefore, I do not have anymore suggestions. Thank you to the authors for their thorough revision.

Reviewer #2:

Remarks to the Author:

The authors did an excellent job and the manuscript is much improved following revision. The analyses are more clearly explained and interpreted, and the figures highlight the findings in an easily interpreted manner. The results remain highly interesting and valuable to the field, so I am pleased to have gotten to review them and thus learn about them early.

Three very minor comments that could be addressed in proofing:

- line 88 has a typo at the beginning of the sentence. Do you mean "Meerkat diet diversity" instead of "Meerkats diversity"
- The legend for Figure 1C should clarify what time period the average climate data comes from. The years 97-2020 sampled for this study or all years studied at the field station? Presumably the climate has been changing there as elsewhere and while there's no need to show those trends, you just need to be clear where the averages are coming from.
- in lines 57-59 and 361-363 you state human infant gut alpha diversity is higher than other ages. This is not accurate, typically it is considered to be lower than adults (including in citations 11 and 37 referenced here) although beta-diversity is higher. You'll need to clarify what "gut microbiome of infants tend to be more diverse" than if not adults or remove the second clause of that sentence in 57-59 and adjust accordingly in the discussion as well.

Reviewer #3:

Remarks to the Author:

In revising the manuscript the authors have addressed my prior concerns. The new analyses are a welcome addition and the current manuscript is a valuable contribution to the field.

## Response to reviewers

We are happy that the three reviewers found our revisions satisfactory. Reviewers 1 and 3 had no further suggestions, and reviewer 2 had some minor suggestions. Below we respond to these. We have also attached our response to the extended comments as a separate document.

Reviewer #2 (Remarks to the Author):

The authors did an excellent job and the manuscript is much improved following revision. The analyses are more clearly explained and interpreted, and the figures highlight the findings in an easily interpreted manner. The results remain highly interesting and valuable to the field, so I am pleased to have gotten to review them and thus learn about them early.

Three very minor comments that could be addressed in proofing:

-line 88 has a typo at the beginning of the sentence. Do you mean "Meerkat diet diversity" instead of "Meerkats diversity"

We have fixed this typo (L89).

-The legend for Figure 1C should clarify what time period the average climate data comes from. The years 97-2020 sampled for this study or all years studied at the field station? Presumably the climate has been changing there as elsewhere and while there's no need to show those trends, you just need to be clear where the averages are coming from.

We have added this information to Fig. 1 legend:

“Seasonal climate across the year measured at the Kalahari Research Station, South Africa, averaged from data between 2009 and 2019”

-in lines 57-59 and 361-363 you state human infant gut alpha diversity is higher than other ages. This is not accurate, typically it is considered to be lower than adults (including in citations 11 and 37 referenced here) although beta-diversity is higher. You'll need to clarify what "gut microbiome of infants tend to be more diverse" than if not adults or remove the second clause of that sentence in 57-59 and adjust accordingly in the discussion as well.

We have changed the statement in the introduction to (L58):

“In humans, microbiome alpha diversity increases over infancy<sup>11</sup>, whereas it decreases in chimpanzees<sup>20</sup>, although the gut microbiome of infants tends to have higher inter-individual variation in both species”.

In the discussion, we have clarified that we are referring to alpha diversity (L369):

“Nevertheless, we do report higher variation in alpha diversity in younger meerkats than older meerkats.”