Red is reviewer comments, Black response.

Response to referee comment 1

I can not agree on this: (1) See the discussion of non-informative priors in the textbook by J. Berger, a seemingly uniformed prior eg for the variance σ^2 might be highly informative for the precision $1/(\sigma^2)$ (2) an informed prior is (of course) subjective in any case as it is in any statistsical posterior assessment of data, but before coming to that point informative prior could come from physical arguments e.g. choosing thermodynamical limits for temperatures

We agree with the referee on (1) that one has to be very careful when working with the notion of ignorance, there are many examples in the literature where what appears to be uninformative under one parameterisation is in fact not uninformative under another, this is the basis for the development of Jeffrey's priors. However, in practical applications of Bayesian inference, the term is sometimes used to denote priors that are not very informative for the values of the parameter, we have now changed the use of the term ”non-informative” to ”vague” to be more precise. We note that our proposed approach is general, and not dependent on the form of the prior.

In terms of point (2), we have added that ”vague priors are sometimes considered preferable when data contains sufficient information or when subjective knowledge is uncertain.”

this does not answer my question, if it is the wish to obtain a univariate predictive density in acc. with the model output one can marginalize every multivariate density..

We agree that one can always work with the more general setup of the multivariate normal density, which will be necessary if the data follows a Gaussian AR process for example. The univariate marginals in the Gaussian case is easily obtained. We added to the end of the discussion that the method can be extended to work with correlated Gaussian data.

Response to referee comment 2

I think the authors could do a better job in presenting and justifying their method. I did not claim that Buser et al. (2009) use Bayesian model averaging, my argument was simply that the methods of both Buser et al. (2009) and of this paper fit into a general framework of Bayesian analysis in a situation where for some parameters the available data provide no information. In such a situation, an informative prior has to be used. I think that this would help the readers to better understand the method and it would also provide a good answer to the criticism of reviewer 1 who finds the method very ad-hoc. In particular, I find it misleading that the authors write that they use non-informative priors throughout because the informative part of their prior is hidden.

Let me briefly repeat this general framework in the notation of this paper. The parameters for which we have no information from data are the intercept a^f , slope b^f and standard deviation σ^f of the future climate y^f . The informative prior used by the authors says that there is a perfect model that has the same parameters as the observations both in the current and the future period (so for instance $a_p = a_m$ and $a^f = a^f_m$ for one model m). The prior does not specify which model is the perfect one; the observations and model outputs in the current period are used to estimate the probability that each model is the perfect one. This is a valid and interesting solution. In Buser et al. (2009) a different approach was chosen where for instance the intercepts of model m are decomposed as $a_m = a_p + \beta_m$ and $a^f_m = a^f + \beta_m + \delta\beta_m$. An informative prior is then used for the bias changes $\delta\beta_m$ because the data give information only about a_p, β_m and and the sum $a^f + \delta\beta_m$.

We fully agree with the referee's point here. We have added a paragraph in Section 2 to reflect these insights. "It is worth noting that even if we specify non-informative priors in Equation 3 for all models, the implied priors used in our approach are not uninformative. As pointed out by Professor H. R. Künsch, some form of informative priors must be used because the data available simply does not contain information for certain parameters of the model for the future (see Buser et al (2009) for an alternative formulation which also require some form of informative prior specifications.) In the current case, our modelling approach assumes that the relationship between future climate and future model output behaves in a similar way as the relationship between present day climate and present day model output. We consider that there is a perfect model that has the same parameters (intercept, slope and standard deviation) in both the present and the future. We then compute the probability that any model m is this perfect model, based on present day data. These assumption can be seen as an informative prior on the parameters governing future observations, although these parameters are not explicitly modelled. "

The addition on l. 19 of p. 3 "In practice σ_p has additional terms" does not reflect my concern that in practice the standard deviation σ_m of many models is larger than the standard deviation σ_p of the observations. A different modeling approach would be needed to take this into account.

yes σ_m can be much larger than σ_p, but we assume that a good model will have σ_m close to σ_p, and penalise model m for large deviations of σ_m from σ_p. However, they are not directly comparable due to measurement errors in the observed σ_p, therefore correction term is only to account for the measurement error.

I strongly disagree with the additional text on l. 8-12 of p. 2: The paper byBuser et al. (2009, 2010) and by Kerkho et al. (2014, 2015) also include internal variability in a principled way, and presumably other authors have done this too. The observation that the projected change of a model is positively correlated with present-day internal variability is due to Buser et al. (2009) (termed ”constant relation”). And the method of this paper does not take this correlation into account.

We have modified the sentence here to ”Several authors have shown that in many regions, future changes are positively correlated with present-day internal variability in the models, see Buser et al (2009), Huttunen et al (2017). This means that knowing internal variability may provide important information and potentially improve future projections. While previous work have included information from internal variability into their statistical model, the information was not used to directly penalise the models for getting the internal variability wrong, see for example Buser et al (2010), Kerkhoff et al (2015).