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Spectral replacement using machine learning methods for continuous mapping of Geostationary Environment Monitoring Spectrometer (GEMS)

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 # General response to the reviewer' comments – minor revision

Again, we appreciate the efforts made by the reviewer to clarify the objective of the manuscript and improve the quality of the manuscript. We have tried to reflect the comments and suggestions as much as possible. Accordingly, the introduction and conclusion parts are revised along with the editorial works to concisely deliver the information of the research. In this document, the reviewer's comments are repeated in blue, our responses to the specific comment are given in red, and the revised manuscript is presented in *italic*.

<Major comments>

#1. Research objective

"The authors have cited several papers describing earlier attempts at replacing bad pixels. The existence of other attempts does not mean such replacement is right for GEMS data products. One might argue that in a situation where a geophysical parameter is over-determined by the available data it is possible to accurately predict and replace missing data. But by the same argument those missing data were not really needed to determine the geophysical parameter. **Other than stating that bad pixels should be replaced, the authors offer no explanation of how replaced pixels can improve a GEMS product.** After all, these are not measurements. If the purpose of a product is to report measurements, why should it report something other than measurements? Gap filling might allow a product to be generated in locations where one was previously unavailable, **but what is the value of that product to the broader user community?** In all likelihood they will treat the synthetic data equally alongside the real data. In that case pixel replacement will have done a disservice to the science. …"
"One example I can think of to support pixel replacement is that of reflecting surface pressure (a.k.a. cloud height). The authors have indicated that Defect 3 affects the primary O2-O2 absorption used to derive an altitude. ML or PCA may be able to identify a correlation between O2-O2 line depth and rotational Raman broadening at other, unaffected wavelengths, and thereby transfer the cloud height information back into a synthetic O2-O2 line. This would relieve the GEMS program from having to develop an entirely new cloud height replacement algorithm based on the RRS signal. I find this a tenuous argument at best, but the authors may choose to cite examples along these lines."

⇨ Thanks again for giving us a chance to revisit the manuscript. We expect that the points raised by the reviewer are clearly presented in the revised manuscript. In section 1, the advantages of replacing Level 1B data have been inserted to state plainly how the replaced pixels improve the GEMS products and what the advantages of the approach are. Because GEMS is a geostationary satellite sensor, bad pixel effects cause a permanent measurement gap for certain areas in the GEMS field of regard. As the reviewer pointed out, the reproduced values could not provide the information possibly obtained from actual measurements. On the other hand, one may need the most probable values likely measured by GEMS for various reasons (practical or scientific) for the information gaps. Here we tried to evaluate the applicability of machine learning in this regard presenting the analysis results and limitations for the issue. The suggested example (O2-O2 & rotational Raman scattering lines for cloud height retrieval) also has been included as one of advantages as it represents the effectiveness of spectral replacement.

#2. Introduction (Section 1)

"… However, **the justification is scattered throughout the introduction section. It reads like it was slipped in as an afterthought.** What this paper still lacks is a clear, up front statement of "this is why we are investigating ML techniques specifically." **Arguments about ease of implementation and benefits to multiple atmospheric parameters should appear at or near the beginning of the Introduction section**. **The authors should state clearly that the purpose of their investigation was to explore how well ML works to describe missing pixel content and not to find the best or most accurate pixel replacement method** (for example, Level 2 product assimilation followed by radiative transfer modeling and instrument modeling might prove more effective)."

- ⇨ Thanks. The reason why we try to provide the most probable Level 1B radiances (rather than the Level 2 properties) with machine learning has been revised considering the reviewer's concerns.
- ⇨ Reflecting our responses for Sect. 1, the revised part of manuscript is:

Section 1 Introduction (Lines 36-56)

… The impact of bad pixels to the GEMS data products is obvious because the given areas affected by bad pixels cannot provide any measured information. It causes spatial discontinuity in Level 1B data and retrieved properties (Level 2) by affecting retrieval processes with contaminated spectral features. ***The defective region is not large so far, but the area could be enlarged as time goes by*** (Kieffer, 1996) ***and the missing areas may increase possibly including scientifically important regions especially for environmental monitoring.***

Because there is a constant measurement gap for certain areas in the GEMS field of regard (FOR), one could need alternative information for the areas for practical or scientific reasons. *To supplement the information and investigate the applicability of machine learning, this study focuses on replacing the Level 1B radiances using spectral relations with simple machine learning methods.* ***One of advantages of replacing Level 1B data (not the Level 2) is that improving spectral features can be an efficient way to solve the bad pixel issue for all Level 2 products.*** *The proposed approach places more emphasis on efficiency and further applicability of machine learning, even though the spatial gaps in Level 2 data can be filled with a suitable method for each product with higher accuracy (e.g., variogram or mathematical filters)* (Fang et al., 2008; Katzfuss and Cressie, 2011; Guo et al., 2015; Llamas et al., 2020; Yang et al., 2021). ***Another advantage is that the approach helps the current retrieval algorithms avoid bad pixel effects without further development.*** *The GEMS cloud height retrieval algorithm, for instance, had to modify the fitting window during the IOT because the targeted O2-O2 absorption lines (around 477 nm) are affected by bad pixels. The proposed approach, however, has the potential to reproduce the O2-O2 absorption features with the information from unaffected wavelengths (e.g., rotational Raman scattering lines) by applying spectral replacement. If it is successful, the retrieval can avoid bad pixel effects without further algorithm development. The main question to be answered for that is whether non-linear spectral relations could be effectively emulated with spectral replacement using machine learning techniques.*

<Specific comments>

Section 3.3.1

"The authors state that cloud height retrievals from Defect 3 appear to have an accuracy 1% when comparing measured and ML values. They also state that this success is a consequence of the spectrally narrow defect. ML is more likely to predict the correct spectra over a narrow range of wavelengths. Is this really the correct logical conclusion? Is it possible the good agreement is caused by natural spatial homogeneity in cloud heights. Cloud heights do not vary much within small spatial regions, so one might expect such agreement regardless of what pixel replacement technique is used. It's hard to believe that ML possesses enough information to accurately predict a high cloud that is surrounded by uniformly low clouds. Showing that it is capable of doing so will demonstrate that the ML technique has some real value."

⇨ Because the spectral replacement we applied only uses spectral relations of radiances in a spectrum, the spatial homogeneity of the retrieval properties hardly affects the replacement results. However, we understand the final statement in the section for cloud retrieval might mislead the point as the reviewer pointed out. The section has been revised and Fig. 12 has been inserted in the revised version for the demonstration as commented.

⇨ Reflecting our responses, the revised part of manuscript is:

Section 3.3.1 (Lines 283-296)

In the previous section for radiances, the overall prediction error with the suggested method is about 5% except for ozone absorption lines. The next question is whether the reproduced spectral features are applicable to retrieval processes. Even if the trained models accurately reproduce radiances at each wavelength, the Level 2 retrieval could be unsuccessful if non-linear relations are too elusive to be properly emulated with the model. ***To prove this, we performed the cloud retrieval with the fitting window in 460.2-490.0 nm containing bad pixels.*** *The replaced radiances at O2-O2 absorption lines related to Defect 3 have the smallest error of 0.5% and the retrieval is successful as shown in Fig. 12. Without the replacement, the retrieved cloud centroid pressure showed unrealistic values on bad pixel areas. Figure 12 presents cloud centroid pressure retrieved with ML and GEMS spectra by zooming in defect-free areas to analyze cloud distribution. The difference of cloud centroid pressure between Figs.12a and 12b is about 1% on average while the cloud properties of ML spectra have weak stripping features. The spectral range of Defect 3 is very narrow within the fitting window and thus the replacement errors could be small enough not to cause additional retrieval errors.*

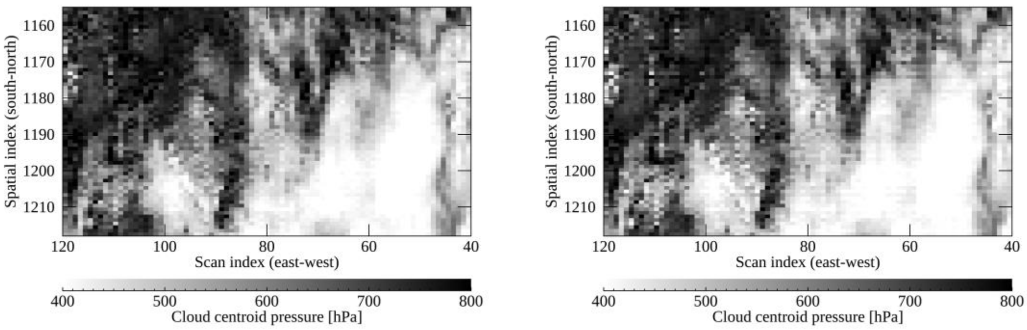

Figure 1 *Spatial distribution of cloud centroid pressure retrieved with (a) GEMS and (b) ML radiances presented in Fig.7. The GEMS spectra are measured on 10 March 2021 (06 UTC).*

Figure 14

"The various colored lines in this figure need more explanation, either in the text or in the figure caption."

⇨ The section in Sect. 3.3.2 and the figure caption has been revised accordingly.

Section 3.3.2 (Lines 319-327)

Figure 14 presents mean absolute errors of reproduced radiances for ozone absorption and Fraunhofer lines with four different input conditions: 1-2) including each near side (within 20 nm) from the output spectral regions (A and B for the left and the right side, respectively); 3) including both near sides of wavelengths (A and B); and 4) all wavelengths in 300-500 nm except for A, B and the output spectral region. Each input case is plotted in Fig 14 with the color of red, sky blue, blue and black line, respectively. *Results show that prediction errors increase at the spectral peaks and overall error patterns differ for different input conditions. As assumed, the errors are higher with farther input spectral bands from the output spectral region. Figure 14a clearly shows that the insufficient information from the input data may cause large errors for radiances at shorter wavelengths as well as the ozone retrieval. Figure 14b also presents that each input case has a different level of information which could determine the accuracy of spectral replacement especially for the weak scattering features.*

Section 4

"This section reads more like a Summary of what has already been discussed in previous section rather than actual Conclusions. Please spend more time describing what works well and what does not work well, and suggest explanations for this performance."

The discussion starting at line ~400 is good, and I would like to the authors to expand this some more. The authors conclude that ML is capable of filling spatial gaps and narrow spectral gaps, but not larger spectral gaps. A little more insight into why this is the case will be appreciated. **It's important for the reader to understand the defect situation where further development of the ML technique might yield better results, and the situations where no amount of additional development is likely to improve the results.** The authors may wish to offer suggestions for alternative gap-filling techniques in this latter situation."

⇨ The following part has been inserted in the revised version. We hope the part could effectively deliver important findings we could provide for readers.

Section 4 (Lines 378-390)

Further investigation reproducing Fraunhofer lines and ozone absorption lines helps conclude the benefits and limitations of the approach as follows: ***1) The closer the input and output wavelengths are, the smaller its reproduction error becomes.*** *This is because radiances at adjacent wavelengths have a high possibility containing common information valid for the replacement. Even though the condition is not satisfied, approximate spatial patterns could be obtained but the accuracy is not guaranteed for both radiances and retrieval properties.* ***2) The input radiances should be carefully selected because machine models (especially ANN) are vulnerable to outliers or erroneous input radiances.*** *If one adopts more complex models, the importance of the selection would increase.* ***3) Errors coming from instrument artifacts such as the stripping feature could be propagated with the method as it seems the feature is not properly emulated in the model so far. 4) Finally, low radiances could have higher uncertainty even when using the spectral***

information as much as possible. *GEMS is the environmental sensor and thus may provide useful information with clear sky conditions. Considering this, additional information would be needed if one pursues very high retrieval accuracy with the replaced spectra. In this regard, combining the external information together with the spectral components would be the next step for developing the approach. Additionally, the research adopts very simple machine learning models which also can be updated further.*

 # General

"I find the text rather 'wordy', and have difficulty in places understanding the point the authors are trying to convey. It will help if the paper contains simple and clear messages. "We did the following because of X, Y, and Z." Or, "we found the method worked best when we included the data between x1 and x2." I know the topic is complex and there is no simple way to describe some of the work that was done, but the job of the author is to condense a complicated subject into something the readers can follow and digest."

⇨ Indeed. We have tried to revise the overall contents as concise as possible especially for Sects. 1 and 3. Please note that some parts have been deleted or reorganized considering that the parts have repetitive information and need refined explanation.

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