22 September 2019

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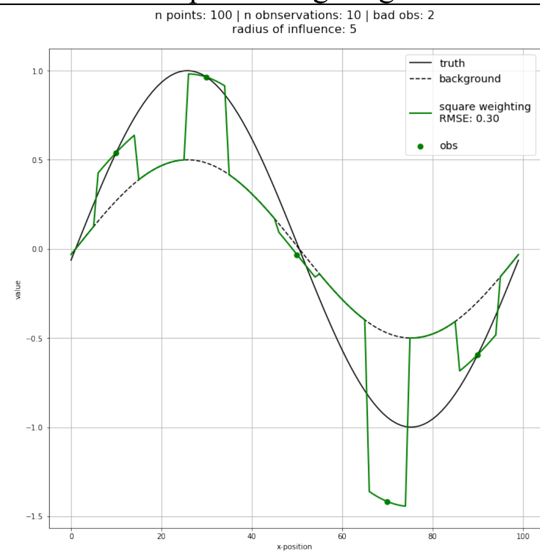
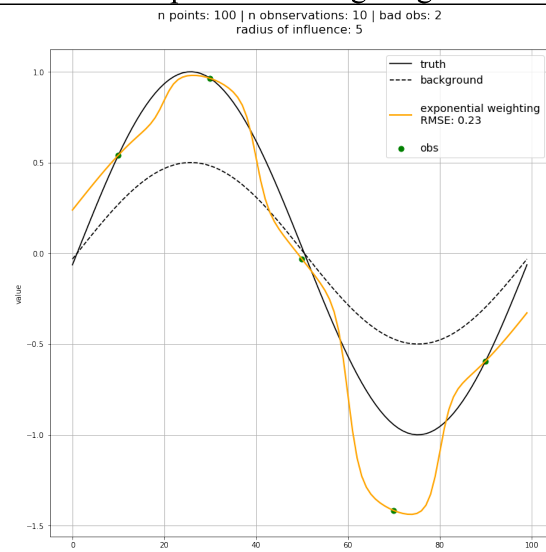
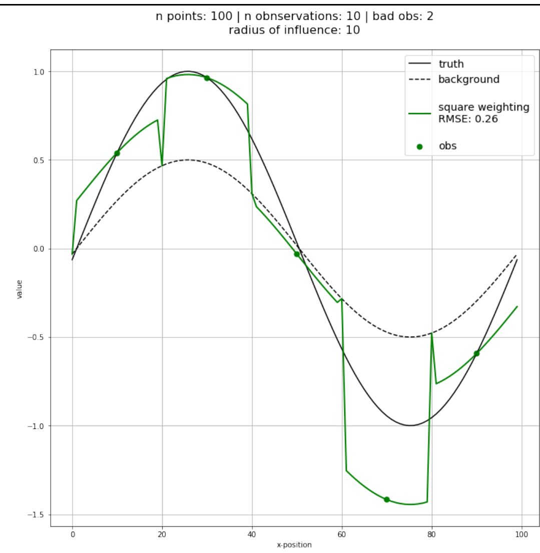
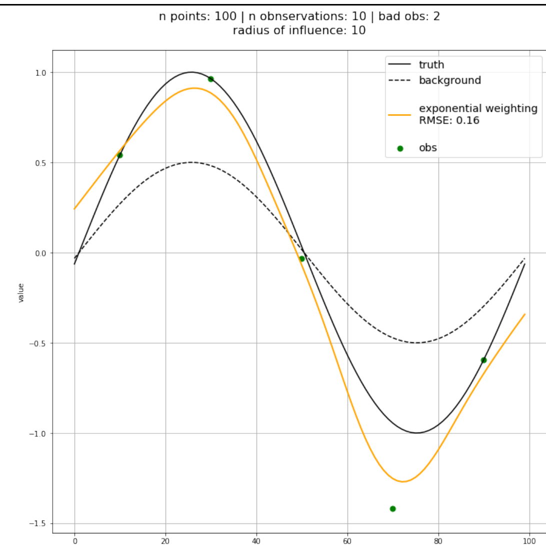
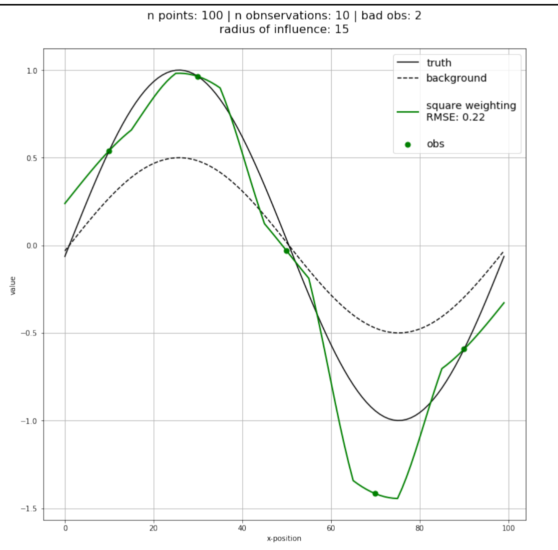
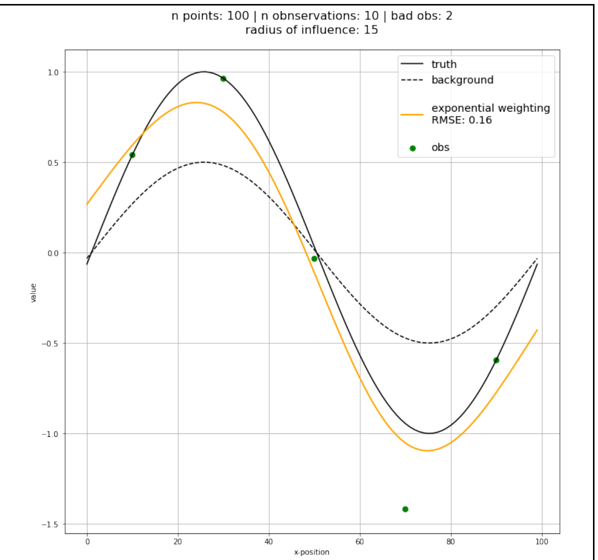
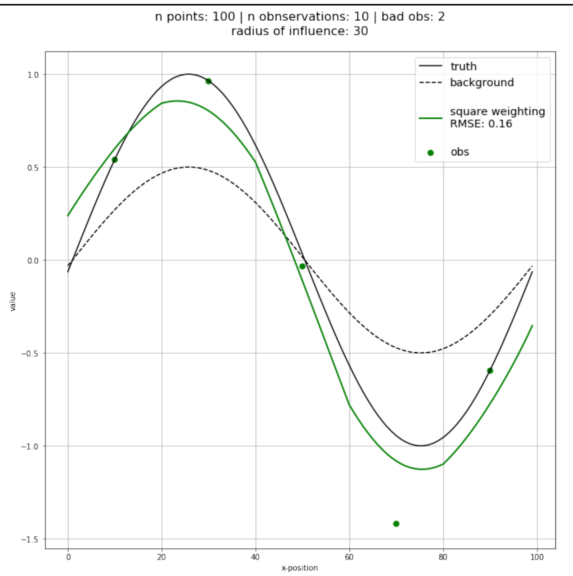
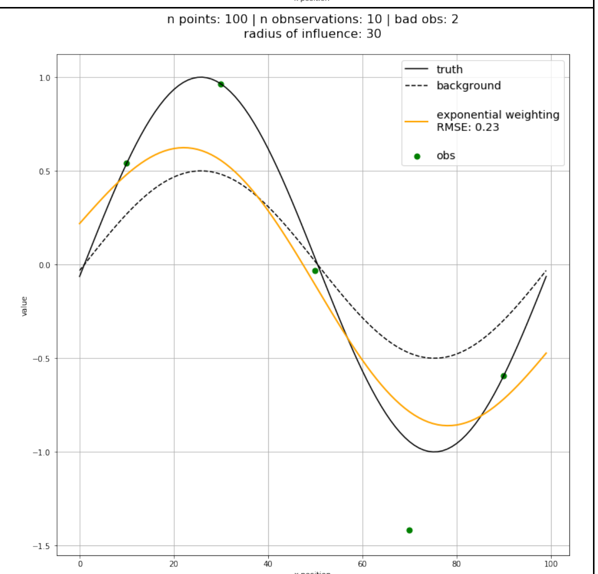
ATMOS 6500 Numerical Weather Prediction

Lab 3 – Cressman Analysis

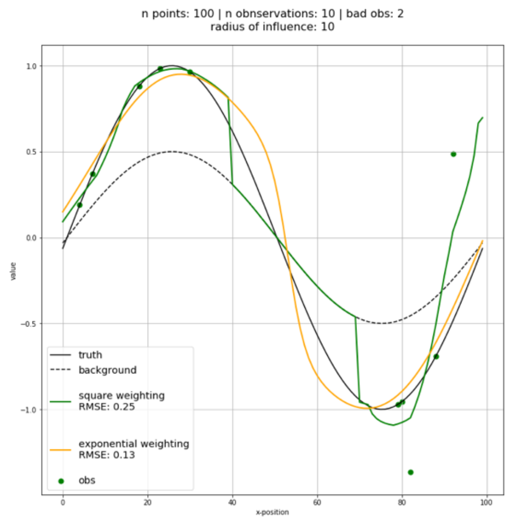
Lab Problems

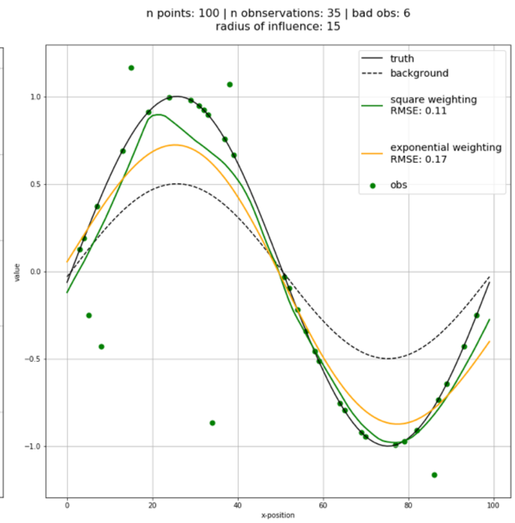
1. Use the sample code to perform Cressman analysis with different weighting functions and different R.

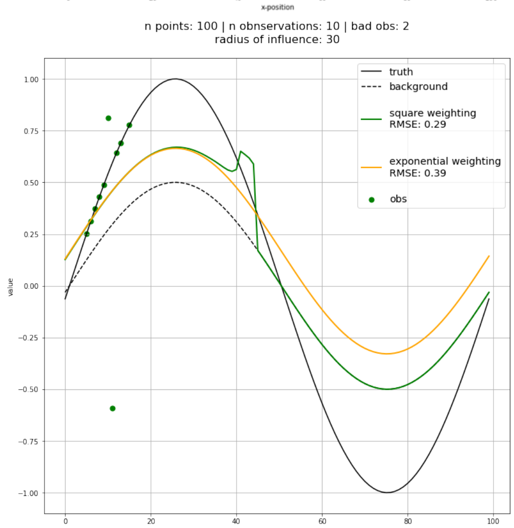
R	Square Weighting	Exponential Weighting
5		
10		

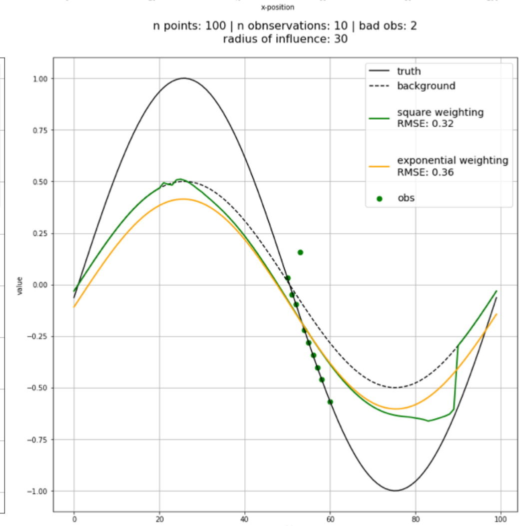
15	 n points: 100 | n obnservations: 10 | bad obs: 2 radius of influence: 15 truth background square weighting RMSE: 0.22 obs value x-position	 n points: 100 | n obnservations: 10 | bad obs: 2 radius of influence: 15 truth background exponential weighting RMSE: 0.16 obs value x-position
30	 n points: 100 | n obnservations: 10 | bad obs: 2 radius of influence: 30 truth background square weighting RMSE: 0.16 obs value x-position	 n points: 100 | n obnservations: 10 | bad obs: 2 radius of influence: 30 truth background exponential weighting RMSE: 0.23 obs value x-position

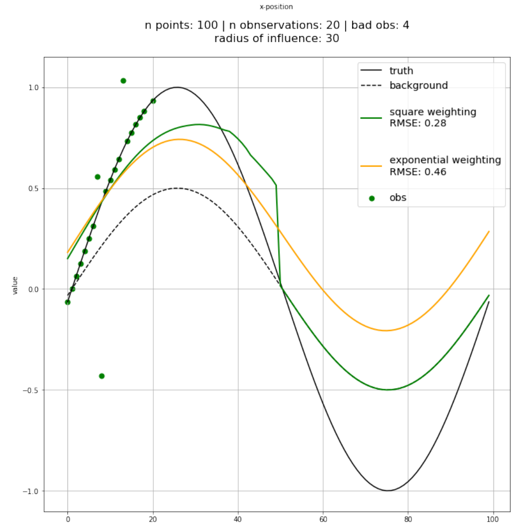
2. Change the observational positions, then, play with the code to see how the density and position of the observations would affect the analysis results.

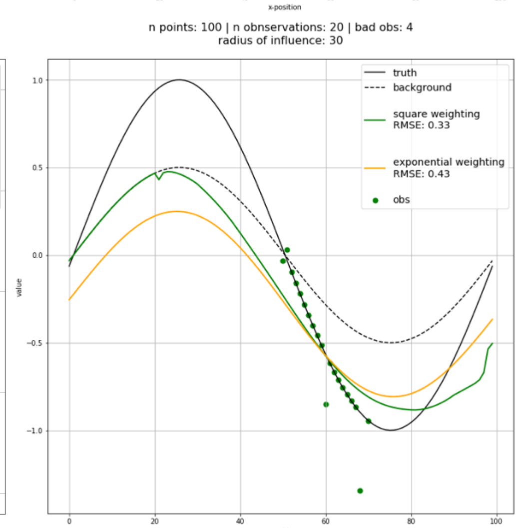




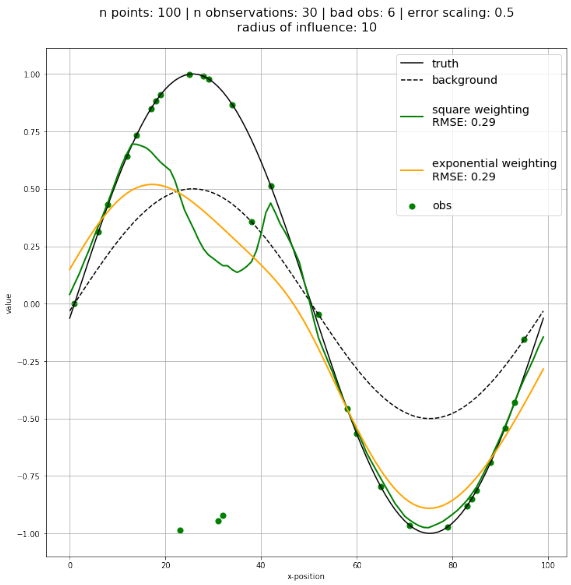


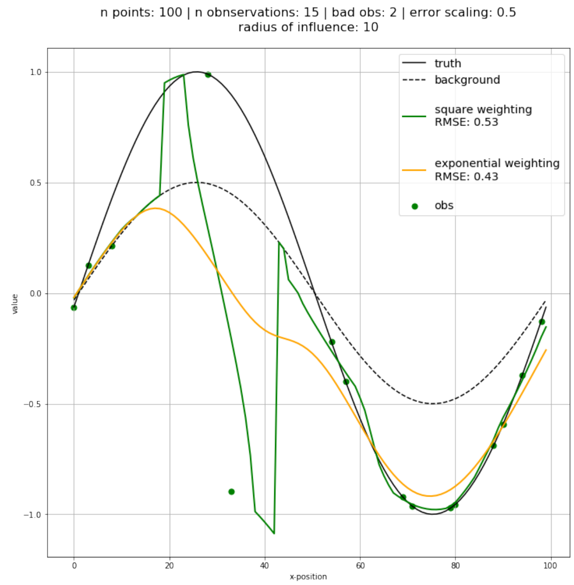


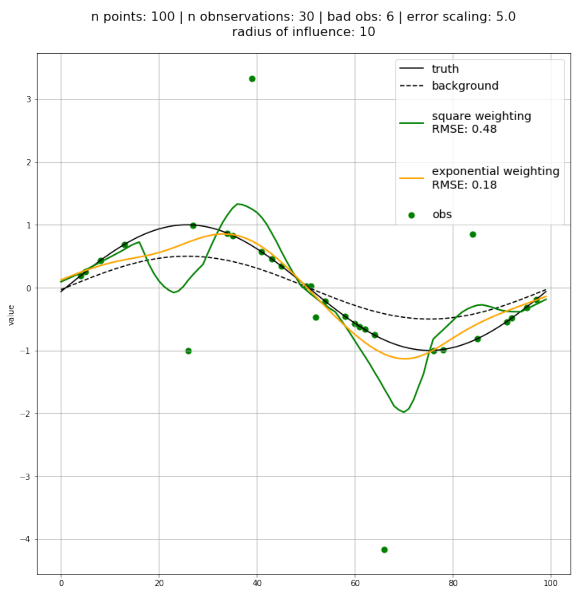


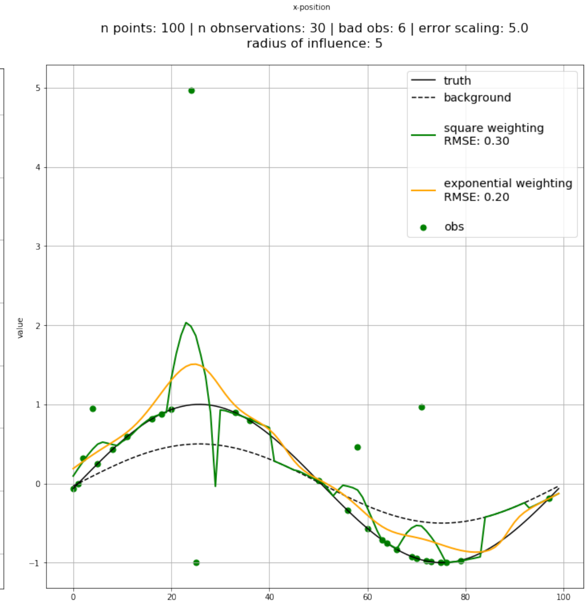


3. Change the observation errors and test the sensitivity of observational errors to analysis results.

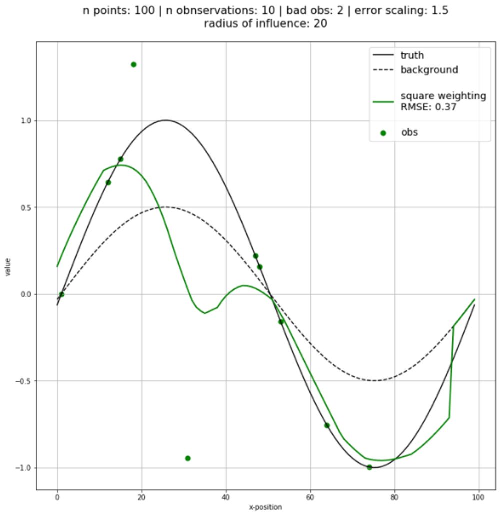


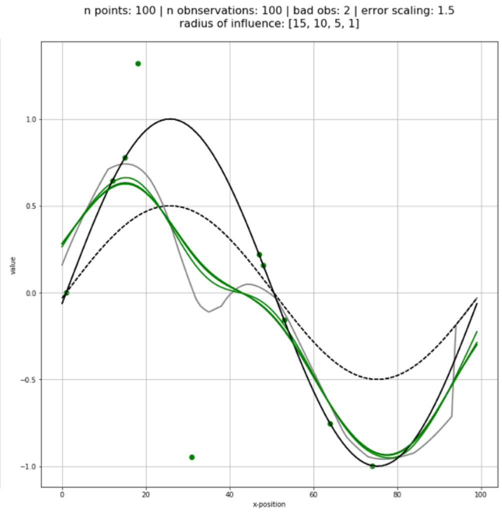


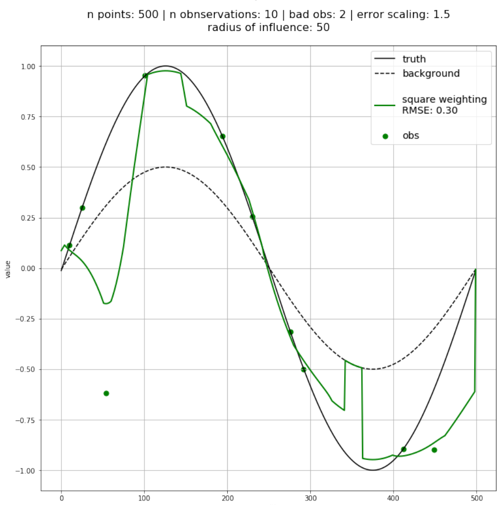


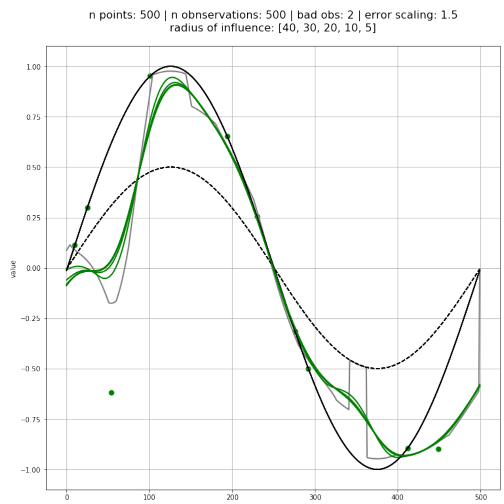


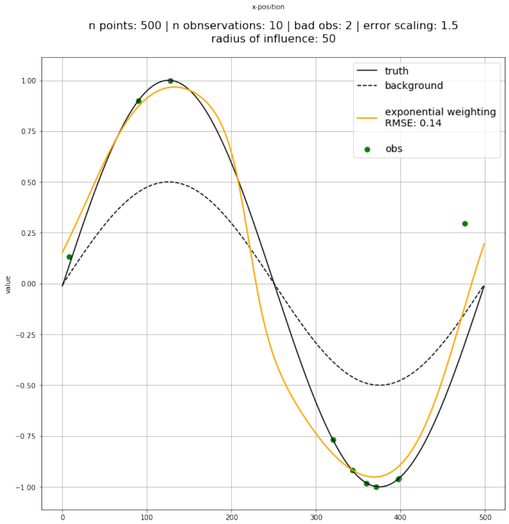
4. Make an iterative analysis cycle, perform analysis and compare results with the case, which uses the single set up of R.

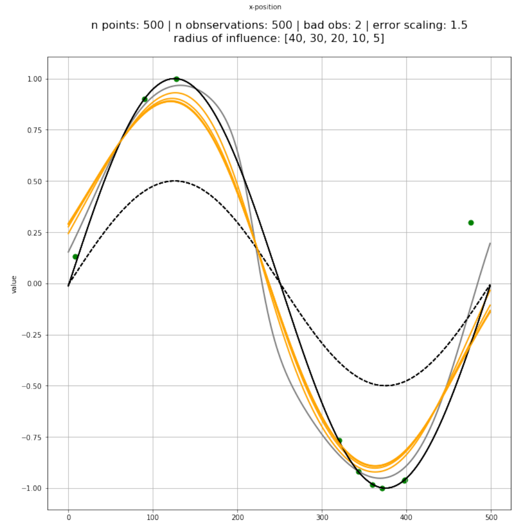












Summary

This lab provided the opportunity to explore the effectiveness of two simple weighting schemes in assimilating observations and a background field into a model analysis. The background field used represents what a model 'first-guess' field would, and the techniques used are similar to those used to modify that first-guess field, though highly simplified. Perhaps the most impactful quantities are the radius of influence and the number and position of observations. These largely dictate the quality of the analysis and interact in ways that are not exactly linear. As will be discussed, even large discrepancies and unrepresentative observations can be made minimally detrimental with the right radius of influence for the number of observations and vice versa. The key takeaway is that a large number of observations and small radius of influence will produce the most accurate to reality result, but a larger radius of influence will improve the analysis given a minimal number of observations. Furthermore, in situations where a minimal number of observations are available, even a single large error in the observed values have the potential to be significantly detrimental to the analysis.

Keeping all other factors consistent, we can examine the impacts of the radius of influence and weighting schemes on the outcome of the analysis. It is clear that for a small number of equally spaced observations, the exponential scheme far outperforms the squared scheme in producing a representative analysis for the same radius of influence. However, we see that if the observations are equally spaced and we increase the radius of influence, the squared scheme approaches the same analysis as the exponential scheme. This is not necessarily the case for unevenly spaced observations, or observations that are heavily concentrated in one region of the field. In this case, the squared scheme with a small radius of influence will produce a much better result in that region than the exponential scheme, though both schemes fail to produce a good analysis elsewhere that observations are not present. Increasing the radius of influence can help, though produces an overall over-smoothing effect where none of the analysis is that accurate, but any egregious errors are minimized overall.

For observational errors, we see that the analysis is much more sensitive both when there are fewer observations and the radius of influence is large and when there are many observational errors and the radius of influence is small. This would suggest that in the case of reliable, heavily populated observation fields, it is preferable to use smaller radii of influence as it will improve the overall analysis. Conversely, if it is known that a large number of data points will have poor observation quality, it may be better to use a large radius of influence to keep these observations in check. The best outcomes exist where there are a large number of observations and the radius of influence is a moderate value. This prevents any single, even extremely large, observation error from having a noteworthy impact on the analysis field.

It is difficult to discern which method, squared or exponential, is a better choice overall, as each scheme performs better or worse under specific scenarios. It would appear that the exponential scheme is less sensitive to being thrown by sparse observations, egregious observation errors, and irregular spacing of data. Thus, it produces a consistent analysis result closer to the truth field in more scenarios than the squared method. However, for regularly spaced data or densely populated observation fields, the squared scheme brings the analysis field much closer to the truth field in more cases than the exponential scheme. The key takeaway is the scheme to choose depends on the users' needs. Given observations heavily concentrated in an important region, perhaps it is beneficial to choose a squared weighting scheme as it will improve the analysis in that area in particular. However, for the same scenario, the broader analysis field will be closer to the truth for the exponential scheme. There is no one solution that can avoid all the problems of the other, and the parameters thus must be tuned to the model's needs.

A method which improves upon the initial analysis field is to use an excessively large R to produce what is essentially a 'smoothed' observation field. We can then iteratively reduce R (e.g. from 40 to 30 to 20 to 10) and produce new analysis fields each time. The analysis field from the prior iteration is then used as the observation input to the next iteration. This has an effect of smoothing the analysis field while nudging it closer to the truth field. For the exponential weighting method, the improvements noted using this method are minimal, as the smoothing effect is already present for an appropriately chosen radius and the quality of the analysis is already fairly good. However, significant improvements using this iterative radius reduction method for squared weighting. This has the benefit of the more accurate analysis field where observations are present in the initial analysis, with the added benefit of the exponential-like smoothing that is noted in successive analysis fields. It seems that the overall best outcomes are produced for squared weighting first with a moderate radius of influence then iteratively improving the analysis field with successive reductions in the radius with the previous run's analysis as input.