**Response to Reviewer #3:**

Thank you for your feedback. We have made the revisions requested to the manuscript and addressed your comments in this document in blue. We hope this adequately addresses the concerns raised.

**To the editor, here are our responses/explanations based on the email:**

**International Journal of Greenhouse Gas Control**Reviewer's Responses to Questions

Note: In order to effectively convey your recommendations for improvement to the author(s), and help editors make well-informed and efficient decisions, we ask you to answer the following specific questions about the manuscript and provide additional suggestions where appropriate.  
  
1. Are the objectives and the rationale of the study clearly stated?  
  
Please provide suggestions to the author(s) on how to improve the clarity of the objectives and rationale of the study. Please number each suggestion so that author(s) can more easily respond.

Reviewer #3:

1. main points in conclusion: As stated in line 412 & 413 of the Conclusion, the model was made to predict the injection rate changes of the CO2 injection by using some of the 34 contemporarily recorded other monitored parameters. And lines 418 & 419 state that the model’s primary objective is to detect anomalies and alert operators to closely inspect the well for potential leaks.

Authors response: Thank you for the comment; there is nothing to action here.

1. There is nothing in the report to show how just the single parameter of the injection rate changes are/can be linked to any anomalies to alert operators of any type of potential leak from the well. No cited publications for this specific linkage or theory. Shouldn’t there be literature review of linkage and not just of modeling in the paper?

Authors response: We thank the reviewer for this response, but it speaks more to a lack of knowledge on the reviewer’s part, and not any lack on the quality of the paper. We would state 2 very clear facts (a) This area of research is novel, and we clearly state this as such in our literature review. However, to emphasize this, we have expanded our literature section (b) None of the other 3 reviewers of this article has raised this issue.

The single delta injection parameter is intricately linked to the responses of multiple sensors deployed both laterally and vertically. Our methodology integrates data from these sensors to derive the single parameter, which serves as a key indicator of anomalous behavior in the system. While, our literature review primarily focuses on the modeling aspects of our research, we recognize the importance of providing a review of the literature on the linkage between injection rate changes and leak detection. To address this, we have expanded our literature section to include relevant publications that discuss the theoretical underpinnings and empirical evidence supporting this linkage. Furthermore, we would like to clarify that this area of research is indeed novel, as stated in our literature review. Lastly, we would like to note that none of the other three reviewers raised this specific issue, which may suggest that the concern raised could stem from a misunderstanding or lack of familiarity with the intricacies of our research methodology.

1. In highlights: Predicting this change can be used to provide a checkpoint against carbon plume migration and can determine if there are losses in the injection process. Not shown or explained in this paper on how knowing an injection rate can tell one about plume migration of CO2 or injection well integrity.

Authors response: Noted; we have extended this explanation in the paper. Note that this is 1 data set. The reviewer is mistaken if they think this is the end of the work. We have a discussion and recommendation section that explains as much.

Firstly, predicting changes in injection rates allows operators to monitor the behavior of the injection process over time. Anomalies in injection rates can serve as early indicators of potential issues such as leaks or changes in reservoir behavior. By detecting deviations from expected injection patterns, operators can investigate further to determine the root cause of these anomalies, which may include integrity issues with the injection well or unwanted migration of CO2.

Secondly, while the paper primarily focuses on predicting injection rate deltas using machine learning techniques, it should be part of a larger framework for monitoring and managing CCUS operations. In practice, the predictive model would be integrated into a comprehensive monitoring and control system that includes real-time data from various sensors, geological monitoring, and reservoir simulations. By combining information from multiple sources, operators can gain a holistic understanding of the injection process and make informed decisions to ensure the safe and efficient operation of CCUS projects.

1. Permit requires monitoring the injection well annulus pressures and periodic casing pressure tests and the use of reservoir saturation tool in the cased hole to try and detect CO2 outside of the casing.

Authors response: ~~Noted on this comment. Is the reviewer saying that this is the case in all countries and in all jurisdictions? In any case, the ML method is additional to all these other “empirical”, hardware centric methods. ML can also help to reduce OPEX, by reducing the frequency of such tests. But we acknowledge this comment and extend this argument in the conclusion section.~~

We appreciate the reviewer's emphasis on the importance of existing monitoring methods such as annulus pressure monitoring, casing pressure tests, and the use of reservoir saturation tools. These approaches are indeed fundamental for ensuring the integrity and safety of injection wells in CCUS projects. Infact, the ML model uses some these parameters as inputs.

It's important to note that the machine learning (ML) method proposed in our study serves as an additional layer of monitoring and analysis, complementing these existing techniques. While traditional methods provide valuable real-time data and direct measurements, ML offers the potential to analyze large volumes of historical data, detect subtle patterns or anomalies, and predict future trends.

Moreover, we acknowledge the potential for ML to optimize operational expenses (OPEX) by reducing the frequency of certain tests or enabling more targeted monitoring strategies. By leveraging ML algorithms to identify trends and anomalies in the data, operators can make informed decisions about when and where to deploy traditional monitoring techniques, thereby maximizing their effectiveness and minimizing unnecessary costs.

We recognize the importance of integrating ML methods with established monitoring protocols and hardware-based tools to create a comprehensive and robust monitoring framework for CCUS projects. This synergy between empirical methods and data-driven analytics can enhance the overall safety, efficiency, and cost-effectiveness of carbon capture and storage operations.

2. If applicable, is the application/theory/method/study reported in sufficient detail to allow for its replicability and/or reproducibility?  
  
Please provide suggestions to the author(s) on how to improve the replicability/reproducibility of their study. Please number each suggestion so that the author(s) can more easily respond.

Reviewer #3: Mark as appropriate with an X:  
Yes [] No [X] N/A []  
Provide further comments here:

1. There is great detail of information on building the model, which in this case is built on training data that the authors’ unsuccessfully attempted to “clean up” the not understood problems with the raw recorded parameter data. Part of the problem also centers around the understanding of basic hydrostatic formation pressures for the verification well data – there can’t be zero formation pressures.

Authors response: We find this response a bit puzzling. This is a time series data set; if 0 pressure is detected; then this can be attributed to sensor error, BUT it is a reality of the data! The ML algorithm must learn to deal with this. We are not saying that zero formation pressure exists. We are saying it is the reality of the data; if the reviewer cannot understand this, then think of the “0” values as noise that the machine learning algorithm must handle via generalization!

The paper describes the workflow of how the zero values are handled. The paper attempts to point out the problem with the dataset and the incorrect zero or lower than formation pressure values. Different methods such as forward fill, dropping the rows with zero values, etc were tested on how to handle the zero values. In the end a forward fill method was used. There are no zero values in the selected model as indicated in Table 4. However, there were lower than formation values included in the dataset and we agree that the more correct method is ensure that there are no values below the formation pressure at the sensor depth. This has now been handled via an additional step in the data cleaning stage.

3. If applicable, are statistical analyses, controls, sampling mechanism, and statistical reporting (e.g., P-values, CIs, effect sizes) appropriate and well described?  
  
Please clearly indicate if the manuscript requires additional peer review by a statistician. Kindly provide suggestions to the author(s) on how to improve the statistical analyses, controls, sampling mechanism, or statistical reporting. Please number each suggestion so that the author(s) can more easily respond.

Reviewer #3: Mark as appropriate with an X:  
Yes [] No [X] N/A []  
Provide further comments here:

1. There are nearly no details on where the 11 pressure/temperature sensors are in the verification well and how the pressures were impacted by the baffles in the Mt. Simon in relation to the injection zone!

Authors response: This is not the primary goal of this paper; our aim is to demonstrate a working prototype for a ML solution to monitor CO2 injection. A discussion into how pressure is impacted by baffles, while an engineering reality, does nothing in furthering the main goal of this work. Instead, the fact that the pressures ARE impacted by baffles/barriers is good for the development of a ML algorithm which should see as much “real” data as possible.

Noted and this has now been addressed in the paper.

1. No explanation on why the only Z05 (Zone 5) pressure/temperature sensor of the verification well was picked for the learning data. Zones 4-9 are above the baffles and are in a part of the aquifer that reacted very little to injection well pressures changes. For Zone 5, with a very, very slow buildup of the 25 psi pressures, took 3 years. It also took 100+ hours to see pressure changes at Z05 following changes in injection while sensors at other elevations below the baffles had increases of 169 psi and 1 hour to see pressure changes.

Authors response: ~~This comment is unclear.~~ ~~We have used other sensors. We used Z01, Z09 and Z05. We state as such in Table 4.~~ Our approach hinges on analyzing deltas, parameter changes, and trends rather than absolute values. As indicated in the correlation matrix presented in the paper, the time series trends from sensors in the verification well are highly collinear. This implies that including additional sensors from these zones would offer limited value in terms of enhancing the predictive capabilities of the model.

Moreover, sensitivity runs were conducted, as detailed in the "Sensitivity Runs" section, to explore various combinations of downhole sensors. These analyses further supported the decision to focus on the Z05 sensor. While we acknowledge that the different rates of pressure buildup across zones may reflect variations in reservoir properties that could impact storage volume, addressing such nuances falls outside the scope of our study. Our primary goal is to detect deviations from expected behavior and identify potential containment issues.

1. Pressure readings through the 3 years of injection are shown in diagrams in several publications to give an overall bounds for some of the “clean up” parameters without directly going through the raw data in detail to find: pressure values below original formation pressures (which includes 0), injection well head pressure values above permitted and equipment capable highs, remove pressure changes after sensor re-installation that had jumps in pressure readings until sensors were re-installed again, pressure values stuck at one value for long periods, major time gaps (up to 3 months), and negative null values.

Authors response: Again, this comment is unclear. What are we to do with the above comment? This is beyond the scope of our paper. We have not intended that this work challenge the raw data; none of remaining 3 reviewers have had an issue with this point!

We have now addressed this issue by incorporating these bounds as an additional layer of data cleaning process.

1. Forward fill of pressure values in verification well data that are associated with very reactive sensors and high pressure changes for some times gaps which are as long as 3 month, would produce fairly fictitious values!

Authors response: There is no perfect method to deal with missing data; this is why experience matters. As authors, we have carefully monitored the data to make sure such a scenario does not occur; we exclude the data if it does.

1. Text says 6 of the 33 parameter variables were used in the model and site Table 2 for the variable. Table 2 has 9 variables, and the two paired temperature/pressure were to only use one of the values – which ones were used and that makes 7 variables that were used?

Authors response: There were 33 parameters to begin with, after data-cleaning and checking co-linearity, this was reduced to 8 excluding the target injection delta. This has been updated in the paper.

1. Parameters such as in table 1 probably should be described what they represent. What is inj-diff and its units?

Authors response: Done.

1. Why isn’t the hold out data modeled injection rate changes shown? Figure 8 covers the time period when the injection rate was at it maximum of 42 to 44 tonnes/hr rate and there were two 0 injection time periods of 10 hours on the 20th and 3 hours on the 26th.

Authors response: We attempted to show the anomalies predicted by the injection pressure deltas and then based on that investigate the sensor parameters. We agree that showing the holding dataset is valuable and have now included it in the paper.

1. Figure 5 for b Check file of small subset of data. The injection rates were at the typical 42-44 TPH rate which is a typical fluctuation range for that entire time period of b.

Authors response: Noted; thank you for the comment. It's important to clarify that our analysis primarily focuses on detecting anomalies and changes in data trends rather than absolute values. As such, the small fluctuations in injection rates, while within the expected range, still could contribute valuable information or rather this work is to determine if it does.

4. Could the manuscript benefit from additional tables or figures, or from improving or removing (some of the) existing ones?  
  
Please provide specific suggestions for improvements, removals, or additions of figures or tables. Please number each suggestion so that author(s) can more easily respond.

Reviewer #3:

1. Tables have data problems and no explanation of some of the data: . Table 4; What is the VW DH Sensor? Pressure or temperature? What is the Temp Sensor? VW Zero Value – there should be NO zero values for temperature or pressure.

Authors response: This has now been addressed in the paper as per above responses.

1. unless the authors converted the times to UTC, all the time data is local time.

Authors response: Noted and amended.

1. Explain what is in the tables and figures. Explain what are the parameters in table 1 and 2 and the colored boxes in figure 8 – as examples.

Authors response: Done.

1. In table 8, do not know what is real input data and what is the predicted values. For Avg\_CCS1\_DH6325Ps\_psi, the raw recorded data is all below 3300 psi with a short downward change of 230 psi on the 20th and 162 psi on the 26th. Doesn’t match the data in table 8.

Author: Figure 8 has the incorrect dates; this has now been updated and it has been verified that there is no change in analysis. The raw recorded data for Avg\_CCS1\_DH6325PS\_psi should correspond to the dates 20 Nov 2014 to 26 Nov 2014.

5. If applicable, are the interpretation of results and study conclusions supported by the data?  
  
Please provide suggestions (if needed) to the author(s) on how to improve, tone down, or expand the study interpretations/conclusions. Please number each suggestion so that the author(s) can more easily respond.

Reviewer #3: Mark as appropriate with an X:  
Yes [] No [X] N/A []  
Provide further comments here:

1. Results for the success of the model was to run 67% of the data to teach the model and use the 33% held back data to run to predict injection rate changes. I believe this was supposed to be accomplished in Figure 8 which has no legend for viewer to figure out which data is which. Couldn’t the predicted parameters be compared to the actual measured parameters of injection rate? Which is not in the graph! Visually it would be nice to see that data as a comparison and not a derivative of the data.  
   19. No results or explanation given for linking injection rate changes to containment issues.
2. Author: Noted and Ground Truth values have now been added to the report.

6. Have the authors clearly emphasized the strengths of their study/theory/methods/argument?  
  
Please provide suggestions to the author(s) on how to better emphasize the strengths of their study. Please number each suggestion so that the author(s) can more easily respond.

Reviewer #3:

1. Hard to come up with a strength when study/theory cited in the title is so incomplete. Question the use a complicated Artificial Intelligence based Time-Series Prediction to predict injection rate changes using Well head injection pressure and temperature, annulus pressures, down hole pressures and temperatures, and two variables from the verification well 1007 feet away, when simple relationships can be examined and developed between just several of the injection well parameters without AI.

Authors response: Again, it’s a complementary method, and not a replacement for any technology out there. It might be useful for operators who run leaner operations. We encourage the reviewer to have an open mind; certainly, the other 3 reviewers did!

While simple relationships between some injection well parameters can indeed be examined and developed without AI, our methodology offers distinct advantages in capturing nuanced patterns and interactions within the data that may not be readily apparent through traditional analyses. Furthermore, our aim is not solely to predict absolute values but rather to analyze deltas, changes, and trends in the data. For instance, consider the relationship between injection rate changes and pressure variations.. This approach allows us to identify anomalies and trends that could indicate potential issues or opportunities for optimization.

While it's true that simpler analyses can be conducted for individual wells, the scalability of such methods becomes a significant challenge when dealing with a large number of wells. In contrast, Machine Learning and AI offer the capability to analyze vast quantities of data from numerous wells simultaneously, enabling operators to prioritize interventions based on predictive insights. For example, if there are thousands or even millions of wells in a field, AI-driven analytics can help identify the most critical areas requiring attention, thereby optimizing resource allocation and operational decision-making.

Lastly, this is a prototype, a start which is why we are using such a dataset that is simple, known and one can easily derive the expected result as pointed out by the reviewer to see what the model does and see how well it does, what breaks the model, etc. The aim would be to scale this to more challenging situations and inputs.

7. Have the authors clearly stated the limitations of their study/theory/methods/argument?  
  
Please list the limitations that the author(s) need to add or emphasize. Please number each limitation so that author(s) can more easily respond.

Reviewer #3: None stated.

Authors response: We acknowledge that while we may not have explicitly labeled them as 'limitations' in our paper, we have indeed addressed areas for improvement within our model. These include dealing with outliers/garbage values effectively, including a feedback loop and reduction of runtime optimization. These suggestions inherently represent limitations that need to be acknowledged and addressed. We kindly ask the reviewer to consider these points and provide a more comprehensive assessment of our work. ~~Noted; thank you~~

8. Does the manuscript structure, flow or writing need improving (e.g., the addition of subheadings, shortening of text, reorganization of sections, or moving details from one section to another)?  
  
Please provide suggestions to the author(s) on how to improve the manuscript structure and flow. Please number each suggestion so that author(s) can more easily respond.

Reviewer #3: Structure is not a problem

Authors response: Noted; thank you

9. Could the manuscript benefit from language editing?

Reviewer #3: No

Reviewer #3:

1. main points: As stated in line 412 & 413 of the Conclusion, the model was made to predict the injection rate changes of the CO2 injection. And lines 418 & 419 state that the model's primary objective is to detect anomalies and alert operators to closely inspect the well for potential leaks. Using predicted parameters to validate CO2 containment in the Well - title. In highlights: Predicting this change can be used to provide a checkpoint against carbon plume migration and can determine if there are losses in the injection process. Not shown or explained in this paper on how knowing an injection rate can tell one about migration of CO2 or injection well integrity.

Authors response: Noted; we have edited where we can

1. Line 62 Mt. Simon Sandstone is the official name. Not Mount.

Authors response: Noted; edited

1. Line 66 Injection started in Nov 2011 not 2009. Drilling was in 2009.

Authors response: Noted; edited

1. Line 67 the distance between the Injection well and Verification well is 1007 ft as shown in Bauer et al. 2016.

Authors response: Noted; edited

1. Line 79 What are the other losses?

Authors response: Noted; edited. We are referring to downhole losses, such as casing leaks, thief zones etc. Some of these changes are small, and conventional logging tools may not be able to detect them.

1. Line 81 Do not understand how knowing injection rate changes, tells one the integrity of the well. Permit requires monitoring the injection well annulus pressures and periodic pressure tests and the use of reservoir saturation tool in the cased hole to try and detect CO2.

Authors response: Noted; ~~we are not sure what permit you are referring to, but standards may not be equally applied in all jurisdictions/countries?~~ Also, ~~well annulus pressure,~~ periodic pressure tests, and use of logs implies an OPEX; a ML method is complimentary to these methods but can help lower costs for the operator by reducing the frequency such operations are conducted. We also want real-time monitoring; the methods recommended by the reviewer are not real-time.

Regarding the understanding of injection rate changes, they serve as indicators of potential anomalies in well behavior. For instance, a sudden change in injection rate, when all other parameters remain constant, could signal an issue that needs attention, such as a breach in containment. Therefore, our method aims to provide valuable insights into well integrity by analyzing these changes and identifying potential anomalies.

1. Line 94 hydrocarbon and water rates - RECOVERY? Rates

Authors response: Noted; edited.

1. Line 124 Data was - data is plural - Data were

Authors response: Noted; edited.

1. Line 133 Illinois Basin - Decatur Project hypen missing

Authors response: Noted; edited.

1. Line 136 checkpoint against carbon migration. Authors are not working with any data showing where the CO2 is or was located and how a single parameter of injection rate is a checkpoint for understanding CO2 migration.

Author: the focus of our paper is on developing a machine learning model to serve as a tool for monitoring well integrity and CO2 containment. While understanding the exact location of CO2 migration is valuable, it falls outside the scope of our current study. The purpose of our model is to detect anomalies in parameters such as injection rate, which could indicate potential issues such as casing-tubing communication failure or reservoir saturation. These anomalies serve as checkpoints for operators to further investigate and take appropriate actions to ensure well integrity and CO2 containment.

1. Line 139 modelling variation in well and storage parameters to validate CO2 containment. Of all the dynamic parameters, which are indicators or are associated with CO2 containment and what is the definition for this? Or even where the CO2 is located - CO2 plume?

Authors response: Noted; edited.

1. Line 142 No details on the annulus monitoring and nearly no details on where the sensors are located in the verification well and how the pressures were impacted by the baffles in the Mt. Simon in relation to the injection zone!

Authors response: Noted; but is this relevant to proving a ML model works? This paper is not meant to discuss the geologic metrics of the measured data. As explained earlier, we are accepting the data as is, and developing a method to help engineers detect anomalies. And even though there are baffles, pressure data indicates hydrostatic communication, and all sensor trends are highly co-linear.

1. Line 145 TD of injection well is 7238 ft as shown in ref. 3.

Authors response: Noted; edited.

1. Line 149 proper name is Precambrian

Authors response: Noted; edited.

1. Line 153 Mt. St Simon delete St

Authors response: Noted; edited.

1. Line 163 There are other problems in the data: Also pressure values stuck at one value for long periods, major time gaps (up to 3 months), in monitoring during removal of sensors, negative null values.

Authors response: Noted; ~~edited. We have not described all these issues; we classify them as “outliers” for succinctness.~~ All these values have been dealt with during the data cleaning process. There are no negative values, no null values. We use multiple inputs to the model in order to mitigate the frozen values. This will be treated as an improvement and has been indicated in the paper.

1. Table 1 shows some of the data problems. Max value for WHCO2Inj of 39,032 psi - permit and the equipment limits are 2,380 psi.

Authors response: This is a comment and well noted. Table 1 is the raw value. Table 2 is the cleaned value which has now been incorporated to include the reviewer’s comment. ~~Such values are the “outliers” we refer to earlier and which we remove as part of our data cleanup.~~

1. Line 171 (i) Would think that the first task for cleaning up the data would be to remove significant outliers, values below original formation pressures (which includes 0), injection well head pressure values above permitted and equipment capable highs, remove pressure changes after sensor re-installation that had jumps in pressure readings until sensors were re-installed again, then do forward fill for some times gaps which are as long as 3 month! This method has many pitfalls without going through the entire data set in detail and determining even small outliers, especially if you are working with only a 25 psi change in 3 years for Z05. Zone 5 was above a set of baffles in the Mt. Simon formation and the injection was below the baffles, resulting in a very slow 25 PSI increase over 3 years of injection with 100+ hours delay in pressure communication between the Injection well and the Z05 sensor. Data needs detailed visual screening.

Author: The data cleaning process now incorporates the reviewer’s comment. As for the choice of sensor, the point here is there is pressure communication. Z05 sees the change albeit small. And the data shows that the Z05 and the other sensors are highly correlatable = to say that the changes detected in the other sensors are also being detected in Z05. We ran sensitivities with other sensors, Z1, Z2 and Z3 in particular and there is no major impact to the model’s objective. As we are dealing with deltas, this is captured and Z5 was picked purely on the basis of the lowest RMSE value.

1. Table 2. Cleaned up data: VW1\_Z05: minimum value of the measured formation pressure can not be lower than the original formation pressure. There is no withdrawal of formation waters to lower it! The original formation pressure for Zone 5 was 3051.8 psi. Going through the data in detail for Zone 5 data, one is looking for changes outside of this overall 25 psi change over 3 years. The median value in Table 2 is at the maximum pressure of about 3076 after 3 years. These values in this table for Z05 show the problems with this data to be easily cleaned up with the method used.

Author: This has now been addressed as per previous responses.

1. Table 2. Cleaned up data: CCS1 well head injection pressures should be cleaned up so that permit required maximum levels of pressure (2,380 psi) and rate are the maximum values. These permitted maximum values are also near the equipment and pipeline maximum operating pressures.

Author: This cleanup now been addressed as per previous responses. But we would like to point out that it does not necessarily mean all operators adhere to the permitted wellhead injection pressures.

1. For all the diagrams with time. The original data is in local time not UTC - unless authors have converted it.

Author: Noted. Thank you.

1. Line 342 Table 4 are the listings of input parameters in the model to test predicted output of the other parameters and as stated authors are predicting the changes in the injection rates by using other recorded contemporaneous data. Final model run has input of injection well head pressure, which can be related to volume from a project developed relationship and volume over time is injection rate. Why the complicated model then?

Author: Indeed, the final model includes input parameters such as injection well head pressure, which can theoretically be directly related to injection volume over time. However, the complexity of the model arises from its ability to capture nuanced relationships and detect anomalies that may not be apparent in straightforward correlations. For instance, while changes in injection well head pressure may directly influence injection rates in conventional scenarios, there could be instances where changes in other variables, not directly tied to well head pressure, impact injection rates.

Regarding the possibility of changes in injection rates without corresponding changes in well head pressure, while it may seem counterintuitive, it's conceivable in certain operational contexts. For instance, changes in downhole conditions, reservoir characteristics, or equipment performance could potentially influence injection rates independently of variations in well head pressure. Therefore, the model's complexity allows for the identification of such nuanced patterns and anomalies, providing a more comprehensive understanding of system behavior beyond simple correlations.

1. Table 4; What is the VW DH Sensor? Pressure or temperature and which one? What is the Temp Sensor? VW Zero Value - there should be NO zero values for temperature or pressure.

Author: Thank you for pointing out the ambiguity. The VW WH DH Sensor refers to the pressure sensor. The table in the report has been amended. As for the zero values, this has now been addressed as per responses above.

1. Figure 8. What are the different colored boxes? Don't understand the flat line data for Z05 from 20 Nov 2012 through about 24 Nov 2012. Pressures during this time period fluctuated from 3069.079 to 3069.65 psi and outside of it not being flat data, it doesn't even match the 3071.5+ values in this graph, which are in 0.1 divisions and should show the raw data fluctuation range or that there are problems with the data clean up method.

Author: Figure 8 has the incorrect dates; this has now been updated and it has been verified that there is no change in analysis. The 3071.5 values should correspond to the dates 20 Nov 2014 to 26 Nov 2014. The different colored boxes represent the interpreted events corresponding to anomalies predicted in the injection deltas.

1. References 3, Authors need corrections and Illinois Basin-Decatur Project - needs caps.

Authors response: Noted; edited.

1. References 10, 15, and 17 need authors fixed.

Authors response: Noted; edited.

1. If verification well data is used for predictions, one may want to use data from zones that were rapidly affected by pressure changes at the injection well. Zones 1 through 3 are below a baffle that affected injection transmitting changes in formation pressures in the Mt. Simon and are near the level of the CCS1 injection and reacted to CCS1 changes within about an hour and had maximum recorded pressure changes of 169 psi. Zones 4-9 are above the baffles and are in a part of the aquifer that reacted very little to pressures changes. For Zone 5, the very, very slow buildup of the 25 psi pressures took 3 years. Once when the sensor was pulled and reset, it took 5 months for it to restabilize to the original pressures.

Authors response : Our approach hinges on analyzing deltas, parameter changes, and trends rather than absolute values. As indicated in the correlation matrix presented in the paper, the time series trends from sensors in the verification well are highly collinear. This implies that including additional sensors from these zones would offer limited value in terms of enhancing the predictive capabilities of the model.

Moreover, sensitivity runs were conducted, as detailed in the "Sensitivity Runs" section, to explore various combinations of downhole sensor. Z05 is the best option in terms of RMSE which is how a LSTM ML model is evaluated on. While we acknowledge that the different rates of pressure buildup across zones may reflect variations in reservoir properties that could impact storage volume, addressing such nuances falls outside the scope of our study. Our primary goal is to detect deviations from expected behavior and identify potential containment issues.