

Dear Editor,

We thank you for your detailed handling of our manuscript and for giving us the opportunity to submit a revised version. We also thank both reviewers for their thorough and constructive evaluation. We are fully aware that the previous version of the manuscript lacked the depth and rigor required for publication, and we have taken the criticisms raised by the Editor and both reviewers very seriously. The manuscript has been extensively revised, as detailed below.

1. Unsupported general claims

The Editor identified several statements that made absolute or overly general claims without sufficient evidence, and warned that the paper would be rejected if any such statement remained. We have removed or replaced all such statements throughout the manuscript. Three specific examples are addressed below.

The statement *"classic DA schemes in gridded space fail to properly estimate the structure properties"* has been replaced by: *"linear Gaussian DA updates performed in gridded space may struggle to accurately represent structural properties, including position and amplitude, when displacement or shape uncertainty dominates."* This formulation is now applied consistently in the abstract, introduction, and conclusions.

The statement *"DA in the parametric space can account for the nonlinearity of the eddy parameters and preserve eddy properties. This is not the case for classic DA in the gridded space"* has been replaced by a formulation explicitly restricted to the idealized setting: *"in the idealized experiments presented here, DA in the parametric space yields improved parameter estimates and preserves eddy structure, whereas linear Gaussian updates in the gridded space can deform the profile when position or shape uncertainty is dominant."*

The statement *"DA in the parametric space considerably reduces the computational cost"* has been replaced by: *"while the parametric formulation may offer computational advantages due to its reduced dimensionality in this idealized context, practical applications would require additional steps such as eddy detection, parameter fitting, and feature association, which may significantly affect the overall computational cost."* In addition, the unsupported claim that the parametric approach does not require a large ensemble (whereas gridded DA requires at least 25 members) has been removed entirely, as no ensemble-size sensitivity analysis was performed.

More generally, the manuscript has been revised throughout to clearly distinguish between conclusions directly supported by the idealized experiments and broader perspectives reserved for future work.

2. Depth, reproducibility, and analysis of results

The Editor noted a lack of depth in the presentation of the DA methodology, missing details about how the results are obtained, and the absence of analysis of both the results and the methodology. These concerns were also raised by both reviewers.

We have addressed these issues through four main changes.

First, the analysis step is now described with full detail in the methodology. In particular, we clarify that the minimizer of the cost function is given analytically by the Best Linear Unbiased Estimator (BLUE), so

that no iterative optimization algorithm is required. The solution is computed directly for each configuration, making the computation very fast. The distinction between the analytical BLUE principle and its ensemble-based implementation (EnOI) is now explicitly made. The EnOI update is written for ensemble members, not ensemble means, which is clarified by the member-wise notation in the equations.

Second, Experiment #4 has been fully integrated into the manuscript as a central methodological component, with its own subsection in the Methodology (Sect. 2.2), the Experiments (Sect. 3.2), and the Results (Sect. 4.2). The fitting procedure, constraints, initialization, covariance estimation, and robustness over 10 independent noise realizations are all described in detail. The parameter correlation matrix is reported in Table 5.

Third, quantitative diagnostics are now reported for all four experiments in Tables 3 and 4, including the Root Mean Square Error (RMSE) and the Continuous Ranked Probability Score (CRPS). These values are discussed in detail in the Results section and key figures are remounted into the conclusions.

Fourth, the EKE diagnostic has been retained as an illustration of the physical consequences of profile deformation but is now explicitly framed as such, with its formula and computation given explicitly (Eqs. 15–16).

Regarding cycling: the manuscript now states explicitly at the start of the Methodology (Sect. 2) and in the Conclusions (Sect. 5) that this study focuses solely on the analysis step and does not perform repeated assimilation cycles. The stability of the system over multiple cycles is acknowledged as an important open question and is identified as a direction for future work.

3. Figure 1

The Editor noted that the concern about Figure 1 raised by Reviewer 1 had not been addressed in the previous revision. We have revised Figure 1 to make it clearer and more informative. The figure now presents the analysis step of the assimilation as a sequential diagram (background → observation → analysis → projection), with the parametric space and the gridded space shown in clearly separated panels. The three parameters — amplitude (a), position (p), and radius (r) — are explicitly indicated and labelled in the parametric panels. We believe the revised figure provides a clear and necessary illustration of the two-space comparison that is central to the paper.

4. English and typographical corrections

The Editor noted that the presence of English mistakes indicated carelessness. We have carefully proofread the entire manuscript and corrected all typographical and grammatical errors identified by both reviewers, including: *"without the the forecast step"*, *"we don't focus not"*, *"Copyright statement. TEXT"*, *"The Figure"*, *"The Table"*, *"correspond to"*, *"gives same values"*, and *"Gaussian profiled fitting"*. All DOI strings have been checked and corrected. The manuscript has been proofread throughout for clarity and fluency by a hired native American English teacher.

5. References to related literature

The Editor noted that the introduction should include references to nonlinear non-Gaussian assimilation methodologies, Lagrangian methods, displacement assimilation, and parametric estimation in the control and stochastic filtering literature.

The introduction has been revised accordingly. References to Lagrangian DA, feature-based DA, and displacement-aware methods were already present and have been consolidated. A new paragraph has been added that acknowledges the long history of working in low-dimensional parameter spaces in the control and stochastic filtering literature. However, we note that in this prior literature the parameters to be estimated are typically internal coefficients of a dynamical model rather than geometric descriptors of coherent structures. Our contribution applies the same principle to an explicitly geometric and physically interpretable representation, and a clear positioning statement to this effect has been added to the introduction.

We believe the revised manuscript fully and rigorously addresses all concerns raised by the Editor and both reviewers. The substantial revisions were the removal of all unsupported general claims, the full integration of Experiment #4, the addition of quantitative diagnostics, the clarification of the DA methodology, and the careful positioning within the existing literature. We hope that makes the manuscript suitable for publication in its revised form.

Yours sincerely,

Solène Dealbera

Response to reviewer #1

July 7, 2026

We would like first to thank the reviewer for his/her careful reading and constructive criticism. The suggested modifications have been a decisive help to revise and improve our manuscript. Specific comments are addressed one by one hereafter. Reviewer comments are recalled below in bold font, while text extractions from the revised paper are in italic font.

It is a very controlled set of experiments and if I am not mistaken there is no cycling? so we do not know how stable the system is after many DA cycles?

You are correct that this study does not include repeated assimilation cycles (forecast–analysis–reanalysis). Time evolution is not considered here, as our focus is solely on the analysis step, where we aim to optimally combine background and observed information. The question of system stability over multiple assimilation cycles is therefore beyond the scope of this work, though we fully acknowledge its importance for operational applications. We have added the following statements in the manuscript Sect. 2, first paragraph: *We focus exclusively on the analysis step and do not perform repeated assimilation cycles (forecast-analysis-reanalysis). The stability of the system over multiple cycles is beyond the scope of this study and will be investigated in future work, when this parametric approach is applied in an operational, sequential assimilation context.* and Sect. 5, fourth paragraph: *This work is intentionally limited to a controlled and idealized setting and does not include sequential assimilation cycles or prognostic model dynamics. Future work will investigate the extension of this framework to realistic, time-evolving situations, where eddy parameters must be inferred from observations through detection and fitting procedures, and updated sequentially.*

There are some English mistakes throughout that need to be addressed.

We have carefully proofread the manuscript and corrected the English throughout to improve readability and clarity. In particular, we have corrected the following: “without the the forecast step”, “we don’t focus not”, “gives same values”, “The Figure”, “The Table”, “correspond to”, and “Gaussian profiled fitting”, as well as improving sentence fluency throughout. The English has been revised by a native American English teacher.

I still have concerns about figure 1 and ask is it really needed?

We have revised Figure 1 to make it clearer and more informative. The figure now separately presents the gridded analysis (left) and the parametric analysis (right). In the parametric analysis panel, the three parameters—amplitude (a), position (p), and radius (r)—are clearly indicated and labeled. For the gridded analysis, the grid is explicitly shown along the lon-axis to enhance readability. We believe the revised figure now provides a clear comparison between the two approaches and is helpful for the reader.

You still have details about the data assimilation that are missing. For example how do you solve for the minimum of the cost function? Which minimization algorithm do you use? How long does it take to solve for the minimum for each situation?

We thank the reviewer for pointing this out. We now clarify that our approach uses the framework of optimal interpolation. Specifically, the Best Linear Unbiased Estimator (BLUE) provides an analytical solution that minimizes the cost function in the linear Gaussian case. No iterative optimization algorithm is needed,

unlike in variational approaches such as 3D-Var, and the optimal solution is computed directly, using linear algebra. Consequently, the computation is very fast for each configuration. We have added the following explanation in Sect. 2, between the cost function J and the update equations: *Under the assumptions of linearity and Gaussian errors, the minimizer of J is given analytically by the Best Linear Unbiased Estimator (BLUE). No iterative minimization algorithm is therefore required; the solution is computed directly for each configuration.*

Is there a way to make the problem a bit further away from idealized to introduce non-linear behavior?

We agree that introducing non-linear behavior is an important direction. A first step in this direction is provided by Experiment #4, which starts from noisy gridded observations and requires a nonlinear least-squares fitting step to recover the eddy parameters before assimilation. This introduces a nonlinear mapping from grid space to parameter space that is absent from the three tutorial experiments. While the assimilation step itself remains linear and Gaussian, the overall workflow is no longer end-to-end linear, and the resulting parameter covariances are non-diagonal due to the coupling introduced by the fitting procedure. We have added the following discussion in Sect. 5: *This work is intentionally limited to a controlled and idealized setting. Future work will investigate the extension of this framework to realistic, time-evolving situations, where eddy parameters must be inferred from observations through detection and fitting procedures and updated sequentially. In particular, the dynamics of eddy parameters in a sequential context are expected to be strongly nonlinear, which may necessitate ensemble-based or nonlinear assimilation methods.*

Response to reviewer #2

July 7, 2026

We greatly appreciate the reviewer’s time and constructive effort in reviewing our manuscript. The suggested modifications and recommendations have been a decisive help to revise and strengthen our methodology and results. Specific comments are addressed one by one hereafter. Reviewer comments are recalled below in bold font, while text extractions from the revised paper are in italic font.

1 Major Comments

1. In the first three experiments, uncertainty is generated in parameter space and then mapped to grid space. This means that the parameter-space method receives the uncertainty in the coordinates in which it is simple and approximately Gaussian, while the grid-space method receives the nonlinear push-forward of that uncertainty. For position and radius perturbations, this setup naturally produces the smearing seen in grid space. I do not view this as a fatal flaw. These experiments are useful didactic examples. However, the manuscript should state explicitly that they are tutorial experiments designed to illustrate the mechanism, not balanced end-to-end comparisons of practical DA workflows. The broader claims should not rely on these experiments alone.

We thank the reviewer for this important clarification. We have now explicitly stated in the manuscript that the first three experiments are intended as tutorial examples illustrating the mechanism by which direct gridded Gaussian updates can smear displaced or rescaled coherent structures, whereas parameter-space updates preserve the imposed structure. These experiments are not intended as balanced end-to-end comparisons of practical data assimilation workflows. To address this limitation, we have included a fourth experiment using noisy gridded fields, which provides a more realistic test of the parametric approach. This is now stated explicitly in Sect. 3 and in Sect. 2.1:

These three experiments are intended as tutorial examples illustrating why direct gridded Gaussian updates can smear displaced or rescaled coherent structures, while parameter-space updates preserve the imposed structure. However, they do not constitute a fair end-to-end comparison because the uncertainty is generated in parameter space and then mapped to grid space. For this reason, a fourth experiment is performed in which the considered observations are noisy gridded fields (Sect. 2.2).

2. The new Experiment #4 is the most important part of the revision. It attempts to start from noisy gridded fields, fit parameters, estimate parameter-space covariances, and then perform the parametric analysis. This is the correct response to the main asymmetry in the original manuscript. At present, however, the experiment is not described in enough detail to reproduce or assess it. The manuscript should specify the fitting objective, the optimizer or fitting method, the initialization, whether constraints such as positive amplitude and positive radius are imposed, how many noise realizations are used, and how the parameter covariance matrices are estimated from the fitting procedure. The manuscript states that non-negligible correlations between fitted parameters arise, but the actual covariance or correlation matrices are not shown. These should be reported, at least in a small table or appendix. As written, Experiment #4 reads like a useful but preliminary add-on. It needs to be integrated into the

methodology and results as the main test of whether the parametric approach remains useful once the inverse mapping from grid space to parameter space is included.

We agree that Experiment #4 is the central demonstration of the method’s applicability to grid-space observations. In the revised manuscript, Experiment #4 is now fully integrated into the methodology and results as its own subsection (Sect. 3.2 and Sect. 4.2), rather than being appended as an add-on.

The description of the experiment has been significantly expanded in the Methods section (Sect. 2.2) to include all elements required for reproducibility:

- *Fitting objective*: nonlinear least-squares minimization of $\mathcal{L}(\boldsymbol{\theta}) = \|\mathbf{u} - h(\mathbf{lon}; \boldsymbol{\theta})\|_2^2$, where $\mathbf{u}$ is the noisy gridded profile and $\boldsymbol{\theta}$ is the parameter vector;
- *Fitting method*: `scipy.optimize.curve_fit` with bounds $a \in [0, 10]$ m, $p \in [-50, 50]$ km, $r \in [0.1, 50]$ km, ensuring positive amplitude and radius;
- *Initialization*: the fit is initialized at the true background or observation parameters respectively, a simplification justified by the idealized nature of the experiment where true parameters are known; in practice, initial values would be provided by a prior detection algorithm;
- *Number of noise realizations*: $N = 10\,000$ ensemble members for covariance estimation, and the full experiment is repeated $n_{\text{iter}} = 10$ times to assess robustness;
- *Covariance estimation*: the parametric covariance matrices $\mathbf{B}^{\text{param}}$ and $\mathbf{R}^{\text{param}}$ are estimated as the sample covariance of the fitted parameter ensembles (Eq. 12).

The resulting parameter correlation matrix, averaged over the 10 noise realizations, is now reported in Table 5 in Sect. 4.2. The dominant off-diagonal correlation is between amplitude a and radius r (-0.47 ± 0.02), reflecting a geometric coupling introduced by the fitting procedure. The correlation between position and the other parameters is negligible ($< |0.01|$).

3. The figures are helpful and should remain. They communicate the qualitative mechanism clearly. However, the conclusions cannot rest mainly on visual comparison of curves. The manuscript should report quantitative diagnostics for each experiment. At minimum, this should include analyzed or fitted amplitude, position, and radius values; errors relative to a prescribed truth or reference state; profile errors such as RMSE or relative L^2 error; and uncertainty estimates. If EKE is retained as a physical diagnostic, the formula and computation should be given explicitly, together with quantitative EKE errors. For Experiment #4, these diagnostics should preferably be reported over several noise realizations. A single plotted realization is not enough to establish robustness.

We have added quantitative diagnostics for all experiments, reported in Tables 3 and 4 in Sect. 4.

The background and observation are constructed symmetrically around a true state $\mathbf{x}^{t,\text{param}}$ by applying shifts of equal magnitude and opposite sign where $\boldsymbol{\delta}$ is the prescribed shift vector, with only the uncertain parameter having a non-zero component. The associated true gridded profile is $\mathbf{x}^{t,\text{grid}} = h(\mathbf{lon}; \mathbf{x}^{t,\text{param}})$. This symmetric construction ensures that the background and observation errors are equal in magnitude, so that the expected BLUE analysis in parameter space recovers the truth exactly: $\bar{\mathbf{x}}^{a,\text{param}} = \mathbf{x}^{t,\text{param}}$, so that all errors are measured relative to a well-defined external reference.

The following diagnostics are reported for each experiment:

- *Profile errors*: the Root Mean Square Error (RMSE) of the analysis mean relative to $\mathbf{x}^{t,\text{grid}}$, and the Continuous Ranked Probability Score (CRPS) of the analysis mean relative to $\mathbf{x}^{t,\text{grid}}$, which jointly measures accuracy and sharpness (Table 3);
- *Parameter errors*: the signed error of each analyzed parameter relative to the truth $\mathbf{x}^{t,\text{param}}$, reported separately for amplitude, position, and radius, for both the parametric analysis and the gridded analysis after Gaussian fitting (Table 4).

Key results are: in Experiment #2, the gridded analysis yields $\text{RMSE} = 0.10$ m against 0.00 m in parametric space, with parameter errors of 0.24 m in amplitude and 2.15 km in radius; in Experiment #4, $\text{RMSE} = 0.09$ m (**grid**) versus 0.02 m (**param**), with parameter errors of 0.21 m and 1.94 km for the gridded analysis against 0.02 m and 0.24 km for the parametric analysis.

The EKE formula and computation are now given explicitly (Eqs. 15–16 in Sect. 4.1), with reductions of 67% and 11% reported for Experiments #2 and #3 respectively. As stated in the text, the EKE is used as a physical illustration of the consequences of profile deformation, not as a primary validation metric.

For Experiment #4, all diagnostics are computed over 10 independent noise realizations. The results are stable: the Gaussian fit of the gridded analysis gives $(a, p, r) \approx (0.79, 0.04, 8.96)$ m/km/km across realizations, with standard deviations of approximately 0.005 m, 0.05 km, and 0.04 km respectively.

4. The notation is still a major obstacle to understanding the method. The same symbols are used for parameter-space states, gridded states, observations, ensembles, and generic DA variables. In particular, x, y, X, Y, B , and R change meaning depending on the space under discussion. This makes it difficult to verify what is being assimilated and which covariance matrix belongs to which space. I strongly recommend introducing separate notation for parameter states and gridded fields. For example, use $\theta = (a, p, r)$ for the parameter vector and $u = h(\theta)$ for the gridded profile. Then define separate background, observation, and analysis variables in each space, such as $\theta^b, \theta^a, z_\theta$ and u^b, u^a, z_u . The cost functions and Kalman gains should also be written separately for parameter space and grid space. This would make the comparison much easier to audit. The EnOI analysis should also be clarified. It is currently unclear whether the update is written for ensembles, ensemble means, or random variables. If the equation is for ensemble means, barred variables should be used. If it is for ensemble members, that should be stated explicitly.

We acknowledge that some symbols in this manuscript appear in multiple contexts. To maintain consistency with the classical data assimilation literature [e.g., [Ide et al., 1997](#)], we retain the standard notation ($\mathbf{x}, \mathbf{y}, \mathbf{B}, \mathbf{R}$, etc.) rather than introducing entirely new symbols for each space, which would risk confusion with the established literature. However, the context is now made unambiguous throughout by using systematic superscripts **param** and **grid** on all variables. For example, $\mathbf{x}^{b,\text{param}}$ denotes the background vector in parameter space, while $\mathbf{x}^{b,\text{grid}}$ denotes the corresponding vector in gridded space. The cost functions and Kalman gains are written with the same convention, and it is explicitly stated that all equations apply separately in each space. The true state $\mathbf{x}^{t,\text{param}}$ and $\mathbf{x}^{t,\text{grid}}$ have also been added to the notation table (Table 1 in Sect. 2).

Regarding the EnOI update: the equations now explicitly describe the update of individual ensemble members rather than ensemble means. The background and observation ensemble matrices $\mathbf{X}^b = [\mathbf{x}_1^b, \dots, \mathbf{x}_N^b]$ and $\mathbf{Y} = [\mathbf{y}_1, \dots, \mathbf{y}_N]$ are first defined, and the covariance matrices are estimated from these ensembles (Eq. 5). Each member $\mathbf{x}_i^b$ is then updated individually using the same Kalman gain $\mathbf{K}$ but with its own innovation $(\mathbf{y}_i - \mathbf{x}_i^b)$ (Eq. 6). The analysis ensemble mean $\bar{\mathbf{x}}^a = \frac{1}{N} \sum_i \mathbf{x}_i^a$ and analysis covariance $\mathbf{P}^a$ are then derived from the analysis ensemble. In the linear case, the ensemble mean analysis coincides with the BLUE analysis of the mean, but the member-by-member formulation is the one actually implemented and allows direct estimation of the analysis covariance from the ensemble.

5. Some claims remain too broad for the evidence presented. The abstract should not state that classic gridded DA generally fails for coherent structures. The appropriate claim is narrower: linear-Gaussian gridded updates without displacement correction can smear or distort coherent structures when displacement or shape uncertainty dominates. The computational-cost claim should also remain conditional. In the synthetic setting, the parameter space is much smaller than the grid space, but practical applications require detection, fitting, covariance estimation, and possibly multi-feature association. Without timing or complexity evidence, the manuscript should only claim potential cost reduction under favorable conditions. The statement that the parametric approach does not require a large ensemble, while

Table 1: Symbols and associated spaces.

Symbol	Meaning	Space
$\mathbf{x}^{t,\text{param}}$	True state vector	param
$\mathbf{x}^{t,\text{grid}}$	True state vector	grid
$\mathbf{x}^{b,\text{param}}$	Background state vector	param
$\mathbf{x}^{b,\text{grid}}$	Background state vector	grid
$\mathbf{x}^{a,\text{param}}$	Analysis state vector	param
$\mathbf{x}^{a,\text{grid}}$	Analysis state vector	grid
$\mathbf{y}^{\text{param}}$	Observation vector	param
$\mathbf{y}^{\text{grid}}$	Observation vector	grid
$\mathbf{B}^{\text{param}}$	Background error covariance	param
$\mathbf{B}^{\text{grid}}$	Background error covariance	grid
$\mathbf{R}^{\text{param}}$	Observation error covariance	param
$\mathbf{R}^{\text{grid}}$	Observation error covariance	grid
$\mathbf{X}^b, \mathbf{Y}$	Ensemble matrices	param or grid
$h(\cdot; \cdot)$	Mapping param $\rightarrow$ grid	n/a

grid-space DA requires at least 25 members, is not supported by the experiments shown in the manuscript. The described experiments use a much larger ensemble, and no ensemble-size sensitivity analysis is presented. This claim should either be supported or removed. Finally, the statement that a machine-learning model is required for parameter evolution is too strong. Machine learning may be one possible approach, but stochastic parameter models, reduced-order models, tracking-based models, or hybrid models could also be used.

We have revised the abstract, introduction, and conclusions to narrow all claims. Specifically:

We now state that linear-Gaussian gridded updates can smear or distort coherent structures specifically when displacement or shape uncertainty dominates, rather than claiming a general failure of gridded DA. This formulation appears consistently in the abstract, in the introduction (Sect. 1), and in the conclusions (Sect. 5).

Computational-cost claims are now explicitly conditional: we state that the dimensional advantage of the parametric approach applies in this idealized setting where parameter extraction is assumed costless, and that practical applications would require additional steps for detection, fitting, covariance estimation, and feature association that are not quantified here.

The unsupported claim regarding ensemble size requirements (25 members) has been removed. No ensemble-size sensitivity analysis was performed, and this claim was not justified by the experiments.

The statement about machine-learning models has been replaced by: *more general dynamical models for parameter evolution will be required, which may include stochastic parameter models, reduced-order models, tracking-based models, or hybrid approaches, rather than being restricted to any specific method.*

2 Minor comments

1. The manuscript still needs careful editing. Examples include “without the the forecast step”, “we don’t focus not”, “Copyright statement. TEXT”, “The Figure”, “The Table”, “correspond to”, “gives same values”, and “Gaussian profiled fitting”. Some DOI strings also appear malformed, for example with duplicated <https://doi.org/>. The language should be revised throughout for precision and fluency.

We have carefully revised the manuscript to correct all typographical and grammatical errors identified by both reviewers, including: “without the the forecast step”, “we don’t focus not”, “Copyright statement. TEXT”, “The Figure”, “The Table”, “correspond to”, “gives same values”, and “Gaussian profiled fitting”. All DOI strings have been checked and corrected. The English has been revised by a native American English

teacher.

2. The parameter constraints should also be clarified. In particular, if radius uncertainty is modeled with an unconstrained Gaussian distribution, negative or near-zero radii may occur. This is physically problematic even if the formula depends on r^2 . The authors should state whether parameters are constrained, truncated, transformed, or sampled without constraints.

We have clarified the treatment of parameter constraints in the Methods section. In the tutorial framework (Sect. 2.1), ensemble members are sampled from unconstrained Gaussian distributions, except for the radius r , which is clipped to a minimum value of 10^{-6} km to prevent non-physical configurations. In the realistic framework (Sect. 2.2), the nonlinear least-squares fitting is performed with explicit bounds $a \in [0, 10]$ m, $p \in [-50, 50]$ km, and $r \in [0.1, 50]$ km, ensuring that all fitted parameters are physically meaningful.

References

K. Ide, P. Courtier, M. Ghil, and A. C. Lorenc. Unified notation for data assimilation : Operational, sequential and variational (gtspecial issue). *data assimilation in meteorology and oceanography: Theory and practice*. *Journal of the Meteorological Society of Japan. Ser. II*, 75(1B):181–189, 1997. doi: 10.2151/jmsj1965.75.1B.181.