

Supplemental Information: Carbon release from Chatham Rise pockmarks may have been climatically relevant during the last deglaciation

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1 Method for Pockmark Identification from Bathymetric Data from the Chatham Rise-Bounty Trough, NZ

Pockmarks were identified using high resolution multibeam bathymetry data from research voyages SO226 and TAN2006, as well as numerous regional transit lines from legacy datasets. Slope and hillshade data help with the visualisation of subtle features, highlighting steeper gradients that typically characterize pockmark sides. The presence of pockmarks was assessed (Fig. 1), with 4456 features identified, the distribution of pockmarks across the full extent of the study area was then interpolated based on these point features. To assess the area of individual pockmark features, five sub-regions were identified across the study area, where good data coverage and quality allowed individual features to be mapped out as polygons (Fig. 1b). A total of 2812 features were manually identified and mapped using QGIS, based on depth, slope and hillshade grids. An average value for the area of a typical pockmark was calculated

29 using these data, and multiplied for the total number identified across the whole study
 30 area, allowing us to derive a total area covered by pockmarks, and determine the
 31 density of these features.

32 These datasets include dedicated mapping surveys (TAN2006 and SO226), which
 33 are generally higher quality and well processed, as well as transit datasets where
 34 the data quality may be significantly lower due to poor weather conditions, higher
 35 vessel speeds during acquisition and limited sound velocity control. Some datasets
 36 (e.g., transit data) require cleaning and processing to identify pockmark features more
 37 accurately. Such work lies outside the scope of the current project; however, the overall
 38 quality is sufficient to identify the presence or absence of pockmarks and assess their
 39 distribution. Only 45% of the seafloor in the study area has been mapped, there is
 40 therefore an element of data bias as some areas have far better coverage than others.
 41 Bathymetric data used in this study is gridded at between 10–50 m cell size, depending
 42 on data quality, water depth and echosounder capabilities. The average resolution
 43 for multibeam bathymetry data grids is 25 m, it is therefore not possible to identify
 44 smaller features (ca. 4x4 pixels = 100 m x 100 m in size). We have manually identified
 45 500 pockmarks and plotted their sizes in the histogram in Figure 1. Small pockmarks
 46 ($< 1.45\text{km}^2$) make up the majority of the population at a total of 476. The average
 47 size of the small pockmarks is 0.308 km^2 and the total area sum is 160.3 km^2 . For our
 48 gas release rate estimations, we focus on the small pockmark population due to the
 49 uncertainty associated with the creation of larger and mega pockmarks.

50 2 Building Temporal Evolution of Vertical Flux 51 Across Seafloor

52 In Figure 2, we identify a row_{sf} ($1 \times nx$) within the computational domain to represent
 53 a conceptualized seafloor 200 m above the fluid reservoir. When the simulated localized
 54 fluid pathways cross the idealized seafloor, we interpret the associated vertical fluxes
 55 as fluid release from pockmarks. We convert 200 m to row_{sf} using,

$$56 \quad row_{sf} = top_{res} - \frac{200}{\delta c} \cdot \frac{ny}{L_y}, \quad (1)$$

57 where top_{res} is the height of the interface between the furthest extent of the fluid
 58 reservoir and the overlying sediment, ny is the vertical resolution of the domain, and
 59 L_y is the dimensionless vertical length. We can then generate plots of mean-subtracted
 60 vertical flux [m/yr] vs time[yr] along row_{sf} , as seen in SI Sections 3 and 5.

61 3 Formation of Localized Fluid Pathways is Robust 62 to Variations in Material Parameters

63 Physical parameters, such as porosity ϕ and permeability k , of a sediment matrix are
 64 often challenging to constrain and experimental work is required to improve estimates
 65 for model use. To explore the robustness of our results to parameter uncertainty,
 66 we vary initial permeability by three orders of magnitude from $k_0 = 5 \times 10^{-18}$ to

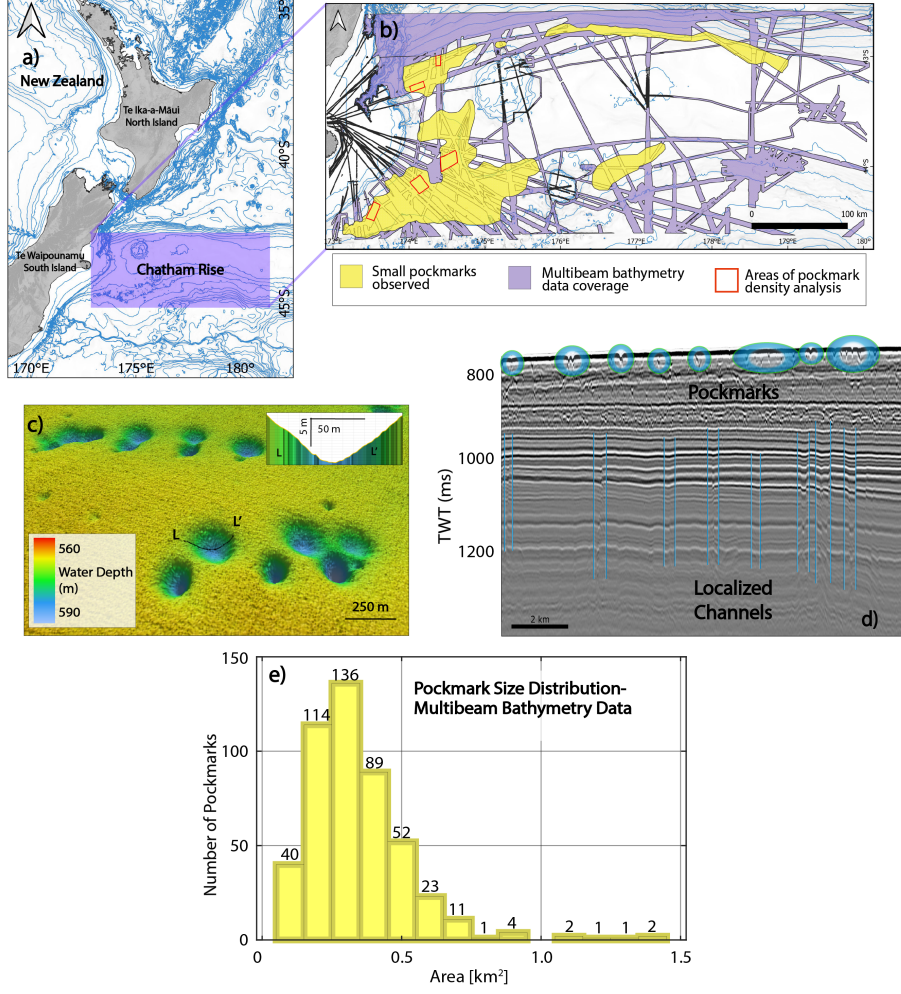


Fig. 1 (a) Map of data coverage of the Chatham Rise Bounty Trough. (a) Map highlighting small pockmarks ($<1.45 \text{ km}^2$) and data coverage. (c) Histograms of smaller pockmarks observed in Chatham Rise. (d) Bathymetric data of pockmark field. (e) Seismic profile of pockmark field. The vertical fluid channel are highlighted in blue and the green circles indicate the crater-like pockmark features on the seafloor.

$5 \times 10^{-14} \text{ m}^2$ and the power-law exponent n_k from 2.1 to 3.3. These values are informed by previous studies of porous flow through carbonate materials [1–5]. We expect that increasing n_k results in faster vertical fluxes, due to the greater exponential increase in permeability within the localized fluid pathways. Furthermore, we expect larger permeability values to lead to order of magnitude changes in the vertical flux.

In Figure 3, we report the temporal evolution of the total mean-subtracted vertical flux across an idealized seafloor for various k_0 and n_k values. We refer to the plots as

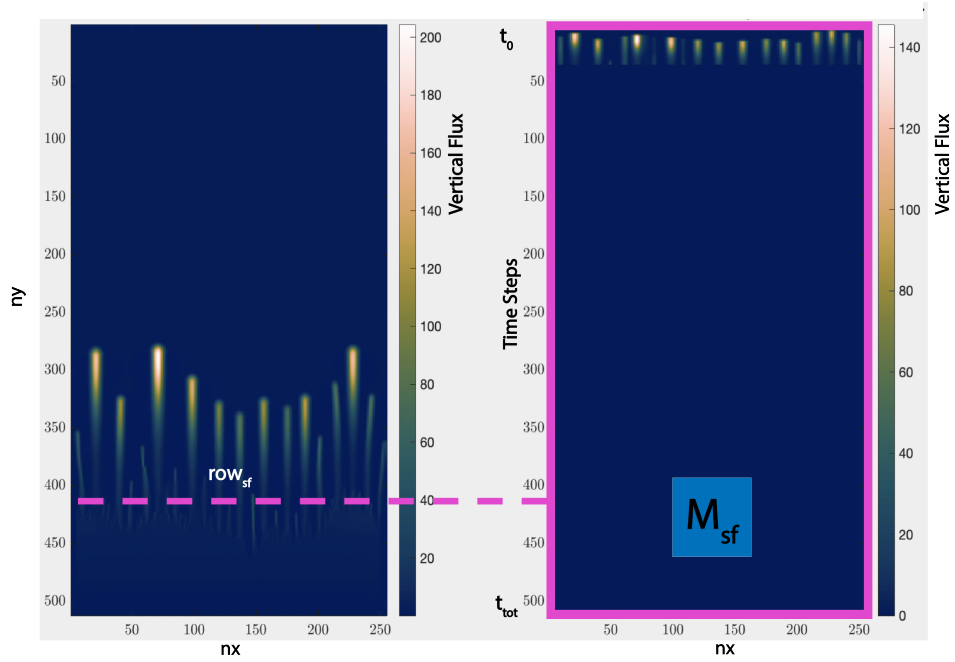


Fig. 2 Row vector data of vertical flux gets collected along row_{sf} and stored in the data matrix M_{sf} with each time step.

fluid release rate curves. To obtain these results, we run the hydromechanical model using $R = 50$, $C = 10$, and $t_{sim}=0.25$ for each simulation. The simulations output the vertical flux for each element in the computational domain at each time step. We extract the non-dimensional vertical flux data from the horizontal slice (row_{sf}) that represents the idealized seafloor 200 m above the reservoir, which is determined using Equation 1. To highlight the elevated fluid flux of the localized fluid channels at each time step, we mean-subtract the vertical fluxes across row_{sf} .

At the beginning of the simulations in Figure 3, we find that the mean-subtracted vertical flux is approximately constant, representing the background flux. When the localized pathways reach the conceptualized seafloor, there is a dramatic increase in the mean-subtracted vertical flux. Afterwards, the depletion of the fluid reservoir results in a drop and return to background levels. In Figure 3a we sweep through $n_k=2.1, 2.4, 2.7, 3.0$, and 3.3 and keep $k=5 \times 10^{-17} \text{ m}^2$. We find that increasing n_k results in an earlier arrival of the localized fluid pathways at the seafloor as well as faster fluid transport. Moreover, the decline in vertical flux becomes steeper with larger n_k . The proceeding, smaller pulses in fluid flux are indicative of the secondary wave of slower moving localized fluid pathways. Next, we sweep through the range of initial permeability values ($k = 5 \times 10^{-18}, 5 \times 10^{-17}, 5 \times 10^{-16}, 5 \times 10^{-15}, 5 \times 10^{-14} \text{ m}^2$) and

92 $n_k = 3.0$. For this suite of simulations, we plot the temporal evolution of the mean-
 93 subtracted vertical flux on a log-log plot (Fig. 3b). As expected from the governing
 94 equations, we find that changes in the mean-subtracted vertical flux [m/yr] and time
 95 [yr] are proportional to variations in k_0 . The flux rate curves shift horizontally and
 96 vertically across the plot with changing permeability. Additionally, while the temporal
 97 variations in the total mean-subtracted vertical flux of each curve are approximately
 98 the same, the curves are stretched or compressed depending on k_0 .

99 The ratio of compaction to decompaction viscosity is represented by R . We explore
 100 a range of values ($R=5, 10, 50, 500$, and 1000) that represents increased dilation of
 101 the sediment matrix in response to pore fluid migration. For each R , Figure 4 includes
 102 heatmaps of the temporal evolution of vertical flux across the entire computational
 103 domain and Figure 5 shows variations in mean-subtracted vertical flux. We find that
 104 increasing R results in more localized flow as well as faster release of fluid.

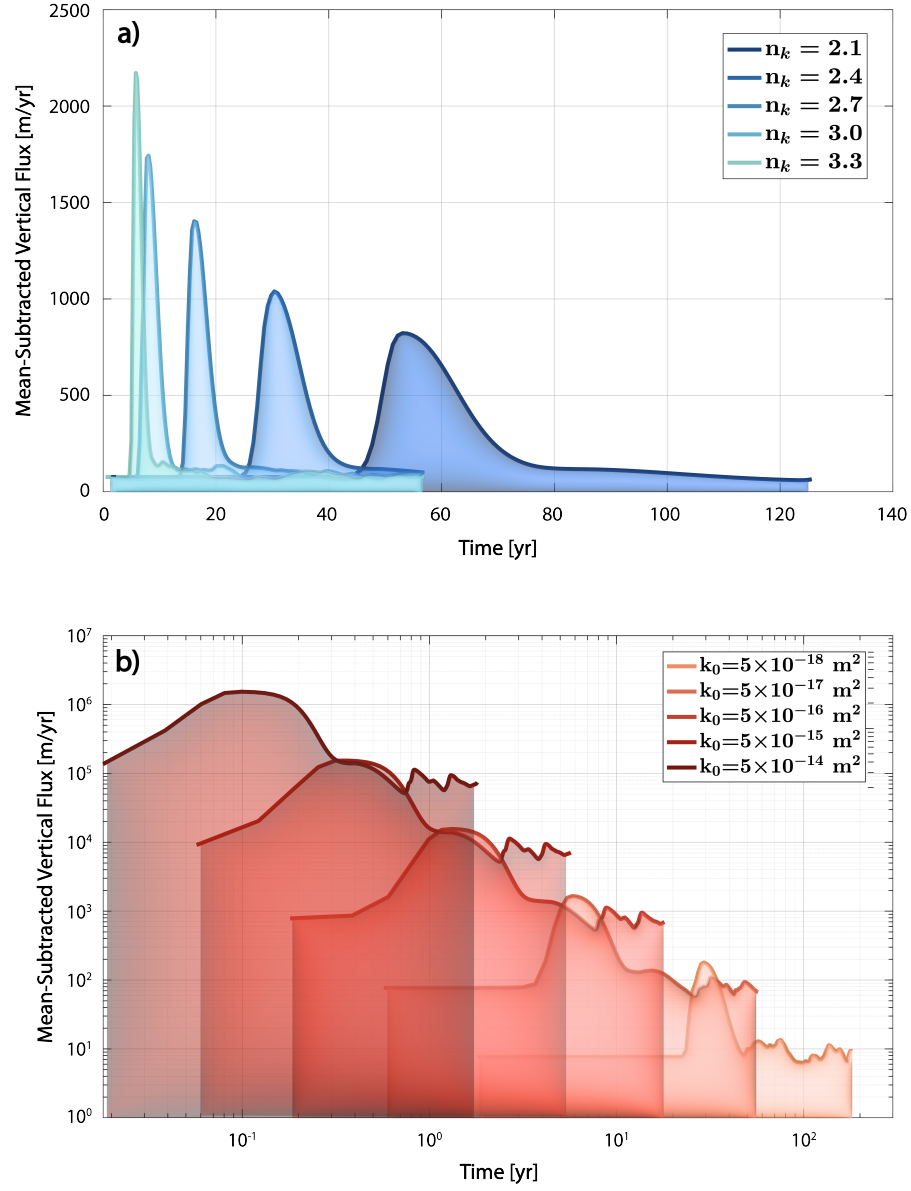


Fig. 3 Sensitivity analysis. a) Total mean-subtracted Vertical Flux [m/yr] for $n_k = 2.1, 2.7, 3.3$. b) Fluid release rate plot for $k = 5 \times 10^{-18}$, $k = 5 \times 10^{-17}$, $k = 5 \times 10^{-16}$, $k = 5 \times 10^{-15}$, and $k = 5 \times 10^{-14} \text{ m}^2$.

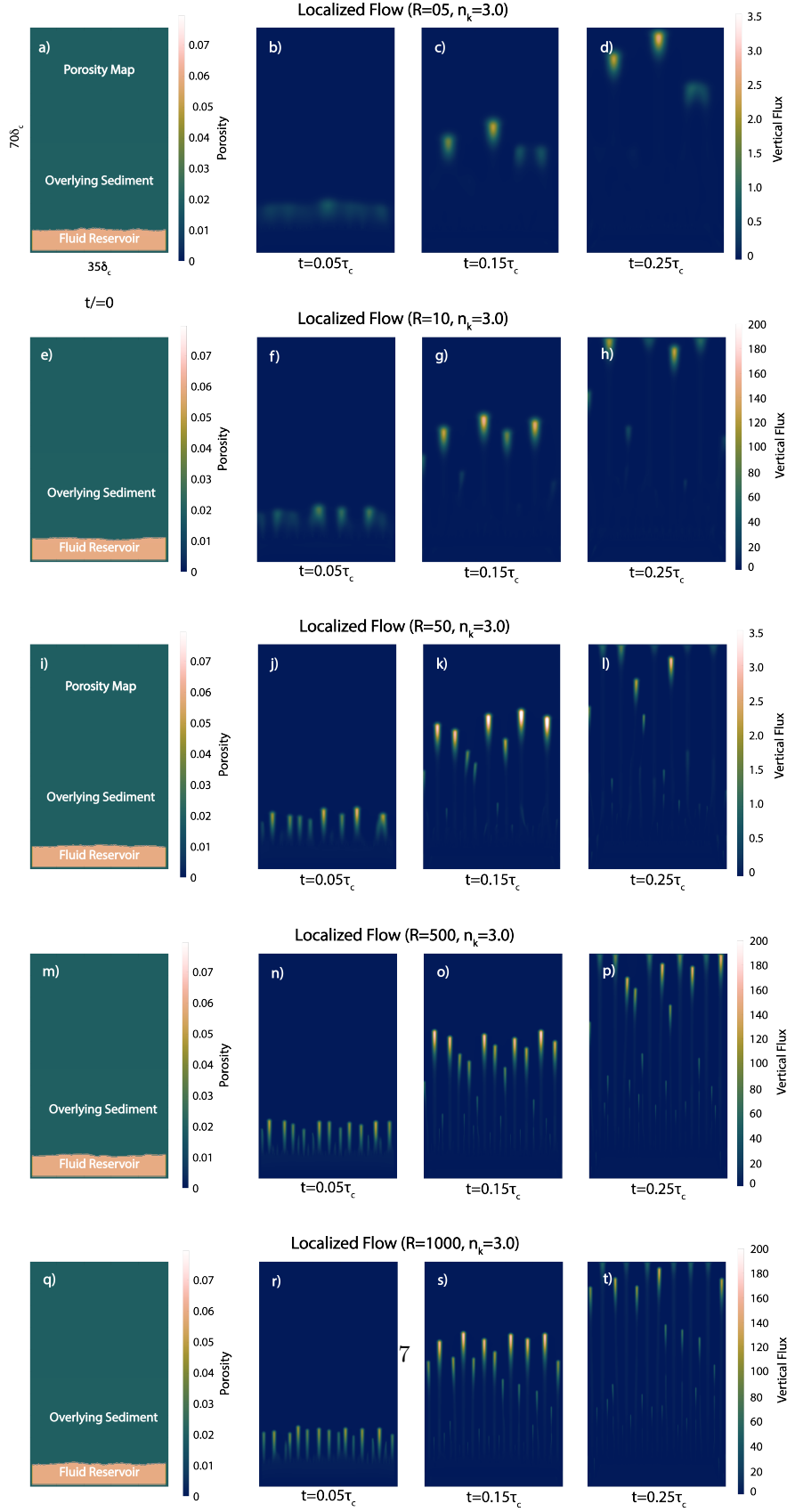


Fig. 4 Temporal evolution of vertical flux heatmaps for localized flow of different R values. (a-d) $R = 5$, (e-h) $R = 10$, (i-l) $R = 50$, (m-p) $R = 500$, (q-t) $R = 1000$, First panels of each row illustrate the initial porosity conditions. As R increases, decompaction viscosity decreases and flow regime transitions more towards localized flow.

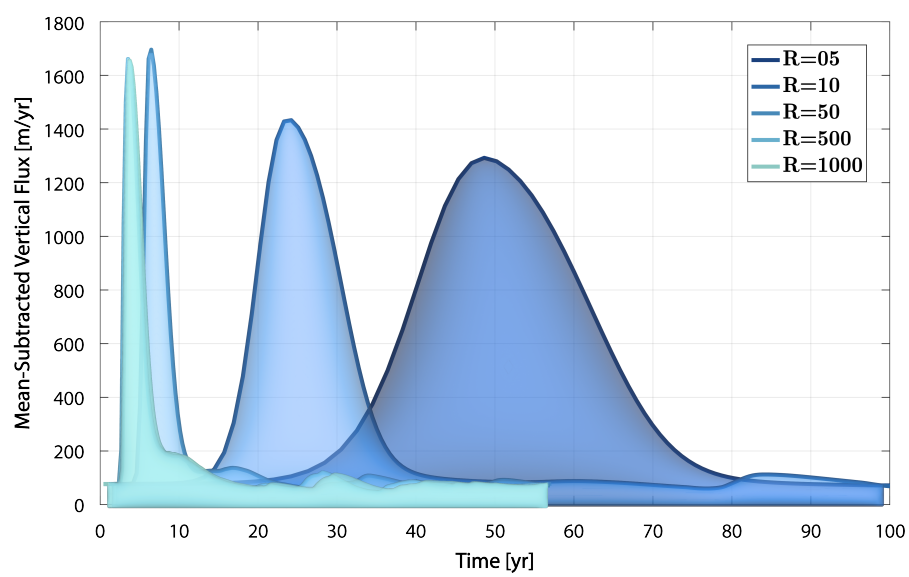


Fig. 5 Comparison of mean-subtracted vertical fluxes [m/yr] over time for each R value.

4 Morphology of Interface Between Upper Reservoir and Overlying Sediment Matrix

The morphology of the upper region of the initial fluid reservoir is created by taking the cumulative sum of a vector ($1 \times nx$) of randomly generated numbers (type Float64). We refer to this cumulative sum vector as the top vector. We then remove linear trends from the top vector, allowing us to isolate the effects of heterogeneity in the morphology of a more realistic reservoir. Afterward, we further process the top vector by subtracting the minimum value of the top vector, normalizing using the maximum value, and scaling by $L_y/n10$, where n is an integer. Then, a smoothing filter is applied to the entire porosity map of the computational domain. This filter effectively uses the finite difference method to average the values of neighboring elements to smooth out sharp fluctuations.

We can amplify the degree of heterogeneity in the interface by increasing n and compare the temporal evolution vertical flux for $n = 1$ (Fig. 6a-d) and $n = 7$ (Fig. 6e-h). The narrow regions in the upper regions of the reservoir act as seeds for localized fluid pathways, by creating distinct areas of elevated vertical flux.

5 Convergence Tests

We ran the hydromechanical simulations for four different resolutions (nx, ny): [64, 128], [128, 256], [256, 512], [512, 1024]. In Figure 7, we find that as the resolution increases, the model requires more iterations to converge and reach the tolerable error. We also note that the localized fluid regime emerges for each resolution (Fig. 8), transporting fluid more efficiently than background flux. The prominence of each mean-subtracted vertical flux rate curve increases and occurs earlier with increasing resolution.

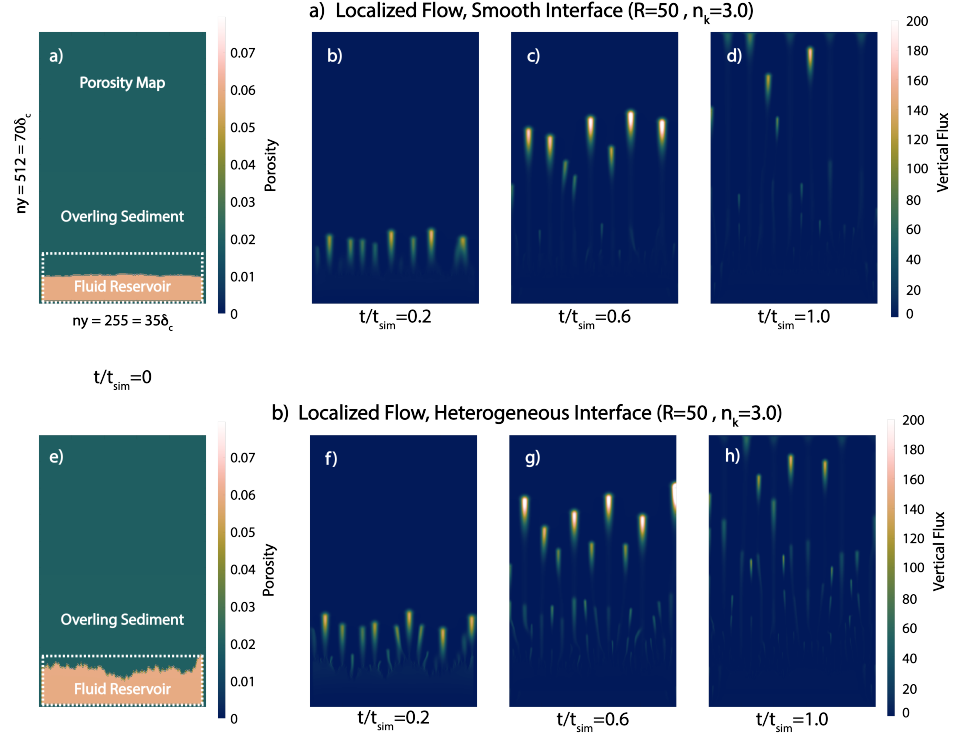


Fig. 6 Temporal evolution of vertical flux heatmaps of localized flow given two different initial morphology between the fluid reservoir and overlying sediment. (a-d) Smoother morphology, $n=1$. (e-h) Heterogeneous morphology, $n=7$.

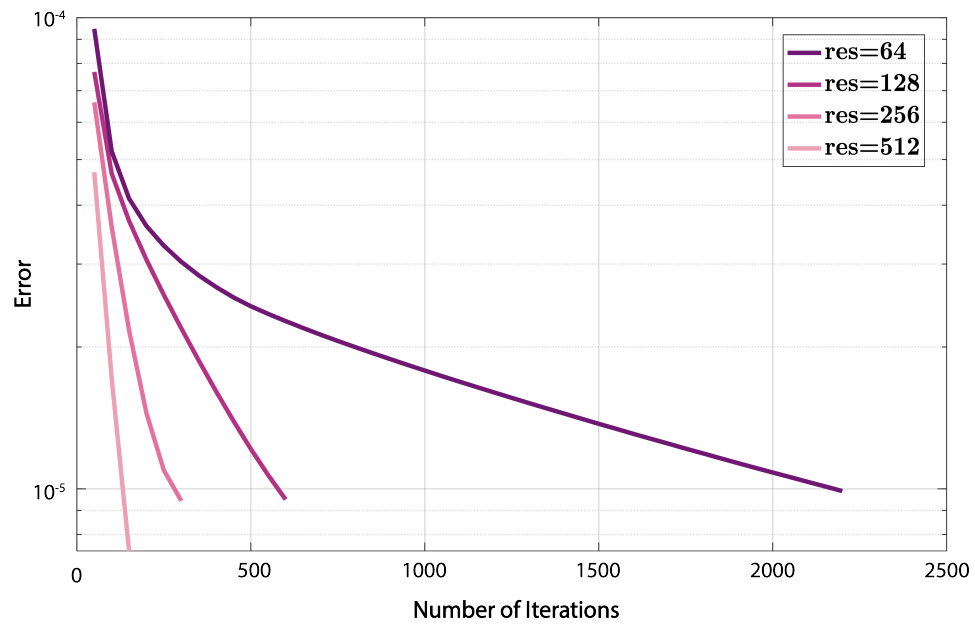


Fig. 7 Plot of error convergence for four different resolutions.

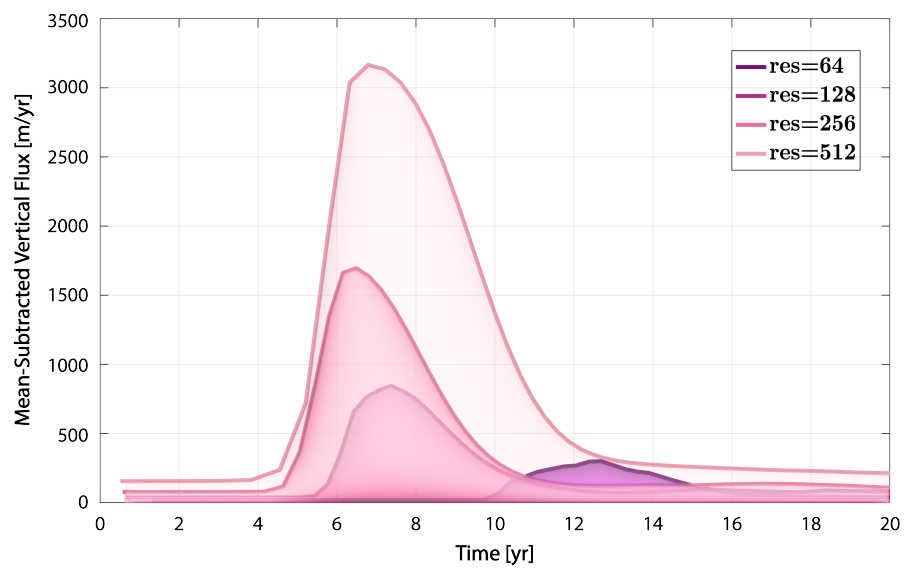


Fig. 8 Temporal evolution of mean-subtracted vertical flux at row_{sf} for four different resolutions. Localized flow regime emerges for each resolution.

6 Converting Vertical Flux to Volume Transport Rates

To remove the dependence of our results on initial fluid reservoir size, we consider the vertical fluxes from only the first wave of pockmarks in our simulations. The end of the first wave is determined by the timing of the first local minimum following the vertical flux peak. This timing is a function of n_k , as shown in Figure 3. To identify pockmarks in our simulation data, we generate a 2D data matrix M_{sf} (time steps $\times$ nx) describing the temporal evolution of the vertical flux along row_{sf} (Fig. 2b). At each time step, or row of M_{sf} , we consider peaks in the vertical flux data to represent pockmarks along the idealized seafloor (Fig. 9a).

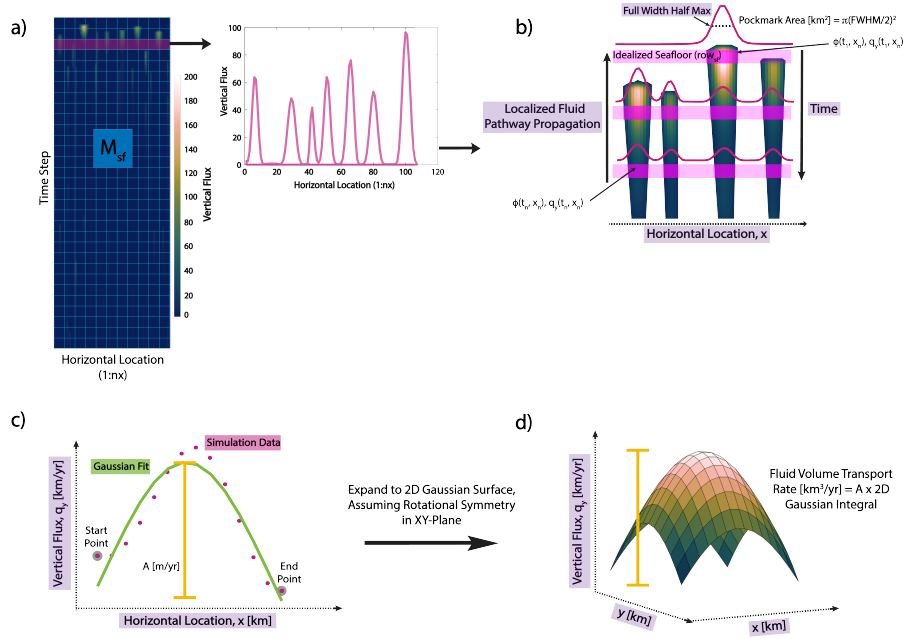


Fig. 9 (a) Temporal evolution of vertical flux along idealized seafloor. (b) Illustration of slices taken across idealized seafloor at each time step to identify localized fluid pathways and collect porosity ϕ and vertical fluxes q_y . We estimate circular pockmark areas from the full width at half maximum for each peak. (c,d) We estimate fluid volume transport rates by expanding our Gaussian distribution to a 2D Gaussian surface.

For each time step t_n , we identify peaks and their respective full width at half maximum (FWHM) within the vertical flux across the idealized seafloor row_{sf} using the *findpeaks* function in the MATLAB Signal Processing Toolbox (Fig. 9b). To address the inherent uncertainty associated with our method, we suppress background noise by thresholding the porosity and vertical flux data. Additionally, we record the horizontal locations of each peak at each t_n and compare them to previously collected

locations to avoid confusing a preexisting pockmark with a newly formed one. If a peak location, $x_{oi}(t_n)$, is equal to or ± 1 away from a previously collected location $x_p(t_{n-1})$, the vertical flux and porosity data are assigned to $x_p(t_{n-1})$. For each unique pockmark location, we have the temporal evolution of the spatially-averaged vertical flux and porosity. The pockmark area is also estimated using the FWHM of a peak at each t_n and is similarly spatially averaged.

We then fit a Gaussian distribution to each peak and assuming rotational symmetry in the XY plane, expand the distribution to 2D Gaussian surfaces (Fig. 9 c,d). By multiplying the integral of the 2D Gaussian [km^2] by the maximum vertical flux of a peak and the mean porosity, we can convert the mean vertical flux [km/yr] of each pockmark to fluid volume transport rate [km^3/yr]. After completing this process for each t_n , we average the fluid volume transport rate for each pockmark over the entire simulation time. We then sort the resulting mean fluid volume transport rates by their associated average pockmark area. This relationship allows us to link the observed pockmark sizes on Chatham Rise, New Zealand to our simulations and estimate a fluid volume transport rate.

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