Evaluating aspects of geodynamic uniformity among subduction zones with large empirical datasets and numerical simulations

Buchanan Kerswell Dept. of Geology & Environmental Earth Science Miami University October 5, 2022

Outline

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Part N: introduction

Observations that suggest subduction zone geodynamic uniformity

Wada & Wang (2009)

Empirical observations

Wada & Wang (2009):

- Thermal parameter ($\phi = v * age$) varies among subduction zone settings
- Seismic characteristics correlate with ϕ
- Volcanic output rates correlate with ϕ
- Depth to the oceanic plate beneath arcs (D) is uniform (narrowly distributed [?] and not correlated with φ)



An explanation for uniform depths to slabs (D)

Adjusting coupling depth in numerical simulations to fit empirical heat flow data suggests **the depth of coupling between plates might be invariant among subduction zone settings**



A poor question?

While Wada & Wang (2009) asked:

• Why is D uniform WRT ϕ ? (implies invariance!)

England et al. (2004) already demonstrated:

- Large D variation WRT ϕ
- D does not correlate with age
- D correlates with descent rate

However imperfect the question of W&W:

- Results suggests D variations might be related to coupling depth variations
- Are coupling depths uniform? Why or why not?



Part I: coupling depths

Evaluating uniformity with numerical simulations

Research questions

What controls the depths of
mechanical coupling?Metamorphic dehydration reactions in the slab?Metamorphic dehydration reactions in the mantle wedge?

Is coupling depth invariantDo coupling depths stabilize after initiation?with time?If so, how quickly?

Is coupling depth invariant with subduction setting?

How much does coupling vary among subduction zones? Is coupling correlated with ϕ ?

Numerical dataset



64 oc.-cont. simulations

Fixed parameters:

- **Rheologic model:** TP-dependent visco-plastic deformation
- **Hydrologic model:** pore fluids & dehydration rxns in crust and mantle
- Material properties: empiricallyderived flow laws
- **Boundary conditions:** open bottom, free surface, insulative, constant horizontal convergence force

Varied parameters:

- Velocity: 40-100 km/Ma
- Oceanic plate age: 32-110 Ma
- Upper plate thickness: 46-94 km

Numerical results



Kerswell et al. (2021)

Coupling depths (Z_{cpl}):

- Vary from ~60-120 km
- Correlate strongly with upper plate thickness (Z_{UP})
- Correlate weakly with the thermal parameter (ϕ)
- Are regulated by thermal feedbacks in the mantle wedge

Variations in Z_{cpl} consistent with variations in D inferred from seismic data

(England et al., 2004, 2010; Syracuse et al., 2006)

Kerswell et al. (2021)

Predicting Z_{cpl}

- Regress expressions with num. results:
 - 1. $Z_{cpl}(Z_{UP}, \phi) = aZ_{UP} + b\phi + c$
 - 2. $Z_{cpl}(Z_{UP}, \phi) = aZ_{UP}^2 + b\phi + c$
 - 3. $Z_{cpl}(Z_{UP}, \phi) = aZ_{UP} + bZ_{UP}^2 + c\phi + d$
- $Z_{cpl} \sim Z_{UP}$ with only a slight correction
- Globally uniform coupling depths require globally uniform $Z_{\mbox{\scriptsize UP}}$
- How thick are upper plates globally?



Part II: upper plate thickness

Evaluating uniformity with a large empirical dataset

Numerical observations



Kerswell et al. (2021)

From Kerswell et al. (2021):

- Z_{cpl} depends on thermal feedbacks in the mantle wedge involving antigorite dehydration
- Z_{cpl} strongly correlates with Z_{UP}

Z_{UP} can be inferred from upper plate surface heat flow

(e.g. Jaupart & Mareschal, 2007; Furlong & Chapman, 2013)

Research questions

How thick are upper plates?	Uniform or variable thickness among subduction zones?
What is the 2D variability?	Uniform or variable thickness along strike? Uniform or variable thickness perpend. to the trench?
How precisely can thickness be inferred?	What dataset(s) can be used, and how? What are the uncertainties?

Empirical dataset



Kerswell & Kohn (in prep)

Thermoglobe

(Jennings & Hasterok, 2021)

- Approximately 70k datapoints
- Variable quality

Kerswell & Kohn (in prep):

- Filtered and cropped Thermoglobe dataset near 13 subduction zone segments
- Applied two interpolations techniques to evaluate 2D heat flow patterns

Kerswell & Kohn (in prep)

Interp. methods

Two interpolation methods based on fundamental laws of geography:

- Similarity: similar geographic configurations should have similar values of the same process under investigation (Zhu et al. 2018)
- **Kriging**: everything is related, but nearer things are more related (Krige, 1951)



Optimization

Different Kriging parameters can produce different results:

- Check accuracy by computing residuals
- Use optimization algorithm to converge on the best fit for 5 different parameters (θ)

 $\theta = \{v_{model}, n_{lag}, max_{lag}, n_{max}, shift_{lag}\}$

Kerswell & Kohn (in prep)



Subtle differences



Vanuatu example:

- Similarity & Kriging interpolations and accuracies are broadly comparable (RMSE: 37.1 vs. 54.6 mWm⁻²)
- Heat flow can vary along strike
- Subtle differences between Similarity & Kriging reflect different mathematical approaches to interpolation

Notice the predicted heat flow for the northern microplate

Useful information for future surveys!

Kerswell & Kohn (in prep)

Kerswell & Kohn (in prep)

Upper plate heat flow continuity

Among all 13 segments:

- A kaleidoscope of profiles exists
- Various profiles suggest various degrees of continuity exist for:
 - Lithospheric thickness
 - Heat-transferring processes
 - Observational density



Part III: high-pressure rock recovery

Evaluating uniformity by comparing numerical and empirical datasets





Empirical observations

From Penniston-Dorland et al. (2015) & Agard et al. (2018):

- Global PT estimates are smoothly distributed across PT-space
- Most rocks are recovered from less than 2-2.3 GPa
- LP-HT rocks are recovered shortly after initiation

Research questions

Where are rocks recovered along subduction interface shear zones?	Continuously or at discrete depths? How does recovery relate to coupling depths?
How do recovery rates and distributions vary among subduction zones?	Are rocks preferentially recovered from rare settings? Could variations in coupling depths explain smooth distributions of global PT estimates?
How do numerical and empirical PT distributions compare?	Can numerical models reliably indicate PT conditions experienced by rocks? How do we interpret global compilations of PT estimates?

Numerical dataset: Lagrangian markers

Challenge: markers' fates are unknown

Solution: write an unsupervised classification algorithm to "recognize" recovery

Over 1 million markers are traced from 64 numerical simulations of oc.-cont. subduction:

- Markers are classified as "recovered" or "not recovered" based on their PTt paths
- "Recovered" markers represent detachment and underplating of material

Kerswell et al. (in prep)



An example



Major recovery (underplating) modes are identified for each experiment that correspond to:

- Mode 1: where most markers are recovered
- **Mode 2:** where the highest PT markers are recovered



Correlations

Major recovery modes vary among subduction zone settings and variably correlate with initial conditions

Kerswell et al. (in prep)







A recovery gap

Across all 64 experiments:

- Few markers are recovered from the highest density region of natural samples (why?)
- Most markers are recovered from near the Moho @ 1 GPa
- Very few markers are recovered from beyond 2-2.3 GPa

Kerswell et al. (in prep)

Comparing markers with rocks

- Marker recovery mode 1: is consistent with the Moho and termination of LVLs @ ~ 1 GPa
- Marker recovery mode 2: is consistent with onset of mechanical coupling @ ~ 2-2.3 GPa
- Marker PTs show appreciable deviations from the rock record
- A marker recovery gap indicates numerical, natural, and/or scientific uncertainties and biases



Conclusions

- Z_{cpl} correlates strongly with Z_{UP}
- Z_{UP} is variably continuous according to interpolated surface heat flow
- Marker recovery shows appreciable differences from the rock record including a curious recovery gap

Future work may focus on:

- Implementing recovery mechanisms into geodynamic codes
- Refining heat flow datasets to improve interpolation accuracy
- Improving methods to rapidly estimate metamorphic PT conditions for a wider variety of rock types

Questions?



Thanks for the attention

My background

Undergraduate:

- BSc Utah Valley University (2015)
- Economic geology & min exploration
- Anthropogenic impacts to Utah Lake
- Paleoseismology

Graduate:

- PhD Boise State University (2022)
- Metamorphic petrology
- Geodynamics
- Applied statistics





Field work & petrologic training





Types: Subduction interfaces, various exhumed HP rocks, metamorphic core complexes

US: UT, CA, ID, NV

International: *France, Italy, Switzerland, Greece, India*

Geodynamics & numerical training





Studied computational fluid dynamics at ETH, Zürich Wrote code to simulate subduction Use high-performance computing

Teaching & outreach





I have a passion for teaching & learning geoscience with students and non-experts

I especially enjoy taking students into the field

An empirical dilemma



- The rock record provides information across deep time, but only near the surface, and is **incredibly sparse**
- Geophysical datasets probe Earth's interior, but only since the 20th century, and are incredibly sparse
- The deeper and farther back in time we try to observe geological processes, the more uncertainty grows
 because of the sparseness of

geological data

Kerswell et al. (2021)

A numerical solution:

Numerical simulations allow us to:

- Explore parameter space
- Perform sensitivity tests
- Train intuition
- Infer unknowns
- Generate new samples
- Discover new questions

Numerical simulations do not:

- Distinguishing "correct" models
- Making precise predictions

