

# Efficient and accurate solvers for nonhydrostatic simulations of the atmosphere: the interaction of high-order IMEX methods and customized algebraic solvers

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# Outline

- 1 Model
- 2 Methods
- 3 Experiments
- 4 Conclusions

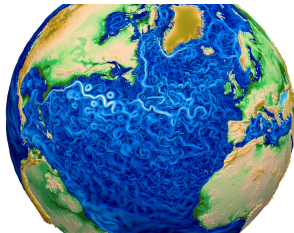
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# Energy Exascale Earth System Model (E3SM)

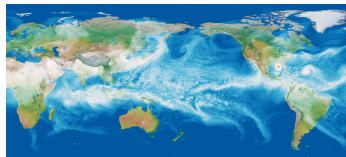
Motivation: 2013 DOE report on energy sector factors

- trends in air and water temperatures
- water availability
- storms and heavy precipitation
- coastal flooding and sea-level rise



Mission (<https://e3sm.org/about/vision-and-mission>)

- develop ensemble strategies for uncertainty quantification
- bridge the gap in scales and processes in existing E3SM ventures
- **integrate ECP advances to push model resolution capability**



<https://e3sm.org>

# Non-hydrostatic Atmospheric Models

- Increased computational power is pushing climate model resolutions beyond the hydrostatic limit.
- Non-hydrostatic models consider the compressible Navier Stokes equations, that support acoustic (sound) waves.
- Acoustic waves have a negligible effect on climate.
- Acoustic waves travel much faster than convection (343 m/s vs 100 m/s horizontal and 1 m/s vertical).
- To overcome this stiffness, non-hydrostatic models utilize split-explicit, implicit-explicit, or fully implicit time integration.



# Non-hydrostatic Formulation (Tempest)

Tempest is an experimental “dycore” used for method development; it considers 5 governing [hyperbolic] equations in an arbitrary coordinate system:

$$\begin{aligned}\frac{\partial \rho}{\partial t} &= -\frac{1}{J} \frac{\partial}{\partial \alpha} (J \rho u^\alpha) - \frac{1}{J} \frac{\partial}{\partial \beta} (J \rho u^\beta) - \frac{1}{J} \frac{\partial}{\partial \xi} (J \rho u^\xi) \\ \frac{\partial u_\alpha}{\partial t} &= -\frac{\partial}{\partial \alpha} (K + \Phi) - \theta \frac{\partial \Pi}{\partial \alpha} + (\eta \times \mathbf{u})_\alpha \\ \frac{\partial u_\beta}{\partial t} &= -\frac{\partial}{\partial \beta} (K + \Phi) - \theta \frac{\partial \Pi}{\partial \beta} + (\eta \times \mathbf{u})_\beta \\ \left(\frac{\partial r}{\partial \xi}\right) \frac{\partial w}{\partial t} &= -\frac{\partial}{\partial \xi} (K + \Phi) - \theta \frac{\partial \Pi}{\partial \xi} + u^\alpha \frac{\partial u_\alpha}{\partial \xi} + u^\beta \frac{\partial u_\beta}{\partial \xi} - u^\alpha \frac{\partial u_\xi}{\partial \alpha} - u^\beta \frac{\partial u_\xi}{\partial \beta} \\ \frac{\partial \theta}{\partial t} &= -u^\alpha \frac{\partial \theta}{\partial \alpha} - u^\beta \frac{\partial \theta}{\partial \beta} - u^\xi \frac{\partial \theta}{\partial \xi},\end{aligned}$$

where  $\rho$  is the density,  $(u_\alpha, u_\beta)$  are the horizontal velocity,  $w$  is the vertical velocity, and  $\theta$  is the potential temperature.

Key: **horizontal propagation** and **vertical propagation**.

# Non-hydrostatic Formulation (HOMME-NH)

HOMME-NH will be the “production” dycore in E3SM v2 responsible for global atmospheric flow (again, 5 hyperbolic equations):

$$\begin{aligned} \frac{\partial}{\partial t} \left( \frac{\partial \pi}{\partial \eta} \right) &= -\nabla_{\eta} \cdot \left( \frac{\partial \pi}{\partial \eta} \mathbf{u} \right) - \frac{\partial}{\partial \eta} \left( \pi \frac{d\eta}{dt} \right) \\ \frac{\partial \mathbf{u}}{\partial t} &= -(\nabla_{\eta} \times \mathbf{u} + 2\boldsymbol{\Omega}) \times \mathbf{u} - \frac{1}{2} \nabla_{\eta} (\mathbf{u} \cdot \mathbf{u}) - \frac{d\eta}{dt} \frac{\partial \mathbf{u}}{\partial \eta} - \frac{1}{\rho} \nabla_{\eta} p \\ \frac{\partial w}{\partial t} &= -\mathbf{u} \cdot \nabla_{\eta} w - \frac{d\eta}{dt} \frac{\partial w}{\partial \eta} - g(1 - \mu), \quad \mu = \left( \frac{\partial p}{\partial \eta} \right) / \left( \frac{\partial \pi}{\partial \eta} \right), \\ \frac{\partial \theta}{\partial t} &= -\nabla_{\eta} \cdot (\theta \mathbf{u}) - \frac{\partial}{\partial \eta} \left( \theta \frac{d\eta}{dt} \right), \quad \theta = \frac{\partial \pi}{\partial \eta}, \\ \frac{\partial \phi}{\partial t} &= -\mathbf{u} \cdot \nabla_{\eta} \phi - \frac{d\eta}{dt} \frac{\partial \phi}{\partial \eta} + gw, \end{aligned}$$

where  $\pi$  is hydrostatic pressure,  $\eta$  is vertical coordinate,  $\mathbf{u}$  and  $w$  are horizontal and vertical velocities,  $\theta$  is potential temperature, and  $\phi$  is geopotential.

Key: **hydrostatic model** and **nonhydrostatic terms**.

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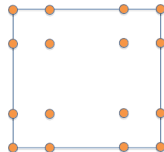


# Spatial Semi-discretization

Both codes use spectral elements to discretize horizontally

- Lagrange polynomials basis  $\{\varphi_j\}$  over GLL points
- Inner product is defined by GLL quadrature:

$$\langle \varphi_j, \varphi_k \rangle = \int \varphi_j \varphi_k \, d\mathbf{x} = w_j \delta_{jk}$$

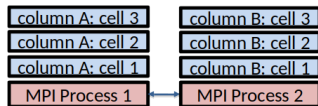


Vertical discretizations differ; both utilize shallow cells (100:1 aspect ratio):

- Tempest uses an up-to- $\mathcal{O}(\Delta\xi^5)$  staggered nodal finite element method
- HOMME-NH uses  $\mathcal{O}(\Delta\eta^2)$  mimetic finite differences

2D parallel domain decomposition stores entire vertical column(s) on a single MPI task.

In both models, Jacobians of discretized RHS have purely imaginary eigenvalues.



Both models explicitly apply “hyperviscosity” between time steps to stabilize discretization [Ullrich et al., JCP, 2018].

# Additive Runge–Kutta (ARK) Methods [Ascher et al. 1997; Araújo et al. 1997; ...]

Both codes use “ARKode” for time integration, that supports up to two split components: *explicit* and *implicit*,



$$\dot{y} = f^E(t, y) + f^I(t, y), \quad t \in [t_0, t_f], \quad y(t_0) = y_0,$$

- $f^E(t, y)$  contains the explicit terms,
- $f^I(t, y)$  contains the implicit terms.

Combine two  $s$ -stage RK methods; denoting  $t_{n,j}^* = t_n + c_j^* \Delta t_n$  and  $\Delta t_n = t_{n+1} - t_n$ :

$$z_i = y_n + \Delta t_n \sum_{j=1}^{i-1} A_{i,j}^E f^E(t_{n,j}^E, z_j) + \Delta t_n \sum_{j=1}^i A_{i,j}^I f^I(t_{n,j}^I, z_j), \quad i = 1, \dots, s,$$

$$y_{n+1} = y_n + \Delta t_n \sum_{j=1}^s \left[ b_j^E f^E(t_{n,j}^E, z_j) + b_j^I f^I(t_{n,j}^I, z_j) \right]$$

Solving each stage  $z_i, i = 1, \dots, s$ 

Each stage is implicitly defined via a root-finding problem:

$$0 = G_i(z) \\ = \left[ z - \Delta t_n A_{i,i}^I f^I(t_{n,i}^I, z) \right] - \left[ y_n + \Delta t_n \sum_{j=1}^{i-1} \left( A_{i,j}^E f^E(t_{n,j}^E, z_j) + A_{i,j}^I f^I(t_{n,j}^I, z_j) \right) \right]$$

- if  $f^I(t, y)$  is *linear* in  $y$  then we must solve a linear system for each  $z_i$ ,
- else  $G_i$  is nonlinear, requiring an iterative solver – ARKode options relevant to this work:
  - *Newton*: inexact or *standard* (depends on linear solver),
    - Scaled, preconditioned, GMRES; “matrix-free” available.
    - *user-supplied* to exploit linear system structure
  - user-supplied (new feature).

# Customized Vectors and Splittings

Unlike some frameworks that force data structures or algorithms on users, SUNDIALS/ARKode easily leverages problem-specific implementations.

Vectors: both Tempest and HOMME-NH pre-allocate all vectors objects to be used throughout a simulation at initialization.

- “Taught” ARKode how to perform vector arithmetic directly on these structures.
- Requested a sufficient number of preallocated vectors for ARKode temporaries.
- Implemented a system for ARKode to “check out” and “check in” these temporary vectors, in lieu of standard allocation/deallocation.

IMEX/HEVI Splittings:

- Repurposed existing physics routines to provide the IMEX splitting(s)  $f^E$  and  $f^I$ .
- Tempest also included preprocessor directives to explore alternate splittings by moving terms between  $f^E$  and  $f^I$ .

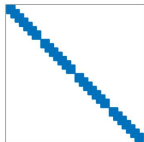
# Customized Algebraic Solvers

Since HEVI splittings only include implicit coupling within each vertical column (decoupled from other columns), *each MPI task is decoupled*.

When beginning this research, ARKode did not yet support custom nonlinear solvers, so we focused on the linear solve (plan to upgrade these soon).

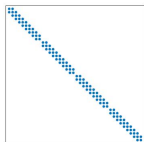
Tempest:

- Block-banded systems on each MPI task
- Direct factorization/solve: DGBTRF and DGBTRS
- For non-HEVI splittings, this preconditions GMRES



HOMME-NH:

- Tridiagonal systems for  $w$  on each MPI task
- Direct factorization/solve: DGTTRF and DGTTRS
- Post-process result for  $\phi$  update



*Unlike most IMEX methods, at large scales the implicit portions of these models are nearly “free” (cost is dominated by explicit RHS MPI communication).*

# Customized Norms and Tolerances

Accuracy/efficiency for both models hinged on the choice of norm and tolerances for nonlinear and linear solvers.

ARKode utilizes a *weighted root-mean-squared norm* for error-like quantities:

$$\|v\| = \left( \frac{1}{N} \sum_{i=1}^N w_i^2 v_i^2 \right)^{1/2}, \quad w_i = \frac{1}{\varepsilon_r |y_i| + \varepsilon_a}$$

where  $y \in \mathbb{R}^N$  is the previous time-step solution,  $\varepsilon_r \in \mathbb{R}$  and  $\varepsilon_a \in \mathbb{R}^N$ .

Newton iterations cease when estimated nonlinear residual norm  $< 0.1$ .

GMRES iterations stop when linear residual norm  $< 0.0005$ .

**Tempest:**  $\varepsilon_r = \varepsilon_a = 10^{-4}$ , based on trial/error in comparisons against native solvers.

$$\text{HOMME-NH: } \varepsilon_r = 10^{-6}, \text{ and } \varepsilon_a = \begin{cases} 10^{-5}, & \text{for } \mathbf{u} \text{ and } w \text{ components} \\ 0.1, & \text{for } \phi \text{ components,} \\ 1, & \text{for } \Theta \text{ components,} \\ 10^{-6}, & \text{for } \frac{\partial \pi}{\partial \eta} \text{ components} \end{cases}$$

# Outline

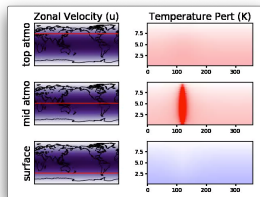
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# Test problems (from 2012 Dynamical Core Model Intercomparison Project)

Both codes used two “standard” climate test problems:

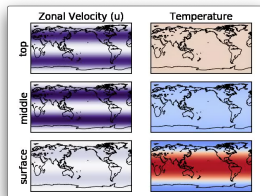
## Inertia Gravity Wave

- Small temperature perturbation from equilibrium on “small Earth” (1/125) – gravity wave propagates around the globe.
- Insignificant nonlinear effects; no need for hyperviscosity or vertical remap
- Used to assess temporal convergence and benefit of higher-order methods



## Baroclinic Instability

- Small zonal velocity perturbation from equilibrium sets off instability.
- More significant nonlinear effects; stabilization required (reduces overall accuracy to  $\mathcal{O}(\Delta t)$ ).
- Measure surface pressure as proxy for overall error.





# Tempest Experiments [Gardner et al., *GMD*, 2018]

We investigated three complementary aspects of integration in Tempest:

① Alternate IMEX splittings:

- HEVI; HEVI-DT (explicit vertical continuity and thermo.)
- IMEX-D (HEVI + implicit  $\rho$ ); IMEX-DTE (IMEX-D + implicit  $\theta$ )

② Alternate Nonlinear solver options:

- Full Newton solve
- Linearly-implicit (only performs a single Newton iteration) – “standard practice” in the field, but may not resolve nonlinearity

③ Performance of various Additive Runge–Kutta methods (21 total):

- 5 from Ascher, Ruuth & Spiteri (1997) –  $\mathcal{O}(\Delta t^2) \rightarrow \mathcal{O}(\Delta t^3)$
- 3 from Kennedy & Carpenter (2003) –  $\mathcal{O}(\Delta t^3) \rightarrow \mathcal{O}(\Delta t^5)$
- 1 from Giraldo et al. (2013) –  $\mathcal{O}(\Delta t^2)$
- 4 SSP from Pareschi & Russo (2005) –  $\mathcal{O}(\Delta t^2) \rightarrow \mathcal{O}(\Delta t^3)$
- 6 SSP from Higueras et al. (2006, 2009, 2014) –  $\mathcal{O}(\Delta t^2) \rightarrow \mathcal{O}(\Delta t^3)$
- 2 from Conde et al. (2017) –  $\mathcal{O}(\Delta t^3)$

# Tempest Results [Gardner et al., *GMD*, 2018]

## HEVI/IMEX splittings:

- Stability  $\propto$  implicitness: IMEX-DTE > IMEX-D > HEVI > HEVI-DT.
- Horizontally implicit terms increase runtime by 25%  $\rightarrow$  60%.
- Resulting IMEX-D cost between HEVI and HEVI-DT; HEVI was best overall.

## Linearly-implicit (LI) solver vs Newton (N) solver:

- LI solve sufficient for gravity wave (accurate to discretization error).
- LI solve insufficient to resolve nonlinearity in baroclinic test at desired step sizes (nonphysical  $w$ ); 2  $\rightarrow$  4 N iterations required to recover nonlinear effects.

## ARK methods:

- No benefit of high over low order (4-5 vs 2-3) at desired step sizes.
- Most SSP methods show nonphysical vertical velocities for HEVI splittings; others unstable except at small  $\Delta t$  (likely due to instability along imaginary axis).
- Best overall stability/accuracy from  $\mathcal{O}(\Delta t^3)$  methods by Ascher, Ruuth & Spiteri (1997) and Kennedy & Carpenter (2003).

# HOMME-NH Experiments [Vogl et al., *in prep*]

Resolved to use a HEVI formulation and a full Newton solve, we then focused on stability, accuracy and novel ARK methods:

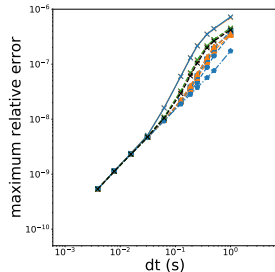
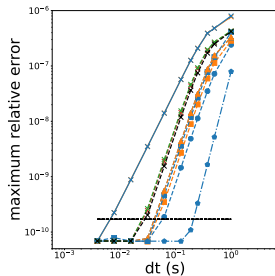
- 1 Effects of post-processing applied to time-step solutions:
  - hyperviscosity
  - vertical remap (dynamic adjustment to vertical coordinate  $\eta$ )
- 2 Performance of various ARK methods (22 total), and one ERK method:
  - 5 from Ascher, Ruuth & Spiteri (1997) –  $\mathcal{O}(\Delta t^2) \rightarrow \mathcal{O}(\Delta t^3)$
  - 2 from Kennedy & Carpenter (2003) –  $\mathcal{O}(\Delta t^3) \rightarrow \mathcal{O}(\Delta t^4)$
  - 2 from Conde et al. (2017) –  $\mathcal{O}(\Delta t^3)$
  - 12 from Steyer et al. (*in prep*) –  $\mathcal{O}(\Delta t^2) \rightarrow \mathcal{O}(\Delta t^3)$
  - 1 by R., from Vogl et al. (*in prep*) –  $\mathcal{O}(\Delta t^3)$
  - 1 ERK method from Guerra & Ullrich (2016) –  $\mathcal{O}(\Delta t^3)$

Methods from Steyer, R., and Guerra & Ullrich are optimized to maximize linear stability along imaginary axis.

HOMME-NH Results (hyperviscosity & vertical remap) [Vogl et al., *in prep*]

Maximum relative  $\theta$  error vs  $\Delta t$  for gravity wave test (top/bottom show without/with post-processing, resp.):

- All ARK methods converge at analytical order to reference accuracy when post-processing is disabled.
- All methods reduce to first order when post-processing is enabled.
- Unfortunately, production runs rapidly go unstable without stabilization.
- However, higher-order methods still show improved error at larger  $\Delta t$  (desired production step sizes).



# HOMME-NH Results (ARK methods) [Vogl et al., *in prep*]

Measured the maximum relative surface pressure error, with accuracy tolerance set by comparison against “trusted” results. Two questions:

- What is the max.  $\Delta t$  for each method to obtain solution within tolerance?
- Which methods can run at the desired hydrostatic time step  $\Delta t = 300s$ ?  
By how much do those methods exceed tolerance?

Question A on left, B on right (only best shown). *WT* is wall-clock (hr), *Exc* is exceedance, *IMKG* (Steyer et al.), *ARK* (Kennedy & Carpenter), *DBM* (Vogl et al.):

Method	$\Delta t$	$\frac{\Delta t}{fI}, \frac{\Delta t}{fE}$	WT
IMKG243b	270	90,68	0.9
DBM453	270	68,54	1.1
ARK324	240	80,60	1.0
IMKG242b	240	120,60	0.9
ARK436	216	43,36	1.6

Method	$\Delta t$	$\frac{\Delta t}{fI}, \frac{\Delta t}{fE}$	WT	Exc.
DBM453	300	75,60	1.0	3%
IMKG252b	300	150,60	0.8	61%
IMKG254 <sup>a</sup> / <sub>b</sub>	300	75,60	1.0	61%
IMKG243b	270	90,68	0.9	55%
IMKG343a	270	90,68	0.9	55%

*Methods tuned for stability on imaginary axis far outperform existing methods.*

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# Conclusions & Future Work

In summary:

- Modular structure of ARKode/SUNDIALS allows use of problem-specific data structures and solvers within high-order time integration.
- Trivial to explore different ARK methods (just supply pairs of Butcher tables).
- Simplified exploration of IMEX splittings and nonlinear solvers – for ‘optimal’ efficiency these should be modified together, but JFNK can ‘clean up’ initially.
- Exploration can identify critical features for newly-derived methods.
- Top ARK methods are newly-developed versions by Steyer and R. – IMKG for raw speed; but DBM overall (stability & accuracy, without significant speed penalty)

Next steps:

- Reconstruct ARKode interfaces in Tempest and HOMME-NH to allow customized nonlinear solves (eliminate MPI communication in implicit solves).
- Investigate hyperviscosity/remap *within* stage solves to retain high order.
- Temporal adaptivity (current lack of a sufficient ‘ecosystem’ of embedded ARK methods). Invent new “IMKG” and “DBM” methods with embeddings.

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- Mark Taylor [SNL]
- Oksana Guba [SNL]



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- SMU Center for Scientific Computation



## Software:

- ARKode – <http://faculty.smu.edu/reynolds/arkode>
- SUNDIALS – <https://computation.llnl.gov/casc/sundials>
- Tempest – <http://github.com/paullric/tempestmodel>
- E3SM (HOMME-NH) – <https://github.com/E3SM-Project/E3SM>

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