BAMS
Meeting Summary

Harnessing Land–Atmosphere Interactions to Enhance Subseasonal-to-Seasonal Predictability

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Surface fluxes;
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Seasonal forecasting;
Data assimilation;
Machine learning

2025 Advancing Understanding of Land–Atmosphere Interactions and Processes on S2S Predictability Workshop

What: 227 registered workshop participants gathered in person (43%) and online (57%) to discuss state-of-the-art scientific understanding and modeling of land–atmosphere interactions and related processes in the context of subseasonal-to-seasonal (S2S) predictability. Topics covered sources of S2S predictability, land model initialization methods, model diagnosis and evaluation metrics, AI/ML analysis and applications, and coordination of future community multimodel S2S forecast-focused experiments. To advance the science, this community workshop, organized by NSF NCAR, NOAA, NASA, and DOE, aimed to 1) identify process- and application-oriented metrics for assessing S2S prediction skill and 2) develop experimental protocols for coordinated experiments to isolate, quantify, and understand the role of land–atmosphere interactions in S2S predictability.

When: 16–18 June 2025

Where: Boulder, Colorado and online

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1. Introduction

Land–atmosphere interactions are an essential element of subseasonal-to-seasonal (S2S) predictability. On time scales of 2 weeks to a few months, slowly varying land conditions have the potential to provide a source of memory that can influence atmospheric behavior and near-surface meteorology, thus enhancing predictive skill (Mariotti et al. 2020). Alongside oceanic and stratospheric influences, observation-based studies show that land processes are major sources of S2S predictability, including for extreme events like droughts and heat waves (Dirmeyer et al. 2021). Accurately initialized land states and well-represented land–atmosphere coupling have been shown to enhance S2S predictive skill (Koster et al. 2010; Xue et al. 2022; Lim et al. 2025).

In the forecasting community, the S2S window is held as a "predictability desert," which poses unique challenges: The lead time is long enough for the memory of atmospheric initial states to dissipate, yet too short for slowly varying ocean conditions to exert a strong and predictable influence (Mariotti et al. 2020; Richter et al. 2024). Forecast skill is limited by model errors in land processes and land–atmosphere coupling, which can translate into sizable S2S prediction biases [Koster et al. 2011; National Academies of Sciences, Engineering, and Medicine (NASEM) 2016]. However, observations of key land states, particularly subsurface quantities (e.g., root-zone soil moisture), are sparse and spatiotemporally inconsistent, limiting initialization realism, verification opportunities, and model improvement. Inconsistencies in land–atmosphere initialization and evaluation practices across models further impede S2S forecast improvements. Addressing the aforementioned gaps requires better land-process understanding, improved assimilation

Fig. 1. In-person attendees at the community S2S Land–Atmosphere Workshop hosted at NSF NCAR, Boulder, Colorado, on 16–18 Jun 2025.

of measurements at the land–atmosphere interface, and enhanced representation of land–atmosphere coupling within S2S forecast systems.

To tackle these challenges, a 3-day community workshop was convened at NSF NCAR in June 2025 (Fig. 1) to discuss how land processes and land–atmosphere interactions contribute to S2S predictability through keynote presentations, modeling center updates, technical talks, and breakout discussion sessions. Focused themes included sources of S2S predictability, land initialization and data assimilation (DA), artificial intelligence/machine learning (AI/ML) tools and applications, process- and application-oriented model evaluation metrics, and coordinated modeling strategies. The format emphasized open discussion and active cross-institutional collaboration to match the latest research advances with the most pressing operational forecast needs.

2. Land–atmosphere interaction as a critical source of S2S predictability

A central workshop theme was that land–atmosphere coupling is an important—yet poorly understood—source of S2S predictability. Because land states evolve more slowly than the atmosphere and directly influence near-surface meteorology, they provide a memory that bridges the gap between weather forecasts and seasonal outlooks. The importance of this memory varies regionally and seasonally: In many midlatitude regions, weaker warm-season oceanic influences make S2S skill more dependent on representations of land states and land–atmosphere coupling; in high latitudes and shoulder seasons, snowpack adds persistence; and in the tropics/subtropics, land anomalies interact with intraseasonal convection and teleconnections to modulate week-3/week-4 predictability. During the workshop, several land–atmosphere interaction mechanisms were highlighted as being important for S2S prediction:

1) Soil moisture memory: Root-zone moisture anomalies can persist for weeks to months and modulate surface fluxes. Where land–atmosphere coupling is strong, these anomalies can influence boundary layer humidity, temperature, and even rainfall, improving predictability. Correctly diagnosing the coupling regimes—water limited, transitional, or energy limited—is essential for models to translate soil wetness anomalies into atmospheric responses. Studies show that initializing model soil moisture alone can account for a notable share of week-3/week-4 skill for near-surface temperature and humidity (Koster et al. 2010; Duan et al. 2025).
2) Snowpack memory: In seasonally snow-covered regions, snowpack acts as a memory reservoir. Anomalies in snow cover, depth, and albedo influence surface energy and water balance, altering soil moisture for weeks. These changes influence near-surface meteorology and can, at times, influence larger-scale circulations. Studies point to a nontrivial contribution of snow anomalies to S2S predictability in winter and spring, especially for surface temperature (NASEM 2016; Broxton et al. 2017; Li et al. 2019).
3) Vegetation–atmosphere coupling: The state of vegetation (e.g., leaf area, vegetation water content, and rooting depth) modulates surface fluxes, feeding back onto atmospheric temperature, humidity, boundary layer evolution, and cloud/precipitation formation. Incorporating prognostic vegetation growth and land-use change in S2S models was identified in the workshop as an important pathway to represent vegetation–atmosphere coupling more faithfully and to capture additional forecast skill.

3. Land initialization and DA for S2S prediction

a. Current capabilities and common practices. Workshop participants agreed that appropriate land initialization is pivotal for improved S2S prediction. Modeling centers use different approaches to initialize land states in their S2S systems, reflecting different historical development pathways, DA approaches, and priorities. Most often, land initial states for S2S prediction are supplied by one of the following:

1) Preexisting modeling and DA systems, such as reanalyses or NWP systems. Most such systems include weakly coupled land/atmosphere DA and assimilate a selection of 2-m temperature, 2-m humidity, satellite soil moisture, station snow depth, and satellite snow cover into their models to constrain model soil moisture, soil temperature, and snowpack.
2) Offline (land only) land model simulations, often referred to as spinup. The land model is forced over a long time period (decades) by observed and/or modeled meteorology, allowing land states to reach equilibrium with the atmospheric forcing. Given the smaller computational cost of such spinups than running coupled S2S models, these spinups can be purpose-designed to run on the same model grid, using the same land model as is used in S2S systems, which yields consistent land model states.
3) Offline land models with land DA. These systems operate as above, but with the addition of land DA, and typically use land DA methods that are more advanced and assimilate a broader range of observations than is currently possible in preexisting coupled modeling systems.
4) S2S models with strongly coupled land–atmosphere DA. Some centers are moving toward jointly optimizing atmospheric and land states using strongly coupled land–atmosphere DA so that initial conditions are dynamically coherent. While this approach requires

more computational resources than the aforementioned methods, it is an attractive option that has been gaining attention.

Many S2S systems require land initial conditions for both real-time S2S forecasts and reforecasts used to estimate S2S model climatology (for use in forecast bias correction and determining anomalies). Given the land influence on S2S forecasts, land initial conditions used in reforecasts and real-time forecasts need to be consistent; if not, a bias correction is usually employed to reduce systematic differences.

b. Challenges and future directions. Several challenges complicate land initialization and DA for S2S prediction. First, direct global observations of key land states—especially subsurface soil moisture and temperature—remain sparse. Reconciling observation-derived estimates with model state variables (e.g., soil moisture) is a nontrivial task, and representativeness errors can be substantial (e.g., comparing station snow depth to that on a model grid). Assimilation of satellite soil moisture relies on rescaling assimilated observations to match model climatology, which limits the DA impact to correcting only local short-term anomalies. The joint assimilation of additional satellite land data streams (e.g., GRACE) is being explored, though most remain experimental for S2S DA. Some long-latency observations also hinder their use in land DA for real-time S2S forecasts.

Additionally, model shortcomings (e.g., misrepresentation of land–atmosphere coupling regime/sensitivity) may limit the incremental forecast skill improvement from even the most accurate land initial conditions. If land processes or land–atmosphere coupling are biased, skill gains from improved land initialization decay quickly with forecast lead time. Improvements to process fidelity in land models help to better predict the persistence of initial anomalies and their influence on S2S forecasts.

The community is actively working toward improving the use of land DA for initializing model forecasts, including S2S forecasts. Land DA in coupled land–atmosphere systems has traditionally used simpler methods (e.g., Optimal Interpolation) than are used in land-only systems (e.g., ensemble Kalman filters or other Monte Carlo–based methods). The latter can potentially better represent model uncertainty by including spatiotemporally varying errors. Recent efforts have focused on implementing Monte Carlo–based methods for land DA in coupled land–atmosphere systems. Additionally, strongly coupled land–atmosphere DA, which updates land and atmosphere states simultaneously within a unified framework, offers methodological advantages over weakly coupled DA (which updates land and atmosphere states separately) by enforcing dynamical and physical consistency within the model. However, strongly coupled DA also adds significant complexity and inflexibility to the system, and it is yet to be determined whether the potential performance gains can justify this.

Moreover, verifying and attributing improvements to land initialization is difficult because S2S skill arises from multiple sources. Carefully paired experiments (e.g., with/without land perturbations) are needed to isolate land contributions. Traditional metrics (e.g., anomaly correlation) may miss gains, especially when atmospheric processes dominate as opposed to when land conditions matter more (e.g., extremely hot and dry seasons), pointing to the need for process-oriented diagnostics and shared observational benchmarks. A shared metric suite to assess impacts of land–atmosphere coupling and land initialization is a community goal.

Accordingly, priority directions include advancing the use of land DA in model initialization, improving vegetation DA, exploiting legacy and new Earth observations, strengthening land physics and coupling, coordinating multimodel intercomparisons (GLACE-2/LS4P-style; Koster et al. 2011; Xue et al. 2021), and deepening cross-institutional collaboration.

4. AI/ML applications in S2S prediction relevant to land–atmosphere interaction

AI/ML techniques are rapidly becoming integral to S2S forecasting. Modern ML models can augment or even rival physics-based models in weather/subseasonal predictions. AI/ML methods are being applied to improve extreme event predictions, though these pose unique data and modeling challenges (Materia et al. 2024). Most of the end-to-end data-driven models often lack a comprehensive integration of land processes and land–atmosphere coupling. These AI/ML frameworks tend to focus on atmospheric/oceanic components, sometimes neglecting the critical role of land in S2S predictability. Thus, there is a need for further research into how AI/ML models can be used to incorporate and optimize land processes for more reliable S2S predictions.

The workshop emphasized the importance of developing transparent, reliable AI/ML approaches to build trust in predicting high-impact weather events. Several land-relevant S2S applications of AI/ML were showcased to illustrate how coupling AI/ML with physical models can enhance S2S predictions of land/hydrological states, such as data-driven downscaling and bias correction of coarse-resolution S2S outputs, and hybrid (AI/ML–physics) modeling for skillful week-3/week-4 predictions of soil moisture in drought applications.

The workshop outlined key challenges and future directions. Model biases and drift in S2S systems can degrade current AI/ML tools' performance. Additionally, the "black box" nature of many AI/ML tools raises concerns about interpretability, explainability, and generalization beyond training data. To overcome these issues, researchers advocated for hybrid modeling frameworks that integrate AI/ML into physical models and for physics-informed AI/ML approaches that enforce physical consistency. Better uncertainty quantification in AI/ML prediction is another priority. By pursuing these strategies, the community aims to develop more robust, trustworthy AI/ML applications to enhance S2S prediction.

5. Land–atmosphere coupling metrics for S2S prediction

a. Process-oriented metrics. The workshop underscored the need for metrics that diagnose the mechanisms of land–atmosphere coupling. A commonly used approach is the "two legged" metric framework (Dirmeyer and Halder 2017), which evaluates land–atmosphere feedback in two stages: a terrestrial leg (e.g., correlation between soil moisture and surface fluxes) and an atmospheric leg (e.g., correlation between surface fluxes and near-surface meteorology). High correlations in both legs indicate strong coupling, where soil moisture anomalies effectively alter fluxes that drive atmospheric responses. Regime analysis is a complementary diagnostic. By identifying water-limited, transitional, and energy-limited regimes via critical soil moisture thresholds, it clarifies when land–atmosphere feedbacks are active. Capturing these regimes and their "break points" is essential, as models that simulate realistic soil moisture thresholds for feedback onset tend to better predict extremes like heat waves and droughts (Benson and Dirmeyer 2023).

The community discussed advanced methods to diagnose coupling strength. Causality analyses (e.g., Granger-type tests) and information-theory measures (e.g., transfer entropy) help establish directionality, distinguishing land-to-atmosphere influence from mere covariability and offering a process-relevant understanding beyond simple correlation. Participants also emphasized separating local coupling from remote (teleconnected) effects.

Overall, there is consensus that no single metric suffices; a combination of diagnostics is needed to capture different aspects of land–atmosphere coupling and to attribute local versus remote influences. Participants agreed on the need to pursue a standardized suite of process-oriented metrics applicable across S2S models, with common data requirements and reproducible implementations. There is an urgent need to develop community protocols to compute these diagnostics in a consistent way.

b. Application-oriented metrics. Operational centers assess S2S forecasts with application-oriented metrics, typically focusing on forecast accuracy and reliability. Frequently used deterministic metrics include anomaly correlation coefficient, root-mean-square error, probability of detection, false alarm ratio, and critical success index. Because S2S forecasts are usually ensemble-based, probabilistic skill scores are equally important, such as the Brier skill score, ranked probability skill score, Heidke skill score, receiver operating characteristic (ROC) curves, and area under the ROC. The workshop highlighted that both deterministic and probabilistic metrics are valuable, and operational centers typically report both types.

There is broad agreement on the need for unified verification practices for S2S prediction. Historically, different modeling centers have used different metrics, but workshop participants proposed identifying a core set of verification metrics applicable across models. This set includes not only the aforementioned standard skill scores but also metrics that are closely linked to influences from land processes, such as soil moisture–temperature coupling indices and flux-based coupling diagnostics. Evidence shows that forecasts are often more skillful when land–atmosphere coupling remains strong throughout forecast periods, motivating plans to incorporate process-oriented metrics into operational monitoring and attribution. Going forward, the community plans to develop standardized verification metrics that pair traditional skill scores with land-process diagnostics, ensuring that any realized gains in S2S forecast skill can be properly attributed to improvements in land initialization, flux parameterizations, and land–atmosphere coupling.

6. Coordinated S2S experiments relevant to land–atmosphere interactions

Participants identified two key goals for coordinated S2S experiments: improving understanding and quantification of the role of land–atmosphere coupling processes in 2-week to 3-month predictions and developing unified verification metrics and experiment protocols. Top priorities include diagnosing and reducing systematic model biases, starting from site-level process analyses to regional/global tests, and enhancing prediction of high-impact extremes (e.g., heat waves, droughts, floods). The need for standardized metrics and protocols was emphasized to guide multimodel experiments, and the need for process-level diagnostics was highlighted to improve forecast representations.

Existing S2S archives and coordinated projects can be leveraged toward these priorities. For example, the GLACE-2 initiative provided a suite of model experiments of subseasonal hindcasts with different land initializations. The WMO World Weather Research Programme (WWRP) S2S Project established a multimodel forecast/reforecast database comprising up to 60-day forecasts from multiple operational centers. The NOAA's SubX program (now Subseasonal Consortium) collects S2S forecasts and hindcasts from multiple agencies. NSF NCAR's CESM S2S data offer 45-day reforecasts during 1999–2020 with different model configurations. ECMWF also produced S2S reforecast datasets. Combined, these multicenter datasets provide a foundation for coordinated analysis of skills and biases across models, fostering cross-institution collaboration. However, these datasets do not always include all the outputs required for land–atmosphere process diagnosis, which calls for additional experiments.

Additional targeted experiments were proposed in the workshop to address key challenges and enable process analysis. For example, to tackle the warm/dry central U.S. summer bias, experiments will compare alternative land–atmosphere and convection schemes, including realistic irrigation and groundwater processes. For extremes, hindcast studies are planned for major heat waves and droughts using regionally refined model configurations at high resolution (~4 km). Ensemble experiments that perturb land initial conditions are also planned. Complementary "land only" sensitivity experiments (forcing the model with observed land states while holding the atmosphere/ocean to their climatology) are planned to isolate land memory effects.

The workshop also emphasized that all centers would ideally use unified (or similar) spatial grids or scale-adaptive physics for fair comparisons. Forecast initialization and outputs will be synchronized and standardized in time and space. The resulting multicenter suite of case studies and decadal hindcasts, with consistent protocols and diagnostics, aims to systematically quantify and mitigate key S2S forecast errors, bridging model development and applications.

7. Future actions

After the workshop, two community-based working groups were established, respectively, to 1) develop a set of process- and application-oriented metrics for assessing S2S prediction skills across modeling centers and 2) develop experimental protocols for coordinated experiments to quantify and operationally exploit the role of land–atmosphere processes in S2S predictability, including leveraging existing S2S reforecast/forecast data and generating new model experiments. These metrics and datasets will be released to the public to facilitate community-driven S2S predictability research on improving understanding and modeling of land–atmosphere interactions and related processes.

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Data availability statement. There are no data associated with this meeting summary.

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