Enabling High-Resolution Input Data in the Land Surface Component of the KIAPS Numerical Weather Prediction System

FINAL REPORT

for the

Korea Institute For Atmospheric Prediction Systems

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1. Preface

The Center for Ocean-Land-Atmosphere Studies (COLA), a national center of excellence for research on climate variability and predictability based at George Mason University, seeks to improve understanding and prediction of the variations of the Earth's climate through scientific research on its variability and predictability, and to share both the results of, and the tools necessary to conduct, this research with society as a whole.

The goal of COLA research is to explore, establish and quantify the predictability of intra-seasonal to inter-decadal variability of the present climate through the use of state-of-the-art dynamical coupled ocean-atmosphere general circulation models and the development of new techniques for analysis of observational and model data. COLA continues its multi-decade service as a unique institution that enables Earth scientists from several disciplines to work closely together on interdisciplinary basic and applied research related to variability and predictability of Earth's climate on intra-seasonal to inter-decadal time scales. The main scientific premise for research at COLA is that, while the chaotic nature of the global atmosphere imposes a limit on climate predictability at a given instant, there is predictability on longer time scales due to low-frequency fluctuations and the interactions between atmosphere and ocean and atmosphere and land. This makes possible accurate and useful climate forecasts with lead times longer than the inherent limit of instantaneous deterministic predictability.

Scientists at COLA use computer models of the Earth's global atmosphere, world oceans and land surface in numerical predictability experiments and experimental predictions, and they develop and use advanced techniques for analysis of observational and model data. By seeking to always use a suite of the best available climate models, COLA scientists remain at the forefront of research advancements. Close coordination of the predictability research and experimental predictions is a high priority.

This report describes work done in collaboration with the Korea Institute For Atmospheric Prediction Systems (KIAPS) that was initiated in 2012 to develop a more robust and accurate weather and climate prediction system.

2. Introduction

There is by now, after more than 60 years of research and demonstrated achievement, ample evidence that numerical models of the global atmosphere are the best tools for making accurate weather forecasts (e.g. Warner 2010).

The importance of land surface variability in modulating and contributing to climate predictability on weather, intra-seasonal and longer time scales has long been recognized.
Based on these two well-established facts, COLA and KIAPS are collaborating to produce a world-class numerical weather prediction (NWP) system that accurately represents the contribution to predictability of the land surface.

3. Background

3.1 Motivation for including a LSM component in NWP

Originally, NWP was done using models of the atmosphere only. The land surface was represented either as a fixed boundary condition or with a very simple scheme for keeping track of water fluxes between the atmosphere and land surface, but that has evolved to the inclusion of quite sophisticated land surface models in today's NWP systems (e.g. Pitman 2003; Ek et al. 2003). This has in part resulted from the recognition of the role that soil moisture anomalies play in enhancing predictability, which has been the focus of a great many numerical experiments that COLA has helped lead (Shukla and Mintz, 1982; Dirmeyer et al. 2009), including the multi-model Global Land-Atmosphere Circulation Experiment (GLACE; Koster et al. 2006) that evaluated the sensitivity of climate to soil moisture anomalies, and the second generation of GLACE (GLACE-2; Koster et al. 2010) that examined the impact of antecedent soil moisture anomalies on climate prediction skill.
Based on the hypothesis that the land surface state, particularly the soil moisture and vegetation, has a large impact on the weather, numerical weather forecasts, subseasonal and seasonal predictions require a realistic representation of the interactions between the land surface and the atmosphere, and the state of the atmosphere and land must be initialized from the most realistic conditions at the start of the forecasts (Shukla and Kinter 2006). This ensures a realistic evolution of the forecast from its start. Atmospheric initialization is an old problem with many decades in the development of data assimilation and procedures to perturb initial states to produce ensemble forecasts that sample the likely range of evolution of weather and shirt-term climate. Similar treatments for the land surface are relatively new, and a variety of methods have been proposed whose strengths and weaknesses remain to be evaluated.

Results from the second phase of the Global Land-Atmosphere Coupling Experiment (GLACE-2; Koster et al. 2010, 2011) quantified, with a suite of long-range forecast systems, the degree to which realistic land surface initialization contributes to the skill of subseasonal precipitation and air temperature forecasts. Significant contributions to temperature prediction skill out to two months were found across large portions of the North American continent, as well as other parts of the globe. For precipitation forecasts, contributions to skill are weaker but are still significant out to 45 days in some locations.
The GLACE-2 models show modest but significant skill especially where the rain gauge network is dense (Koster et al. 2011). Given that precipitation is the chief driver of soil moisture, and thereby assuming that rain gauge density is a reasonable proxy for the adequacy of the observational network contributing to soil moisture initialization, this result indeed highlights the potential contribution of enhanced observations to prediction. Land-derived precipitation forecast skill is much weaker than that for air temperature. The skill for predicting air temperature, and to some extent precipitation, increases with the magnitude of the initial soil moisture anomaly.

Skill improvements for surface air temperature forecasts are tied to the sensitivity of surface fluxes to soil moisture, which are optimum in a middle range between wet and very dry conditions. Thus, humid regions have more predictability and skill realized during relatively dry conditions for the area, while arid regions experience more skill when conditions are wetter than normal.

Another factor that can be exploited to improve forecasts during spring in mid-latitudes is an apparent rebound in predictability from soil moisture states (Guo et al. 2011, 2012). The sensitivity of forecasts to the initial soil moisture state emerges over much of the United States in late May, with realistic land initialization leading to much more predictability. Predictability is stored in the soil moisture states, and is released to the atmosphere only after the coupling between the two has been established, late in spring.

Recent assessment of the operational forecast model from the U.S. National Centers for Environmental Prediction (NCEP) shows that forecast skill for precipitation on subseasonal time scales, including the deterministic range for weather forecasts (the first 7 days of the forecasts), is also sensitive to the initial soil moisture state (Dirmeyer 2013). There is considerably more skill over much of the globe when the initial soil moisture state is in the wettest or driest fifth of its range than for all forecasts taken as a whole. There is a strong ling between extreme soil moisture states and subsequent precipitation.

3.2 Land surface model parameters from native high-resolution datasets

Land surface simulations need ancillary land surface parameters such as vegetation class, soil texture, and green vegetation fraction. As ancillary files are based on various data sources with different land-sea masks and resolution, it is not adequate simply to interpolate the existing ancillary parameters provided in the modeling system from one resolution to another. Instead, ancillary land surface parameters on any desired resolution should be externally generated directly from the original high-resolution data sources through appropriate regridding procedures. Regridding, also called remapping or interpolation, is the process of changing the grid that underlies data values while preserving qualities of the original data.

The cubed-sphere mesh of the KIAPS global weather forecast model does not contain evenly-spaced latitude/longitude grid boxes. Instead, a conformal mesh with eight poles and six faces each composed of a locally orthogonal grid is used. This has the advantage that the areas of grid boxes are relatively uniform across the entire globe, unlike latitude/longitude grids where areas decrease toward the north and south poles due to the convergence of meridians.

However, most land surface data sets that contain information needed to set parameters and boundary conditions for land surface models are on regular or projected grids at much higher resolution than global weather and climate models. For continuous data fields away from water bodies, interpolation is straightforward provided each grid is properly georeferenced. Correspondence between coastlines (land versus ocean/water/ice grid boxes) is not exact between different gridded data sets or the target model grid, requiring careful and intelligent adjustments and extrapolation of data. Furthermore, some data is in the form of discrete categories, such as vegetation types or soil classes, represented as integers. These cannot be interpolated but must be aggregated and remapped. For all of these reasons, the regridding process for the KIAPS model is more complicated than basic interpolation.

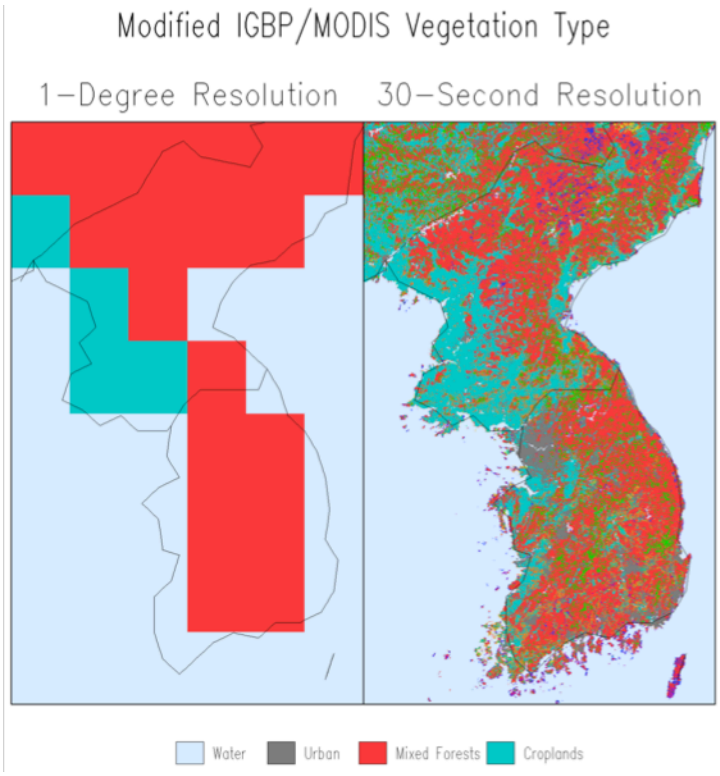


Figure 1 Comparison of the modified IGBP MODIS vegetation type between GLDAS 1-degree resolution and the raw 30-second resolution.

Regridding from high to lower resolution necessarily loses information. Figure 1 gives an example of regridding of the modified IGBP MODIS vegetation type to the GLDAS 1° grid from the original 30-second resolution. The dominant land cover type is preserved in the regridding procedure. It is evident that any time data are needed on a lower resolution, regridding should start from the highest resolution with the greatest information content.

4. Work Performed

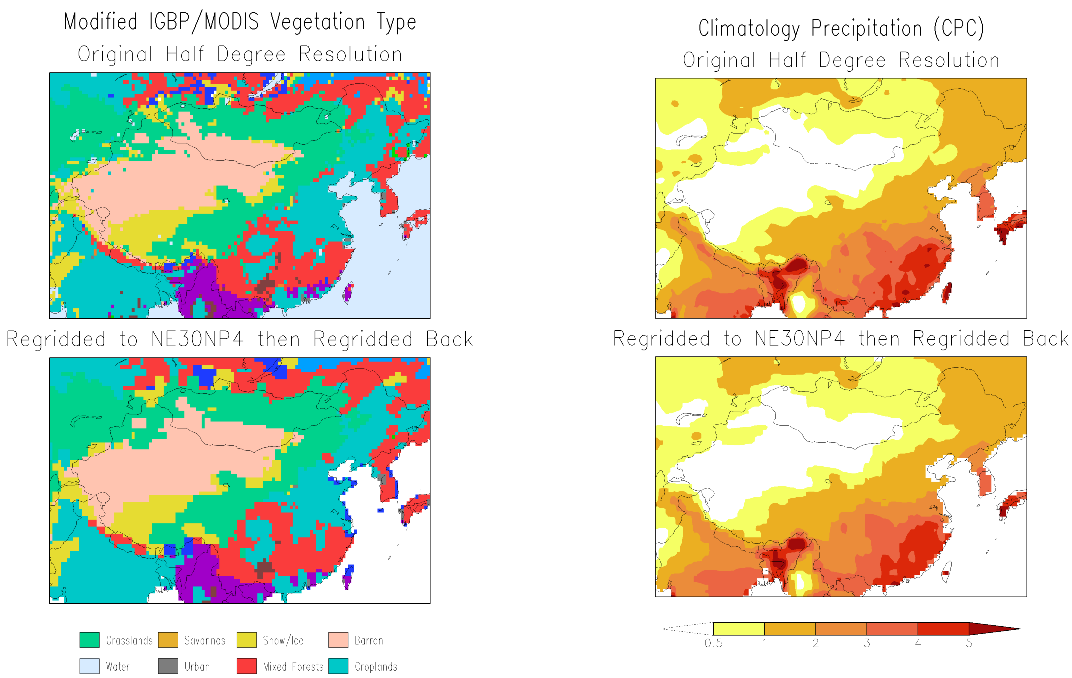
4.1 Accomplishments

The following tasks were accomplished in the course of this project.

- Codes suitable for using high-resolution data sets of land surface properties in the KIAPS NWP system have been prepared – the interpolation processes are described below.
- Sample data sets on the NWP model grids (1-degree grid and 25-km grid) have been generated
- Original high-resolution land surface datasets have been generated
- The code has been subjected to a number of basic tests
- Documentation of the code and its usage has been prepared (see below)

<u>Interpolation Processes for KIAPS Project</u>

The cubed sphere grids of the KIAPS model consists of quadrilateral and pentagon cells. The regular longitude/latitude grid can be regarded as a special case of the cubed sphere grid. Thus, we assume the interpolation is a mapping process from one cubed sphere grid to another. Our interpolation scheme mainly focuses on calculating fractional areas of each grid cell in the target mesh grid covered by grid cells in the source mesh grid, and uses the fractions as weights for the interpolation. The program regrid_mesh2mesh_info.f90 deals with calculating the fractions and weights, and the program regrid_mesh2mesh_data.f90 provides a sample code of interpolation with the weights. For each grid cell in the target mesh grid, the module m_regrid_mesh.f90 finds all the grid cells in the source mesh grid that intersect with the target grid cell, and calculates the overlapping areas and the fractions. The program regrid_mesh2mesh_info.f90 reads in the metadata information for the source and target mesh grids, uses the module m_regrid_mesh.f90 to calculate the weights, and outputs all the parameters for the interpolation. Examples of the regridding procedure are shown below for vegetation type and precipitation.



4.2 Deliverables

Datasets and model source codes have been developed that are available to KIAPS researchers in the COLA computer system in the /project/kiaps/KIAPS_Fin/ directory as follows:

- NOAH Model Codes:
  /project/kiaps/KIAPS_Fin/NOAH/
- Meteorological Forcing Data for Offline Simulations:
  /project/kiaps/KIAPS_Fin/NE30NP4_FORCING
- NE30NP4 Interpolation Codes and Related Datasets
  /project/kiaps/KIAPS_Fin/
- Various Datasets for High-Resolution Fixed Fields
  /project/kiaps/KIAPS_Fin/Fixed/

Documentation of procedure:

1. Generate the interpolation parameters:
    a. use "gmake" to generate the executable code regrid_mesh2mesh_info.bin
    b. use "regrid_mesh2mesh_info.csh GLDAS NE30NP4" to generate interpolation parameters from GLDAS to NE30NP4 mesh grid
    c. use "regrid_mesh2mesh_info.csh NE30NP4 GLDAS" to generate interpolation parameters from NE30NP4 mesh grid to GLDAS
    d. use "regrid_mesh2mesh_info.csh CPC NE30NP4" to generate interpolation parameters from CPC (720x360 0.5-degree grid) to NE30NP4 mesh grid
    e. use "regrid_mesh2mesh_info.csh NE30NP4 CPC" to generate interpolation parameters from NE30NP4 mesh grid to CPC (720x360 0.5-degree grid)
2. Interpolate the integer (for example soil type) or float (for example precipitation) data from one source mesh (or global gridded grid) to NE30NP4, then interpolate it back to the source mesh grid from NE30NP4
    a. use "run regrid_mesh2mesh_data" to generate the executable code regrid_mesh2mesh_data.exe
    b. use "regrid_mesh2mesh_vtyp.csh CPC NE30NP4" to interpolate the IGBP vegetation type from 0.5 x 0.5 degree resolution to NE30NP4 mesh grid
    c. use "regrid_mesh2mesh_vtyp.csh NE30NP4 CPC" to interpolate the vegetation type back to the 0.5 x 0.5 degree resolution from NE30NP4 mesh grid
    d. use "regrid_mesh2mesh_data.csh CPC NE30NP4" to interpolate the CPC precipitation from 0.5 x 0.5 degree resolution to NE30NP4 mesh grid
    e. use "regrid_mesh2mesh_data.csh NE30NP4 CPC" to interpolate the precipitation back to the CPC 0.5 x 0.5 degree resolution from NE30NP4 mesh grid

Data sets:

1. Meteorological Forcing Data for NE30NP4:
    c. Frequency: Three Hourly
    d. Periods: 1948-2010
    e. Variables: Downward Long-wave Radiation(dlwrf), Downward short-wave Radiation(dswrf), Precipitation (prcp), Surface Pressure (pres), Specific Humidity (shum), Near-Surface Air Temperature (tas), Wind Speed (wind)
2. Modified IGBP/MODIS Vegetation Type:
    f. half-minute resolution: igbp.ctl, rd_igbp_0.5m.f90 can be used to read the dataset
    g. 0.15-degree resolution: igbp_veg_0.15.ctl
    h. half-degree resolution: igbp_veg_0.5x0.5.ctl
    i. NE30NP4: NE30NP4_Vegetation_Class_IGBP.nc
3. USGS Vegetation Type
    a. half-minute resolution: veg30susgs, rd_usgs_0.5m.f90 can be used to read the dataset
    b. 0.15-degree resolution: usgs_veg_0.15.ctl
    c. NE30NP4: NE30NP4_Vegetation_Class_USGS.nc

4. STATSGO Soil Texture:
    a. half-minute resolution: topsoil30snew.ctl, rd_stat_0.5m.f90 can be used to read the dataset
    b. 0.15-degree resolution: stat_soiltyp_0.15.ctl
    c. NE30NP4: NE30NP4_Soil_Texture_STAS.nc
5. Monthly Albedo
    a. 0.144-degree resolution: albedo0.144.ctl
    b. NE30NP4: NE30NP4_Albedo.nc
6. Monthly Green Fraction
    a. 0.144-degree resolution: gfrac0.144.ctl
    b. NE30NP4: NE30NP4_GreenFrac.nc
7. Deep Soil Temperature
    a. 1.0-degree resolution: tbot_360x180.ctl
    b. NE30NP4: NE30NP4_Tbot.nc
8. Fixed Fields for Running NOAH Model at NE30NP4 Grids
    a. NOAH_NE30NP4_FIXED.nc

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