Clim Dyn (2011) 36:1277–1290
DOI 10.1007/s00382-010-0743-0

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states. It is known that TIWs prevent the cold tongue water from cooling down by mixing the warm off-equatorial water and the cold tongue water; therefore, seasonal TIW variability (TIWV) is closely related to seasonal variation of the cold tongue intensity (Yu et al. 1995; Swenson and Hansen 1999). In addition, several recent researchers have shown that TIWV strongly interacts with ENSO (Vialard et al. 2001; Yu and Liu 2003; An 2008a). Among them, Jochum and Murtugudde (2004) demonstrate that ENSO can be significantly modulated by TIWs. For example, during El Niño (La Niña) season, TIWV is weakened (strengthened) due to decreased (increased) horizontal temperature gradients between cold-tongue water and the surrounding ocean, suggesting that there is negative relationship between ENSO and TIWV. Building on these findings, An and his colleagues (An and 2004 An

Uppala et al. 2005; Carton and Giese 2008). Because the model error covariance in these schemes is only formulated to represent time-averaged physical relationship, it is unable to resolve TIWs, which have complicated shapes, in assimilated states. In addition, it is possible that the shear of the background state can be smoothed by the assimilation scheme, and therefore less TIWs can be generated.

Since most reanalysis data does not fully resolve TIWs, nudged initial conditions using these reanalysis data also fail to resolve TIWs. Figure 1 shows the 20-year averaged TIW activity (variance) in SST from the free integration of Seoul National University (SNU) air-sea coupled GCM and nudged initial conditions using Global Ocean Data Assimilation System (GODAS; Behringer and Xue 2004). Note that TIWs are defined as perturbations whose zonal scale is smaller than 10 by applying high-pass filters in the zonal direction, and the unit of TIW variability (TIWV) is C^2 (Duchon 1979). It is clear that TIWV from free integration of the forecast model is active over cold tongue regions where the meridional SST gradient is largest. Because both oceanic component of SNU CGCM and model to produce GODAS reanalysis are based on MOM, TIWV in GODAS data would be not much different from that in free-run if initialization process properly resolves TIWs. However, TIWV in nudged initial conditions is one order smaller than that of free run. It implies that current initialization techniques fail to resolve TIWs or TIWV into initial conditions for climate forecasts.

This deficiency has not been highlighted until now, because TIWV was thought not to be important for climate forecasts. However, recent work on TIWs imply that it is important to resolve TIWs correctly into initial conditions for skillful climate forecasts, because the interaction between TIWs and climate plays an important role in simulating and predicting climate variability using CGCM. Therefore, in this study, the role of TIWs in the initial conditions of seasonal forecasting skill is investigated using an SNU CGCM. The new scheme to incorporate TIW perturbations into initial conditions helps to enhance TIWV which have been excessively suppressed due to a coarse observational network and a deficiency in the initialization techniques.

This idea is similar to the bogusing technique for typhoon simulation using numerical weather prediction (NWP) models (Anderson and Hollingsworth 1988; Leslie and Holland 1995; Wang 1998). The bogusing technique is to force a tropical cyclone vortex into the initial conditions of a regional climate model (RCM), because GCM based initial conditions are spatially-smoothed. Similarly, in this study, three-dimensional TIWs are seeded into spatially-smoothed nudged initial conditions to simulate the right intensity of TIWV during forecasts. The difference between TIWs-seeding technique in this study and bogusing is that seeded TIWs are extracted from free integration of CGCM, and no observed information is required. It is plausible because a major focus in this study is to simulate

Fig. 1 Time-averaged TIW activity (variance) in SST on May 1st from the free integration of SNU coupled GCM and nudged initial conditions using GODAS (Unit C^2). Note that a 20-year average is taken to calculate eddy activity. TIWs are defined as perturbations whose zonal scale is smaller than 10 seasonal TIW variability (TIWV) not to simulate the detailed pattern of TIWs.

The paper is organized as follows. In Sect. 2, descriptions of SNU CGCM are included. In Sect. 3, generation of TIW perturbations and initialization methodology are explained. Impacts of TIWs on seasonal forecasts are demonstrated in Sect. 4. A summary and discussion are included in Sect. 5.

2 Model descriptions

The model used in this study is the Seoul National University CGCM (SNU CGCM, Kug et al. 2008; Kim et al. 2008; Ham et al. 2009). The oceanic part of the coupled model is the Modular Ocean Model (MOM) developed at the Geophysical Fluid Dynamics Laboratory (GFDL). The ocean model of version MOM2.2 uses a B-grid finite difference treatment of the primitive equations of motion, and covers the global oceans with realistic coastlines and bathymetry. The zonal grid spacing is 1.0 The meridional grid spacing between 8S and 8N is 1/3, gradually increasing to 3.0 at 30 S and 30N, and is fixed at 3.0 in the extratropics. There are 32 vertical levels with 23 levels in the upper 450 m. A mixed layer model, developed by Noh and Kim (1999) is embedded into the ocean model to improve the climatological vertical structure of the upper ocean.

The atmospheric part of the coupled model is a SNU AGCM, which is a global spectral model at T42 resolution, with 20 vertical sigma levels. The deep convection scheme is a simplified version of the relaxed Arakawa-Schubert scheme (SAS, Numaguti et al. 1995). The large-scale condensation scheme consists of a prognostic microphysics parameterization for total cloud liquid water (Le Treut and Li 1991) with a diagnostic cloud fraction parameterization. A non-precipitating shallow convection scheme (Tiedtke 1983) is also implemented in the model for the mid-tropospheric moist convection. The boundary layer scheme is a non-local diffusion scheme based on Holtslag and Boville (1993), while the land surface model is from Bonan (1996). Atmospheric radiation is parameterized by a two-stream k distribution scheme as in Nakajima et al. (1995). Recently, convective momentum transport (CMT) parameterization (Wu and Yanai 1994) was applied to the present coupled GCM (Kim et al. 2008). In addition, a minimum constraint rate referred to as ‘tokioka constraint’ was introduced. The minimal entrainment rate was set to 0.1. Other details of the model physics are described in Lee et al. (2001, 2003).

The coupled model exchanges SST, wind stress, freshwater flux, longwave and shortwave radiation, and turbulent fluxes of sensible and latent heat once every 2-h. No flux correction is applied, and the model does not exhibit significant climate drift in long-term simulations. In addition, the CGCM reasonably simulates the observed climatology and ENSO, though some systematic biases are found (Kug et al. 2008).

3 Initializations for seasonal forecasts

3.1 Generation of three-dimensional TIW perturbations

The spatial pattern of TIW perturbations, added to nudged initial conditions, is obtained from free integration of the coupled GCM. The procedure to obtain TIWs from a free integration is as follows. First, TIW perturbations are obtained by calculating the difference between 9-point averaged fields and original fields to retain small-scale features. Note that the definition of TIW perturbations is achieved by applying a high-pass filter technique for analyzing TIW properties in the rest of this study. TIW perturbations in temperature, salinity, zonal and meridional currents for all vertical levels are obtained. Then, TIWs pattern when its activity is strongest is picked up from free integration.

Figure 2 shows the spatial pattern of the strongest TIWs in SST on May 1st from free integration. Note that the TIW patterns on May 1st are shown because the summer season is the target for seasonal forecasting in this study. Among free-integration years for decades, TIW perturbations at largest La Niña year are selected based on NINO3.4 SST anomalies, because spatial pattern of TIWs would be dominant and robust during La Niña among small-scale variability. Hereafter, the selected three-dimensional TIWs pattern is denoted as $\mathrm{TIWs}_{\mathrm{Free}}$. The magnitude of TIWs is from −1 to 1 C. It is clear that TIWs are active around 2.5 N and 2.5S, which is consistent with other studies (Contreras 2002; An 2008a).

As well as the spatial pattern of TIW perturbation, it is essential to determine the magnitude of TIW perturbations for each hindcast year. It is well known that TIW activity is proportional to such large-scale features as shear instabilities of the equatorial current system (e.g. barotropic instability, Qiao and Weisberg 1995, 1998), and the meridional gradient of the SST over cold tongue regions (e.g. baroclinic instability, Yu et al. 1995). In this study, it is assumed that TIW activity is largely dependent on large-scale SST gradient for simplicity.

The procedure to estimate magnitude of TIW perturbations for each forecast year is as follows. First, define three boxes over the equatorial eastern (EPSST 170W–120W, 2 S–2N), equatorial central (ECSST 150E–180E, 2 S–2N), and off-equatorial eastern Pacific (OESST 170 W–120W, 2 N–5 N) regions. Then, the magnitude of

Fig. 2 Spatial pattern of strongest TIWs in SST on May 1st from free integration

the cold tongue SST (MCSST) is defined using the SST of three boxes as follows.

$$\text{Magnitude of Cold tongue SST (MCSST)} = (\text{ECSST} - \text{EPSST}) + (\text{OESST} - \text{EPSST})$$

Note that index is larger as the zonal or meridional SST gradient over the eastern Pacific becomes larger. And the correlation coefficient between MCSST index and monthly TIW variability in free-run is 0.83 with 99% significance level, which means the proposed index well captures the monthly TIW variability in the model. Then, the magnitude of cold tongue SST (MCSST) at the strongest TIWs year in free integration and nudged initial conditions of each hindcast year are estimated. Finally, the magnitude of TIW perturbations are determined by the ratio of MCSST in nudged initial conditions to that in free integration. The TIW perturbations of year Y (Y is from 1981 to 2000) can be determined as follows.

$$\text{TIW perturbations of year } Y = \frac{\text{MCSST}_{\text{ICof}Y}}{\text{MCSST}_{\text{Free}}}\,\text{TIWs}_{\text{Free}}(x, y, z)$$

3.2 Initializations for seasonal forecasts

The seasonal forecast experiments have been carried out using the SNU CGCM. To obtain the initial conditions, the SNU coupled GCM is integrated from January 1980 to December 2000 by nudging the observed variables of both ocean and atmosphere. For oceans, the ocean temperature and salinity obtained from GODAS reanalysis are nudged from surface to 500 m with a 5-day restoring time scale. For the atmosphere, zonal and meridional wind, temperature, and moisture fields obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF) 40-Year Reanalysis (ERA40; Uppala et al. 2005) are nudged for all vertical levels with a 6-h restoring time scale. Given the initial conditions, the 20-year hindcast forecasts are carried out with a 4-month lead time, starting from 1st May for the period 1981–2000. Four members, generated by 1-day lag using Lagged Averaged Forecast method (LAF), are used for ensemble forecasts. Hereafter, the CGCM forecast with conventional nudged initial conditions is denoted as CNTL forecasts. The CGCM forecast with perturbations-added-initial conditions is denoted as EDDY forecasts. Note that the only difference between CNTL and EDDY forecasts is whether TIW perturbations are added or not.

4 Seasonal forecast results

4.1 Impact of initial TIWs perturbations on seasonal TIW variability

A question we have sought to address is how long initial TIWs-seeding affects the seasonal TIW variability (TIWV). If initial TIW perturbations are abruptly damped as soon as forecast starts, seasonal TIWV would be similar in both CNTL and EDDY forecasts. To investigate how long the initial TIWs-seeding effect is sustained, SST evolution during forecasts in 1984 is shown in Fig. 3. Note that the magnitude of TIW perturbations is largest in 1984 among those data obtained on May 1st for the 20 years from 1981 to 2000. As expected, TIWs-seeded initial conditions have more high-frequency fluctuations than conventional nudged initial conditions over the equatorial Pacific on the initial day. Note that prescribed TIWs in SST on May 1st 1984 vary from −2 to 2 C. With conventional nudged initial conditions, significant TIWs are not shown after 30 day forecasts. On the other hand, TIWs seems to be active in EDDY forecasts. After 60 day forecasts, TIW perturbations are slowly formulated in CNTL forecasts; however, TIW activity is still stronger in EDDY forecasts. It implies that TIWs-seeding impact is sustained on the seasonal time scale.

It is interesting the cold tongue temperature in EDDY forecasts is higher than that in CNTL forecasts. This may be due to the stronger TIW mixing in EDDY run. If this

Fig. 3 SST evolution during seasonal forecasts of 1984 in CNTL and EDDY forecasts

mechanism is working for all hindcast year, TIWs-seeding in initial conditions can increase SST climatology over the cold tongue region and can, therefore, reduce the col climate drift during seasonal forecasts using CGCM. Not that cold SST drift during seasonal forecasts is a commo problem of many seasonal forecast systems using CGC (Luo et al. 2005; Jin et al. 2008). As expected, it is found that there is a positive tendency to reduce cold climate drif over the cold tongue region in EDDY forecasts. However, the magnitude of climatology reduction in EDDY forecasts is only about 0.1C, which is relatively small value compared to the magnitude of the cold climate drift, about 1C, during JJA season (not shown).

Fig. 4 20-year mean of area-averaged TIW variability (TIWV) in SST with respect to forecast days in CNTL and EDDY forecasts. EDDY_RSIGN denotes the forecast experiments in which the sign of initial TIW perturbations is reversed. Note that TIWV are averaged from 170 W to 110 W, 6 S–6N, where the prescribed TIWs anomaly is significant. The unit of TIW variability is C^2

The impact of initial TIW perturbations on seasonal TIWV is still rigorous when TIWV averaged for all the hindcast periods are compared. Figure 4 shows the 20-year mean of area-averaged TIWV with respect to forecast day in both forecasts. Averaged region for TIWV is over 170 W–110W, 6 S–6N, where TIW anomaly is significant due to strong large-scale instability. Note that the increase of TIWV with longer forecast lead day is associated with intensification of the cold tongue during the autumn season. This feature is also shown in the free-run, even though the magnitude of TIWV in free-run is stronger than that in the forecasts. It is due to the fact that the seasonal cycle amplitude and related baroclinic instability is stronger in free-run.

It is interesting that there is an initial shock of TIWV in EDDY forecasts, inferring an abrupt change of TIWV during early forecast lead days. That may be due to a crude estimation of baroclinic instability using simple boxes, or no consideration of barotropic instability due to oceanic current shear. In addition, it implies that initial TIW perturbations are discarded abruptly without large-scale instability in initial conditions. For example, the TIW variability is abruptly damped during El Nino season even though initial TIW perturbation is implemented, however, during La Nina season, the prescribed TIW perturbations amplifies with respect to forecast lead days without any damping (not shown).

It is clear that there is a clear difference in TIWV between EDDY and CNTL forecasts. The TIWV difference between EDDY and CNTL forecasts is excessive 99% significance level calculated by TIWV difference between ensemble members in CNTL run (not shown). The difference is sustained until 70–80 forecast lead days. It implies that initial TIWs-seeding enhances seasonal TIWV, not be discarded within several forecast lead days. In addition, it is interesting that the enhanced seasonal TIWV in EDDY forecasts is still shown when the sign of initial TIW perturbations is reversed (EDDY_RCISN experiment), which implies that our results in this study are still rigorous irrespective of the detailed sign of TIW perturbations.

Figure 5 shows the 20-year averaged seasonal TIWV difference of EDDY forecasts from CNTL forecasts. Note that TIWV is averaged for the first two forecast lead months (e.g. from May 1st to June 30th). Note that the averaged TIWV in EDDY forecasts is about twice than that in CNTL forecasts (not shown). This enhanced TIWV amplifies both linear and nonlinear relationships between TIWs and ENSO. The role of enhanced TIWs in ENSO forecasts will be discussed in the next sub-section.

4.2 Role of initial TIW perturbations on ENSO forecasts

According to several studies there is strong negative relationship between TIWs and ENSO (Qiao and Weisberg 1995; Jochum and Murtugudde 2004; An 2008a, b). That is, during El Niño (La Niña) season, TIWV becomes weaker (stronger) than normal due to weaker (stronger) instability of large-scale temperature or currents. For example, the cold tongue temperature becomes higher than the normal states during El Niño, and it reduce the large-scale temperature gradient (e.g. baroclinic instability). At the same time, westerly currents over the mixed layer during El Niño reduce the vertical current shear between the westerly Equatorial Undercurrent and the easterly South Equatorial Current (e.g. barotropic instability).

The impact of TIWs on ENSO can be measured through nonlinear temperature advection due to TIWs (An 2008a). To calculate the nonlinear temperature advection due to TIWs, TIWs in temperature and zonal, meridional, and vertical currents of each level are defined from the surface to 50 m. Then, nonlinear advection due to TIWs is calculated as follows.

Fig. 5 20-year averaged seasonal TIWV difference of EDDY forecasts from CNTL forecasts. Note that TIWV is averaged for the first two forecast lead months (e.g. from May 1st to June 30th). Note that the unit of TIW variability is C^2

Fig. 6 Correlation coefficient between nonlinear TIW advection and NINO3.4 index. *Red* (*Black*) color denotes the results from EDDY (CNTL) forecasts

$$\text{Nonlinear advection} = \frac{\int_{x=170\,\mathrm{W}}^{120\,\mathrm{W}}\int_{y=3\,\mathrm{S}}^{3\,\mathrm{N}}\int_{z=50\mathrm{m}}^{0\mathrm{m}}\left[u'\frac{\partial T'}{\partial x}+v'\frac{\partial T'}{\partial y}+w'\frac{\partial T'}{\partial z}\right]\mathrm{d}x\mathrm{d}y\mathrm{d}z}{\int_{x=170\,\mathrm{W}}^{120\,\mathrm{W}}\int_{y=3\,\mathrm{S}}^{3\,\mathrm{N}}\int_{z=50\mathrm{m}}^{0\mathrm{m}}\mathrm{d}x\mathrm{d}y\mathrm{d}z}$$

Note that prime denote the perturbation defined as TIWs.

To examine whether there is an inverse relationship between nonlinear TIWs advection and ENSO in both forecasts, the correlation coefficient between nonlinear TIWs advection and NINO3.4 index with respect to the forecast lead month is shown in Fig. 6. It is clear that there is seasonality in the correlation coefficient in both forecasts. This may be related to the ENSO SST evolution and seasonal cold tongue evolution.

In CNTL forecasts, the correlation coefficient at a 1-month lead time is slightly smaller than −0.4. By contrast, the correlation coefficient in EDDY forecasts, which is −0.52 for a 1-month lead time, is robust than that in CNTL forecasts. This implies that the initial seeding of TIW perturbations helps to simulate the negative relationship between TIWs and ENSO. The difference between TIW advection associated with ENSO in EDDY forecasts and that in CNTL forecasts is biggest at a 1-month lead forecast, and becomes smaller as the forecast lead time becomes longer. There is still a small initial TIWs-seeding impact at a 2-month lead time; however, it disappears after a 3-month lead time.

Note that weaker (stronger) TIW advection during El Niño (La Niña) reduces the ENSO magnitude in EDDY forecasts. The standard deviation of the JJA NINO3.4 index in CNTL forecasts is 0.80, which is slightly larger than that in observations (0.74). This is related to the strong ENSO magnitudes in SNU CGCM (Kim et al. 2008; Ham et al. 2009). On the other hand, the standard deviation of JJA NINO3.4 index in EDDY forecasts is 0.74. From this result, it is clear that there is a positive bias to the simulation of ENSO magnitudes.

Figure 7 shows the magnitude of horizontal (zonal plus meridional) and vertical TIW advection over the eastern Pacific region regressed onto NINO3.4 index in EDDY forecasts. It is clear that horizontal (vertical) TIW advection is negatively (positively) correlated to the ENSO. Also, it is shown that horizontal TIW advection during the ENSO is much larger than vertical advection. This result is consistent with that of Menkes et al. (2006) that TIW-induced vertical advection is negligible in the SST budget, at least in the mixed layer. Note that the positive correlation between vertical TIW advection and ENSO is from the fact that stronger warming in subsurface layer during El Niño reduce the vertical temperature gradients and TIW activity, then reduced TIW mixing between surface and subsurface layer leads to warming of surface layer.

In addition to the linear relationship between TIWs and ENSO, An (2008a) recently argued that nonlinear advection due to TIWs can lead El Niño–La Niña asymmetry. That is, enhancement of TIW advection during La Niña is stronger than reduction of TIW advection during El Niño. It is expected that this nonlinear relationship would also be well simulated in EDDY forecasts, because simulated TIW activity becomes more realistic through initial TIWs-seeding.

Figure 8 shows an El Niño and La Niña composite of the area-averaged nonlinear TIW advection in both forecasts. Being consistent with the results of Fig. 7, the negative relationship between TIW advection and ENSO is robust in EDDY forecasts. For example, an ENSO composite nonlinear TIW advection at a 1-month lead time is about −0.2 (°C/month) in EDDY forecasts; however, that in CNTL forecasts is less than −0.1 (°C/month). This difference in ENSO composite TIW advection in EDDY forecasts mainly comes from that during La Niña season. That is, at a 1-month lead time, heating due to TIW advection during La Niña in EDDY forecasts (0.13) is about 6 times larger than that in CNTL forecasts (0.02). On the other hand, cooling due to TIW advection during El Niño in EDDY forecasts (−0.03) is only three times larger than that in CNTL forecasts (−0.01). It may lead to stronger La Niña damping in EDDY forecasts; therefore, ENSO asymmetry must also be well simulated, with aids to better nonlinear TIWs temperature advection simulation.

To investigate ENSO asymmetry in both forecasts, 'asymmetricity' recently developed by An et al. (2005) is applied. Asymmetricity is similar to skewness, whose coefficient is defined as the normalized third statistical moment. However, there is a problem in that a small standard deviation can cause a large skewness. To avoid this, asymmetricity has been developed, which is variance-weighted skewness, defined as follows.

Fig. 7 The magnitude of horizontal (zonal plus meridional advection) and vertical TIWs advection over the eastern Pacific region (170°W–110°W) regressed onto the NINO3.4 index in EDDY forecasts (Unit: °C/month)

$$\text{Asymmetricity} = \frac{m_3}{(m_2)^{1/2}}$$

where m_k is the kth moment,

$$m_k = \sum_{i=1}^{N} \frac{\left(x_i - \overline{X}\right)^k}{N}$$

and where x_i is the ith moment, $\overline{X}$ is the mean, and N is the number of samples ($N = 20$; from 1981 to 2000).

Figure 9 shows the asymmetricity of the NINO3.4 index in both forecasts with respect to forecast lead month. In observations, the asymmetricity of the NINO3.4 index is nearly zero in May and June, and it becomes about 0.2 and 0.4 in July and August, respectively. This seasonality of asymmetricity is also well captured in the free-run. Validation with 50-year free-run data shows that asymmetricity is changed from negative at May and June (−0.64, and −0.96) to positive at July and August (0.51, and 1.12). In CNTL forecasts, ENSO asymmetry is poorly simulated, that is, the asymmetricity of the NINO3.4 index is about −0.2 from June to August. It means the magnitude of the simulated La Niña is stronger than that of El Niño, which has opposite features to observations. On the other hand, the asymmetricity in EDDY forecasts becomes more realistic, especially for longer forecast lead months. For example, the asymmetricity of August in EDDY forecasts is larger than 0.2, while that in CNTL forecasts is still negative.

One may ask why the improvement of ENSO asymmetry simulations in EDDY forecasts is significant in August, even though the TIWV and TIWs advection is robust during early forecast lead months. It is because nonlinear TIWs advection modulates the temperature time tendency; therefore, the heat budget changes due to TIWs accumulate in time. For example, time-averaged nonlinear temperature advection from May to August is similar during El Niño in both forecasts (CNTL −0.12, EDDY −0.13 K/month), however, the difference during La Niña season is almost twice in EDDY run (CNTL 0.10, EDDY 0.18 K/month). It means that accumulated (or time-averaged) nonlinear temperature advection due to TIWs can explain stronger SST damping during La Niña at August in EDDY forecasts. The better simulation of ENSO asymmetry improves the seasonal prediction skill in EDDY forecasts. Figure 10 shows the scatter plot of the observed and simulated NINO3.4 index in August, and the reduction of RMS errors in EDDY forecasts compared to that in CNTL forecasts. Note that observation to measure the RMS error in both forecasts is the Improved Extended Reconstructed Sea Surface Temperature Version 2 (ERSST V2) data set (Smith and Reynolds 2004). In CNTL forecasts, the simulated NINO3.4 index is too small compared to the observed index, especially during La Niña season. On the other hand, the simulated NINO3.4 index during La Niña in EDDY forecasts is increased to reduce RMS forecast errors, which means that the magnitude of La Niña is reduced.

Then, why is RMS error reduction of NINO3.4 index in EDDY forecasts robust during La Niña season? The reason is that during La Niña season, the impact of initial

Fig. 8 El Niño and La Niña composite of the area-averaged nonlinear TIWs temperature advection in CNTL and EDDY forecasts (Unit: C/month). *Red* (*Black*) color denotes the results from EDDY (CNTL) forecasts

Fig. 9 Asymmetricity of observed and simulated NINO3.4 index with respect to forecast lead month *Black*, *red*, and *green* color denote the results from observations, EDDY forecast, and CNTL forecasts, respectively

Fig. 10 Scatter plot of observed and simulated NINO3.4 index in August, and reduction of RMS errors in EDDY forecasts compared to that in CNTL forecasts. *Red* (*Black*) dots denote the results from EDDY (CNTL) forecasts

TIWs-seeding becomes more significant because TIWV and nonlinear temperature advection due to TIWs should be stronger than normal during La Niña. It means that initial TIW perturbations are not damped, but sustained or amplified, especially during La Niña season. That leads to a significant difference between the simulated NINO index in EDDY forecasts and that in CNTL forecasts. On the other hand, during the El Niño season, whose TIWV becomes weaker than the normal states, the magnitude of TIWV and nonlinear TIW advection is not significantly modulated with or without initial TIW perturbations, because the initial TIW perturbation is abruptly damped due to weak large-scale instability.

To investigate improvements in the seasonal forecast skills in both forecasts more detail, the correlation coefficient of various simulated ENSO indices with respect to forecast lead month is calculated in Fig. 11. Note that the statistical significance about the improvement of correlation skill is performed by generating two more forecast sets (total six ensemble members) without TIWs perturbations (CNTL run) by using Lagged Averaged Forecast (LAF) method. With 6 ensemble members, all possible forecast sets of four ensemble members (a total of 15 cases) are generated, then, 95, 99% significant level is defined from the standard deviation of each month by assuming Gaussian distribution. It is clear that the correlation coefficient of various ENSO indices (e.g. NINO4, NINO3.4, and NINO3 index) in the EDDY forecasts is significantly higher than that in CNTL forecasts. For example, the correlation coefficient of the NINO3.4 index in CNTL forecasts is slightly less than 0.8 at a 4-month lead time (e.g. August prediction), while that in EDDY forecasts is about 0.85. Among them, the correlation skill improvement in August is most significant over the NINO3 region (e.g. over 0.1), where TIWV is strongest. Note that the correlation improvement becomes larger as the forecast lead month is longer, which is consistent with better ENSO asymmetry simulation in the EDDY forecasts.

Figure 12 shows the correlation map between observed and simulated August SST in both forecasts. In both, the correlation coefficients are higher over central-eastern Pacific regions than other regions. For example, the correlation coefficient over the central-eastern Pacific is between 0.6 and 0.8, while that over the western Pacific is less than 0.5. However, note that correlation over the equatorial eastern Pacific is relatively lower than other central-eastern Pacific regions, which is about 0.5 over the equatorial far eastern Pacific region. This deficiency is significantly improved in EDDY forecasts, whose correlation coefficient becomes larger than 0.6. In addition, correlation coefficients over the central Pacific becomes also higher in EDDY forecasts than that in CNTL forecasts, which implies that there is a significant seasonal forecast skill improvement by simply adding TIW perturbations obtained from free integrations to spatially-smoothed initial conditions.

5 Summary and discussion

In this study, the positive impacts of initial TIW perturbations on seasonal forecasts are investigated. Due to a lack of TIW variability (TIWV) in reanalysis data produced by 3DVAR or OI methods, we have shown that TIWs are barely included in initial conditions, even though forecast models are able to simulate TIWs with the aid of high horizontal resolutions. We have tried to settle this deficiency, because lack of TIWV in initial conditions can ruin the simulation of nonlinear interaction between TIWs and climate states. In this study, TIW perturbations obtained from free integration are added to spatially-smoothed nudged initial conditions to simulate realistic TIWV on a seasonal time scale. Through 20-year ensemble forecast experiments, it is shown that the TIWV is stronger in TIWs-seeding experiments until 70–80 forecast days, which implies that TIWs-seeding impact is sustained on a seasonal time scale.

Fig. 11 Correlation skill of a NINO4, b NINO3.4, and c NINO3 indices with respect to forecast lead month from 20-year hindcast experiments. *Red* (*Black*) *lines* denote the results from EDDY (CNTL) forecasts. The *thin solid lines* denote 95 and 99% confidence level

Fig. 12 Correlation map between observed and simulated August SST in CNTL and EDDY forecasts *Upper* (*Lower*) panel shows correlation coefficients of CNTL (EDDY) forecasts

The enhanced TIWV amplifies the negative relationship between TIWs and ENSO. That is, the magnitude of non-linear TIWs temperature advection associated with ENSO is stronger when initial TIW perturbations are seeded into spatially-smoothed initial conditions. In addition to an enhanced linear relationship between TIWs and ENSO in EDDY forecasts, El Niño–La Niña asymmetry is also well simulated because nonlinear TIWs temperature advection leads to stronger La Niña damping. The better simulation of ENSO asymmetry significantly improves the seasonal forecast skill especially over equatorial Pacific regions. For example, the correlation improvement of the NINO3 index for a 4-month lead time is over 0.1.

In this study, seasonal forecast experiments are initiated from May (e.g. summer season forecasts). However, TIWV is strongly dependent on an annual cycle (e.g. the magnitude of the cold tongue temperature). In addition, it is found that there is seasonality in the relationship between nonlinear TIWs advection and ENSO (Fig. 6). This implies that there should be seasonality to the impact of TIW perturbations on seasonal forecasts. It could be another interesting scientific issue whether there is a relationship between the strength of the negative relationship between TIWs and ENSO and any seasonal forecast skill improvement due to TIW perturbations. Therefore, it is necessary to expand seasonal forecast experiments to another season.

The authors have mentioned that spatially-smoothed initial conditions are inevitable as long as the initialization technique is 3DVAR, nudging, or the OI method, whose weighting coefficient for observations is fixed in time. However, TIW patterns can be maintained in initial conditions with an Ensemble Kalman Filter (EnKF) to some extent, because the model error covariance in EnKF is time-varying and able to represent small-scale physics. To examine whether EnKF is able to resolve TIW patterns, Fig. 13 shows the covariance of SST ensemble perturbations between values at 140°W, 2°N and values over the Pacific during El Niño and La Niña season using 32 ensemble perturbations. Note that ensemble perturbations are generated using EnKF in a perfect model assumption. It is clear that small-scale TIW patterns are resolved in covariance mapping during La Niña season. It is related to the enhanced TIWV due to cooler cold tongue temperature. However, during the El Niño season, covariance patterns show large-scale features that are nearly gaussian. It is consistent with the results that there is a negative relationship between TIWV and ENSO. It means that initial conditions (or reanalysis data) using EnKF contain TIWs, which are balanced to large-scale instabilities. Therefore, using state-of-the-art initialization techniques can be another way to resolve TIWs into initial conditions.

Even though EnKF is one of the attractive methodologies for initialization, however, it is still highly problematic that a huge amount of computational time is required to generate initial conditions with EnKF. In addition, there are several controversial issues with regard to applying EnKF to a global ocean model, such as localization and balance issues. Therefore, simple nudging or 3DVAR initialization techniques for seasonal prediction in various operational seasonal prediction centers are still employed (Palmer et al. 2004 (DEMETER); Wang et al. 2008 (CliPAS)). Under these circumstances, the TIW-seeding methods developed in this study can be a powerful tool to resolve TIWs, because they are easy to apply. It means that this method will give a chance to improve current state-of-the-art seasonal prediction skill.

Until now, few studies have highlighted TIWs in initial conditions. Rather than incorporating TIWs into initial conditions, small-scale TIW perturbations in initial conditions are sometimes discarded because they are regarded as un-wanted noise to ruin large-scale signals. For example,

Fig. 13 Covariance of SST ensemble perturbations between values at 140°W, 2°N and values over the Pacific during El Niño and La Niña season using 32 ensemble perturbations

Laplacian smoother or Gaussian filter are used to damp the high-frequency oscillations by smoothing the spatial structure of a model error covariance matrix (Zhang et al. 2005; Keppenne and Rienecker 2008). However, with on the help of recent studies that emphasize the interaction between TIWs and large-scale climate states, this study has laid the foundations for understanding the role of initial TIW patterns on the optimal seasonal forecast systems with complex coupled GCMs.

Acknowledgments This work supported by the Korea Meteorological Administration Research and Development Program under Grant CATER_2006-4206 and In-Sik Kang was supported by the second stage of the Brain Korea 21.

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