Testing the robustness of semi-empirical sea level projections

Stefan Rahmstorf · Mahé Perrette · Martin Vermeer

Received: 19 April 2011/Accepted: 17 October 2011/Published online: 10 November 2011 © Springer-Verlag 2011

Abstract We determine the parameters of the semiempirical link between global temperature and global sea level in a wide variety of ways, using different equations, different data sets for temperature and sea level as well as different statistical techniques. We then compare projections of all these different model versions (over 30) for a moderate global warming scenario for the period 2000-2100. We find the projections are robust and are mostly within $\pm 20\%$ of that obtained with the method of Vermeer and Rahmstorf (Proc Natl Acad Sci USA 106:21527–21532, 2009), namely ~ 1 m for the given warming of 1.8°C. Lower projections are obtained only if the correction for reservoir storage is ignored and/or the sea level data set of Church and White (Surv Geophys, 2011) is used. However, the latter provides an estimate of the base temperature T_0 that conflicts with the constraints from three other data sets, in particular with proxy data showing stable sea level over the period 1400-1800. Our new best-estimate model, accounting also for groundwater pumping, is very close to the model of Vermeer and Rahmstorf (Proc Natl Acad Sci USA 106:21527-21532, 2009).

Keywords Ocean · Sea level · Global warming · Projections

S. Rahmstorf (⊠) · M. Perrette Potsdam Institute for Climate Impact Research, Potsdam, Germany e-mail: rahmstorf@pik-potsdam.de

M. Vermeer

Department of Surveying, Aalto University School of Engineering, Espoo, Finland

1 Introduction

In recent years, semi-empirical approaches for projecting future sea level rise have been used by several authors (Grinsted et al. 2009; Horton et al. 2008; Jevrejeva et al. 2009; Rahmstorf 2007b; Vermeer and Rahmstorf 2009). The fundamental idea of these approaches is to exploit the link between global sea level and global temperature in past observational data for projecting the future. The motivation behind this is the fact that more detailed physics-based approaches to projecting sea level, using explicit modeling of thermal expansion of ocean waters and the ice loss of mountain glaciers and ice sheets, do not yet adequately capture the complex physics involved. This is seen e.g., by the mismatch of these models with past sea level observations (Rahmstorf et al. 2007) and with the observed accelerating ice sheet mass loss (Rignot et al. 2011). On the other hand, there is a close relationship between past global sea level and temperature changes that may continue to hold into the future and that may be used to project sea level for a given warming scenario.

The form of this relationship is motivated by basic physical considerations, whilst the parameters of the relationship can be determined from empirical data—hence the term "semi-empirical". Several different versions of the form of this relationship have been proposed (Grinsted et al. 2009; Jevrejeva et al. 2009; Rahmstorf 2007b; Vermeer and Rahmstorf 2009). At the heart of all of these is the concept that the *rate* of sea level rise will increase as global temperatures go up, which in the simplest linear approximation reads:

$$\mathrm{d}H/\mathrm{d}t = a\left(T(t) - T_0\right),\tag{1}$$

(Rahmstorf 2007b) where *H* is sea level, *T* is global temperature and T_0 is a baseline temperature at which sea level

is stable. The central parameter is therefore the "sea level sensitivity" a, which measures how much the rate of sea level rise accelerates for a unit change in global temperature. To determine this parameter from data, the key issue is therefore not how much sea level has risen in the past, but how much the rate of rise has *accelerated* in step with temperature changes. How well this correlation can be constrained from uncertain sea level data is a critical issue discussed in this paper. A good constraint on T_0 is of prime importance to determine a.

Vermeer and Rahmstorf (2009) have proposed a variation which they call the "dual model" by including a second term to capture short-term variations:

$$dH/dt = a (T(t) - T_0) + b dT/dt,$$
(2)

They show that this greatly improves the fit to synthetic (model-derived) data for short-term fluctuations in sea level, e.g., those following volcanic eruptions.

Grinsted et al. (2009) have proposed a form which explicitly takes into account that sea level will approach a new equilibrium over a characteristic time scale τ . If this time scale is long compared to the period under consideration (as in the 'historical' case favored by Grinsted et al., where the time scale found is ~ 1200 years) then this approach reduces to Eq. 1 (Rahmstorf 2007b). (Jevrejeva et al. 2009) used a variation of this where sea level is directly linked to radiative forcing, not to global temperature.

Finally, Kemp et al. (2011) combine a finite response time τ with Eq. 2 and show that their sea level proxy data are consistent with global temperature proxy data over the past millennium, although a discrepancy is found for 500–1000 AD.

As a caveat it should be noted that a simple connection between global sea level and global temperature can only be expected for temperature changes related to global forcings (e.g., greenhouse gases, solar luminosity) for which different amplitudes of warming may, to first order, have a similar spatial pattern (e.g., polar amplification, greater changes over land than ocean). Such a link will not hold for orbital forcing, which has a strong regional expression with only a very weak global-mean signal. For example, the sea level high stand during the Eemian interglacial can be largely explained by the large increase in local summer insolation causing the Greenland Ice Sheet to retreat (Overpeck et al. 2006) and is not related to a global mean warming relative to today, which was very small (Montoya et al. 1998). Hence, paleoclimatic data relating to the glacial-interglacial sea level changes are illsuited for constraining the sea level sensitivity to future greenhouse gas forcing.

In the following we will systematically explore how robust semi-empirical sea level projections are with respect to the choice of data sets, the choice of analysis techniques and various other assumptions.

2 Sea level data

We use three types of sea level data in this study: (1) proxy data from salt marshes for the past millennium (Kemp et al. 2011), (2) tide gauge data from coastal stations in form of various global compilations (Church and White 2006, 2011; Jevrejeva et al. 2008), and (3) satellite altimeter data starting from 1993 (Cazenave and Nerem 2004) (see Fig. 1). There is a trade-off of temporal and spatial coverage: satellite altimeter data give a near-complete global coverage (from 66°S to 66°N) but the record is too short to derive any meaningful acceleration. Tide gauge data extend for over a century (with coverage declining back in time) but cover only coastal locations. The proxy data constrain acceleration very well by reaching back to an extended period of stable sea level, but they only come from a few locations.

The various tide-gauge based global mean sea-level reconstructions differ with respect to the selection of gauges, the correction for glacial isostatic adjustment (GIA), the correction for changes in atmospheric pressure ("inverse barometer") and, most importantly, the method for aggregating worldwide tide-gauges into a synthetic global mean sea-level curve.

One problem to overcome when combining tide-gauge data from around the world is to have a common vertical datum. Gornitz and Lebedeff (1987) and Trupin and Wahr (1990) (hereafter GL87 and TW90) address this issue by applying a vertical offset to each tide-gauge equal to the linear regression intercept, and then average the sea-level curves directly. The approach is subject to errors in estimating the linear trend (and therefore the vertical shift), especially for short records. Instead, Holgate and Woodworth (2004) (HW04) and subsequent authors stack the rate of change of sea-level to aggregate several stations which allows many more stations to be included in the reconstruction. The Jevrejeva et al. (2008) (JE08) dataset is built with the "virtual station" technique (Jevrejeva et al. 2006), which consists of recursively combining the two closest tide gauges in a new, "virtual" station, located halfway between the two original stations. The virtual station is re-used as an actual tide gauge in the subsequent iteration steps. As in HW04, regional sea-level curves are first derived before combination into a global mean sea-level time-series. The 1750-1800 section in JE08 consists of only 3 tide gauges from the northern Atlantic that are assumed to represent the global mean (after subtraction of a long-term trend).

While the above reconstructions effectively compute coastal sea-level rise and assume it to be representative of the global mean. Church and White (2006, 2011) (subsequently referred to as CW06 and CW11) combine tidegauge records into a global estimate by means of spatial empirical orthogonal functions (EOF) derived from altimetry data. They assume that dominant modes of spatial sea level variability obtained during the altimetry period (i.e., since 1993) are representative for earlier periods as well. If this assumption holds, the technique does a better job at capturing global sea level variability than simple averaging of tide gauge records. As a result, the global mean sea-level reconstructions making use of the EOF technique are typically smoother than other reconstructions. The main difference between CW06 and the CW11 update is the length of the altimetry time-series used to compute the EOF, and an extended number of tide-gauges. Further details on the datasets can be found in the original references.

Finally, we use the proxy data of Kemp et al. (2011) for the last millennium, which is to date the best available data set going back so far in time. The main drawback is that this proxy reconstruction stems from just two sites in North Carolina and is thus just a local record for the western North Atlantic. Kemp et al. estimate in detail how far this can deviate from global sea level variations through various physical processes; they conclude that this record should be representative of global-mean sea level variations to within ± 10 cm. On the time scales resolved by the proxies, it agrees with the reconstruction of global-mean sea level by (Jevrejeva et al. 2008) since 1700 AD everywhere to within ± 6 cm (Kemp et al. 2011).

The proxy data have lower time resolution and larger uncertainty than the other data, but they go back much further in time. The latter makes them uniquely useful for constraining T_0 in Eq. 1, since the proxy data show an extended period of 400 years of stable sea level, from 1400 to 1800 AD. Even if there were a sea level trend of plus or minus 10 cm over this period (which could be accommodated within data uncertainty), this would constrain the average rate of sea level rise to within 100 mm/400 years $= \pm 0.25$ mm/year. For a typical value of a = 0.3 cm/year/ K (see (Rahmstorf 2007b) in Eq. 1, this constrains T_0 to within at most ± 0.08 K, which is less than the uncertainty in the proxy temperatures for 1400-1800 AD. Hence the uncertainty in the temperature proxies, rather than in the sea level reconstruction, is the limiting factor in using the proxy data to constrain the sea level acceleration.

3 Short-term variability

We start by looking at the short-term variations in the rate of sea level rise found in the tide gauge data. Figure 2 shows the decadal linear rates of sea level rise and demonstrates the well-known fact that the derivative of 'noisy' data is invariably much more noisy. It is apparent that the peaks and troughs of the decadal rate of rise are to a large extent inconsistent between different data sets, most evidently in their amplitude but also in their timing. In some time intervals data sets even disagree over the sign (rising or falling sea level). Much of the short-term ups and downs in the rate of sea level rise thus cannot be considered a feature of the real global mean sea level but must be some data limitation, most likely due to regional sea level variability which is insufficiently sampled to compute a correct global average. This conclusion is supported by tests with surrogate data from a climate model made to investigate how well changes in global sea level can be reconstructed from a limited number of tide gauges along coasts and islands (Christiansen et al. 2010). This study concludes that spurious inter-annual variability is a major problem of such reconstructions, regardless of the reconstruction method. This is supported by the smaller inter-annual variability in the altimeter data as seen in Fig. 1. It is further supported by a recent inter-comparison of tide gauge and altimeter data (Prandi et al. 2009), although that study focused on interannual variability rather than decadal trends. The fact that some coherence is seen between the various tide gauge data sets shown in Fig. 2 will be to some extent due to these reconstructions partly using the same input data,



Fig. 1 A collection of different sea level data sets, shown from 1850 with an arbitrary vertical offset for clarity. Legend: CW06, CW11 = Church and White 2006, 2011; JE08 = Jevrejeva et al. 2008: HW04 = Holgate and Woodworth 2004; TW90 = Trupin and Wahr 1990; GL87 = Gornitz and Lebedeff 1987. In this paper we use the top three long series (CW06, CW11, JE08) for further analysis. The *dashed grey line* is a quadratic fit to the CW06 data, shown here merely to help the eye in the comparison of the data sets. Note the visibly smaller inter-annual variability in the altimeter data. All series shown are already corrected for glacial isostatic adjustment



Fig. 2 Decadal trends (i.e., least-square linear trends for overlapping 10-year intervals) for the tide gauge and altimetry data shown in Fig. 1

while to some extent it may also reflect true decadal variations in global mean sea level.

A discrepancy between tide gauge compilations and the true global mean is not surprising considering the physics. Even in a situation of constant global mean sea level (i.e., conserved total ocean water volume), changes at individual tide gauge stations arise due to the ocean water moving around under the influence of winds or tides. There is no guarantee that at a limited number of tide gauge stations along coastlines such volume-conserving ocean motions would average out to zero. In other words, a network of tide gauge stations can falsely register seemingly global sea level variations, which are caused by physical processes (i.e., water motions) which in reality cannot cause any global sea level changes.

We illustrate the effect of 'noise' in the sea level data with an example of a synthetic sea level time series, consisting of a smooth sea level rise plus artificial noise generated with a random number generator (Fig. 3). The noise has a standard deviation of only 5 mm and is slightly auto-correlated (zero crossing of the lagged covariance at 3.5 years lag). The properties of the smooth function and of the noise are chosen to resemble the data of Church and White (2006) (i.e., the smooth curve shown is low-pass-filtered CW06 data, and the noise has the same standard deviation and similar lagged covariance as the residuals of the CW06 data). The figure illustrates that even such a small amount of noise in the data, as it is expected from under-sampling due to the limited number of gauges, obscures the signal when looking at decadal rates of rise (bottom panel). For their tide-gauge based annual reconstruction, Church and White (2011) estimate a one-standard-deviation uncertainty (as compared



Fig. 3 *Top*: A synthetic sea level time series (*blue*) consisting of a smooth function (*grey*, a smooth fit to the CW06 data) plus added random noise with 5 mm standard deviation (*green*). *Bottom*: Linear trends in the blue sea level curve for overlapping 10-year periods (*red*). The *grey line* shows the true signal, i.e., the rate of sea level rise from the smooth curve. Despite this signal of a fourfold acceleration, the noise leads to the maximum decadal rate being observed in the 1940s in this example

to the true global mean) ranging from ± 25 mm in the year 1880 to a minimum of ± 6 mm in 1988, so the sampling error alone is large enough to explain the observed variability in decadal sea level trends.

From the above analysis it is clear that statements like "the two highest decadal rates of change were recorded in the decades centred on 1980 (5.31 mm/year) and 1939 (4.68 mm/year)" (Holgate 2007) are a discussion of sampling noise, not of a meaningful global-mean signal. The large variations in decadal trends have also been used by Houston and Dean (2011) to question whether the relatively high satellite sea level trend reveals acceleration over the mean twentieth century rate or merely just another decadal peak, as one might at first sight conclude from Fig. 2. However, such a comparison is not valid given that the peaks and troughs in the decadal tide gauge trends are largely an artifact of inadequate spatial sampling, a problem which does not apply to the altimeter data.

The main conclusion of this section is that the sea level data contain short-term (interannual to decadal) noise that is physically unrelated to the climate signal we want to extract from those data. Hence, it will be useful to filter the data with a low-pass filter in order to improve the signal-to-noise ratio in the analysis (as e.g., in (Rahmstorf 2007b).

Alternatively, regression can be performed on sea level H itself rather than on dH/dt, which also effectively filters out short-term noise. This approach naturally exploits the fact that undersampling of regional variability may cause large fluctuations in dH/dt but only much lesser ones in H, because the character of the undersampling is that it causes spurious variability around the true global mean sea level evolution. Both methods, filtering and regression on H, will be tested and discussed below.

4 Analysis method

In the following we will generate a large number of sea level projections using a range of different input data sets and assumptions in the analysis, in order to test how sensitive the projections are to various aspects of the analysis method. We start by producing a whole range of sea level model versions to compute sea level from global temperature, each based on a different fit to past sea level data. We then use only two future global temperature scenarios to drive projections with each model version, since this paper focuses on and isolates the uncertainties inherent in projecting sea level from temperature, rather than the uncertainty in projecting future temperatures from emissions. For a full emissions scenario analysis, these two independent types of uncertainty need to be suitably combined e.g., by adding them in quadrature.

To drive the future projections we primarily chose a medium warming scenario which is characterised by a global temperature rise of 1.8° C between the years 2000 and 2100 and a corresponding sea level rise of ~1 meter during this period. This is based on the RCP 4.5 emissions scenario (Moss et al. 2010), a moderate scenario leading to a radiative forcing of 4.5 W/m² by 2100, which resembles SRES B1 used in the IPCC 4th Assessment Report. As additional test we also used the RCP 8.5 emissions scenario, a high scenario leading to a radiative forcing of >8.5 W/m² by 2100, which resembles SRES A1FI. In both cases we use the best temperature estimate computed using the same model as Meinshausen et al. (2009) and shown in Fig. 4.

Once suitable temperature and sea level data sets were selected, the following analysis steps were performed:

- The temperature time-series is smoothed using the SSAtrend filter of Moore et al. (2005) with 15-year half-width (embedding dimension), to keep only the low-frequency variability. The sea-level time-series is not smoothed.
- A generalized least square (GLS) estimation is then performed on the integral form of Eq. 2. This method accounts for correlation between residuals and therefore yields a better estimate of the model parameters,



Fig. 4 Temperature scenarios, based on the RCP 4.5 and RCP 8.5 emissions scenarios, used in forcing the sea level projections (including a hindcast for 1900–2000, which is shown for illustrative purposes but not analysed further)

especially of their uncertainty, provided that the error covariance matrix (or its structure) is known. For each dataset, an analysis of the residuals is performed to determine an appropriate error model whose parameters are then chosen using a maximum likelihood approach (see details below). For the hindcast, we sample one set of parameters from the full covariance matrix of the model coefficients (obtained by inverting the Hessian matrix of the likelihood function at the maximum), including the error parameters, and make a deterministic temperature-based prediction with added random noise (based on the particular error structure). This operation is repeated 1,000 times to obtain reasonable estimates of the 90% (i.e., 5–95 percentile) envelope.

• For the projections to the year 2100, the same approach is taken but only uncertainty in the model parameters is considered. This is because we are only interested in the change in the mean sea-level, not its interannual variability (for an estimation of which the semi-empirical model is neither designed nor suitable). Note that random variations around the mean projection would add a few centimeters uncertainty, but this effect is less and less significant as large sea level changes are considered, as is the case for projections to the year 2100.

In general, the error can be viewed as the sum of an observational error (inaccurate representation of global mean sea-level from aggregation of tide gauges) and a model error (short-coming of the semi-empirical model to represent global sea-level on a yearly time-scale). While the covariance matrix of the observational error should be provided with the data, the covariance matrix of the model error has to be estimated to best describe the residuals. In practice, the full covariance matrix is available only for the JE08 data (Grinsted et al. 2009). For this dataset the observational error is much larger than the regression residuals, hence we consider only the observational error as representative of the total error (omitting the observational errors' covariance matrix, or considering only uncorrelated variance, decreases the maximum likelihood of the fit). For CW06 and CW11, the observational error is smaller and much more homogeneous in time (because of the improved spatial representation technique and the shorter time span) and its correlation structure is not available. We have therefore constructed a covariance matrix based on the analysis of the residuals only. In both cases, the residuals are consistent with an AR1 process based on a visual analysis of the empirical auto-correlation and partial autocorrelation functions, and AR1 is preferred over an AR2 process based on the Akaike Information Criterion for small samples (AICc) (Akaike 1974)).

The likelihood function depends on the model residuals r and the (estimated or a priori) covariance matrix Σ . For computational reasons, its logarithm is considered:

$$\ln(Lik) = -\frac{1}{2} \left[\ln(|2\pi\Sigma|) + r'\Sigma^{-1}r \right]$$
(3)

where 1.1 and ' represents the determinant and transpose operators, respectively. The residual r is given by $r = Y - X\beta$, with Y the vector of observations, X the matrix of predictors, and β the vector of model parameters from Eq. 2. The covariance matrix Σ describes the multivariate Gaussian law of the residuals, which is parameterized in the case of an AR1 process as $\Sigma(i,j) = \sigma^2 \rho^{|i-j|}$, where σ^2 is the variance, ρ the auto-correlation between residuals, and (i, j) the time indices of the residuals. The maximum likelihood estimate therefore consists in optimizing both the model parameters β and the error parameters σ^2 and ρ . If the covariance matrix is known, the solution is given by the GLS estimator:

$$\beta = (X'\Sigma^{-1}X)^{-1}X'\Sigma^{-1}Y \tag{4}$$

Using Eq. 4, the log-likelihood function (3) can therefore be expressed as a function of the two error parameters σ^2 and ρ only. The solution (β , σ^2 , ρ) was obtained by maximizing the 2-parameter problem in Matlab with the function fmincon using the interior-point algorithm, while updating β at each iteration according to Eq. 4. It was checked that the final solution does not depend on the initial value of σ^2 and ρ —the same global optimum is always found when trying 100 randomly chosen initial values.

Note that very similar results are obtained with an ordinary least-squares fit (OLS), but parameter uncertainty is underestimated due to correlation in the residuals (Fig. 9). Very similar results are also obtained with various

other error models that we tried, and with the uncertainty estimation originally used by Vermeer and Rahmstorf (2009).

In addition to this default approach, several sensitivity tests were performed with respect to smoothing and input data, as described below.

Figures 5 and 6 show the resulting fit for sea level (left column) and for the rate of sea level rise (right column) for the tide gauge data, for the simple (i.e., Eq. 1) and the dual (i.e., Eq. 2) models, respectively. Note that in all cases the rate of sea level rise increases strongly over time superimposed with some multi-decadal variations, and that this evolution correlates well with global temperature. We see that the simple model reproduces the changes in rate of sea level rise on the long time scales, whereas the dual model in addition captures the multi-decadal variability much better, e.g., that seen from 1700 onwards in the JE08 data (bottom panel). The amplitude of the multi-decadal sea level variations in the JE08 data is somewhat larger than what is explained by the temperature variations (grey range), but it is also larger than that in the other sea level reconstructions and could be exaggerated as the reconstruction method does not account for water redistribution between coastal and open ocean areas. Note that the observational errors' covariance matrix provided by Grinsted et al. (2009) attempts to describe the possible deviations between North Atlantic tide-gauges and global mean sea-level in the early part of the record, where data are only available from the North Atlantic. The approximately ± 10 cm found statistically by Grinsted et al. is consistent with the physics-based estimate of Kemp et al. (2011).

Note that when confining the analyses to the period from 1930 onwards, one starts with a relative maximum in the rate of sea level rise and a subsequent decline, so no significant acceleration of sea level rise is found over this period (Houston and Dean 2011). As Fig. 6 shows, this time evolution correlates well with the global temperature evolution with its well-known plateau in the mid-twentieth century. The lack of acceleration during this time interval thus does not call into question the proposed link of sea level rise and global temperature, but rather confirms it, since the semi-empirical models in fact predict a lack of acceleration since 1930 (Rahmstorf and Vermeer 2011).

In addition to the three tide-gauge data sets we also use the proxy data of Kemp et al. (2011). For these, we use the parameter fit for 1000–2000 AD obtained by Bayesian analysis as described in that paper and shown in Fig. 7. For 500–1000 AD, the model fails since warm proxy temperatures then suggest strong sea level rise, while the sea level proxies show a flat sea level. There are three possible explanations for this discrepancy: (i) a bias in the proxy temperatures, (ii) an erroneous trend in the sea level data, and (iii) inadequacy of the model. Regarding option (iii), it

Fig. 5 Fit of the simple model to three tide gauge data sets. Grev curves and ranges show the prediction of Eq. 1 when the GISS global temperature data are used as driver; colored curves the actual sea level data. The grev range shows the uncertainty arising from the parameter fit as a 90% confidence interval (5-95 percentile), while the *dashed* lines represent the full annual uncertainty including the random error. Note that the sea level data shown are adjusted for reservoir storage according to Chao et al. (2008) and for groundwater pumping according to Konikow (2011) (see Sect. 7) to obtain the climatic sea level rise

Fig. 6 Fit of the dual model to three tide gauge data sets. Grey curves and ranges show the prediction of Eq. 2 when the GISS global temperature data are used as driver: colored curves the actual sea level data. The grey range shows the uncertainty arising from the parameter fit as a 90% confidence interval (5-95 percentile), while the dashed lines represent the full annual uncertainty including the random error. Note that the sea level data shown are adjusted for reservoir storage according to Chao et al. (2008) and for groundwater pumping according to Konikow (2011) (see Sect. 7) to obtain the climatic sea level rise



is important to realise that then *any* simple and plausible model linking the rate of sea level rise to temperature changes would fail in this situation: the proxy data show a clear downward step in temperature between 1000 and 1100 AD, with temperatures in the following centuries $\sim 0.2^{\circ}$ C cooler than in the preceding centuries, but the proxy rate of sea level rise remains unchanged. The basic idea that a change in global temperature leads to a change in the rate of sea-level rise would have to be invalid around 1100 AD, although it holds well during the following nine centuries. The right panel of Fig. 7 shows this clearly; note that the model-predicted rate of rise (black curve) there



Fig. 7 Sea level proxy data (*dark green*) and semi-empirical model fit (*black with grey range*) for 500–2000 AD, following Kemp et al. (2011). The base period for the sea-level curve is 1400–1800. The *dashed line* in the data indicate an uncertainty of ± 6 cm, and the grey

closely resembles the temperature proxy curve used. Regarding option (ii), we consider this unlikely since the sealevel error would have to be several times larger than the stated uncertainty of the reconstruction, and none of the other available reconstructions (as shown in Fig. 3 of Kemp et al. (2011)) show such a rise up to the year 1100 AD. Finally, regarding option (i), as shown by Kemp et al. a bias of only 0.2°C would suffice to explain the discrepancy, which is well within the expected overall uncertainty of the temperature reconstruction. An alternative global reconstruction with the CPS method, also presented by Mann et al. (2008), is on average 0.26°C cooler during 500-1000 AD than the reconstruction with the EIV method used here. We used the latter because only it covers land and ocean, whilst the CPS reconstruction is for land only. However, after 1100 AD these two temperature reconstructions agree well and we find it highly unlikely that the discrepancy before 1100 AD is due to a real difference between land and ocean anomalies. In the EIV reconstruction, temperature during 500-1000 AD is 0.19°C warmer than during 1100–1400 AD (this is the cooling step that causes the discrepancy), but in the CPS reconstruction temperature during 500-1000 AD is 0.05°C cooler than during 1100–1400 AD. We cannot think of a mechanism that would simultaneously warm the land but cool the oceans, so we interpret this discrepancy as indicative of uncertainties in the temperature reconstruction before 1100 AD, most likely due to the sparseness of data at this time. Hence, the most likely explanation of the discrepancy before 1000 AD shown in Fig. 7 is too-warm proxy temperatures, and therefore we use only the data of the last millennium to fit the model.

The Bayesian analysis of Kemp et al. (2011) results not in a single parameter set but in an ensemble of models, the projections of which are weighted based on their statistical likelihood. This automatically produces uncertainty ranges for the future projections. However, the average of the Bayesian ensemble (representing our best estimate) can be well described by the single 'illustrative' parameter set $a = a_1 + a_2 = 5.6$ mm/year/°C, b = -48 mm/°C, $T_0 = -0.41$ °C, very close to the values obtained by Vermeer

range for the model fit indicates the 68% uncertainty range, based on a Bayesian analysis. Note that the proxy data only record slow variations

and Rahmstorf (2009) for the CW06 data. (Note that T_0 varies slowly with time in this case, with a characteristic time scale of 520 years, and the number given is the mean for 1880–2000. This variation is mathematically equivalent to the time scale τ introduced by Grinsted et al. (2009) as discussed in the Introduction; for details we refer the reader to Kemp et al. (2011)).

5 Sensitivity to choice of input data

Since the semi-empirical relationship was put forth in 2007 (Rahmstorf 2007b), several new global sea level data sets have been published (Church and White 2011; Jevrejeva et al. 2008; Kemp et al. 2011). We therefore investigate how sensitive projections of sea level rise for the period 2000–2100 are to the choice of input data set. We perform the calibration of the model parameters for each of the four sea level data sets as described in the previous section, with the additional twist that we alternately use the HadCRUT and GISS global temperature data in each of the tide gauge cases. For the proxy data, the two different versions correspond to the standard and a loose Bayesian constraint on the prior. In the standard case the prior distributions of the a and b parameters are taken from Vermeer and Rahmstorf (2009) in order to include tide-gauge information, while in the loose case the prior uncertainty in a and T_0 is enlarged by a factor of 10 (and b, which is ill constrained and confounded with a using only proxy data, is set to zero in the simple model and to the best estimate of VR09 in the dual model), making the fit practically ignorant of the tidegauge data. For comparison with the earlier publication, we also show the projection with the same method as used by Vermeer and Rahmstorf (2009).

All in all we obtain 9 different sea level projections as shown in Fig. 8. These results are also summarised, together with the other sensitivity experiments discussed below, in Fig. 9, and all parameter values and regression diagnostics are provided in Table 1. We find that 7 of these 9 projections are remarkably close together, within ± 10 cm (mean values). This is despite rather different values of *a* and *b* found for the JE08 data as compared to the others. The reason here is the larger range of variability in the JE08 data which gives more weight to the *b*-term. However, this is compensated for in the *a*-term to give approximately the same overall



Fig. 8 Sea level hindcasts and projections driven by the temperature scenario shown in Fig. 4 for different models calibrated with different temperature and sea level data. The *error bars* on the *right* indicate 90% confidence intervals (5–95 percentile, using the GISS temperature dataset); for the proxy-based projection the uncertainty is as presented in Kemp et al. (2011)

Fig. 9 Summary of sea level projections for 2000-2100 for the RCP 4.5 warming scenario and of the best-fit baseline temperature T_0 for all the model versions described in this paper. The 90% uncertainty ranges (5-95 percentile) shown describe the parameter uncertainty for the mean sealevel projections (excluding random short-term variability) as described in the text, except for the VR09 case where the same approach has been taken as in that paper

twentieth century and twentyfirst century rise as in the other data sets. To understand this it should be realised that in case of a temperature rise that is exponential in time, $T \sim dT/dt$ and there is no distinction between the *a*-term and the *b*-term in Eq. 2. The *b*-term thus only measures deviations from a general exponential-type warming, i.e., the multi-decadal temperature variability seen in Fig. 6f. For the future response, the *a*- and *b*-terms can partly cancel to give a similar projection, as long as the warming scenario is approximately of exponential shape. Note that the RCP 4.5 temperature scenario used here (Fig. 4) involves a slowing down of the warming during the last 30 years; it is thus not an exponential rise and therefore distinguishes between the a- and b-terms. Larger differences for different combinations of a and b will arise for more complex temperature scenarios, e.g., those with a peaking and subsequent decline in global temperature. Scenarios with a greater, unmitigated global warming (like RCP 8.5) will be closer to exponential shape and hence less sensitive to this.

The remarkable agreement between these seven projections is due to the very similar values of T_0 obtained in each case. T_0 sets the baseline temperature (here given relative to the mean temperature for 1951–1980) at which sea level is stable. Once this baseline is fixed, the overall observed sea level rise as compared to the overall warming tightly constrain the sensitivity of sea level to temperature and hence the future sea level projection. It is clear that the



Table 1 Parameter values for the semi-empirical model according to the Eqs. 1 and 2, for each of the sensitivity cases explored in Fig. 9

	a (mm/year/°C)	b (mm/°C)	T _o (°C)	σ (mm or mm/year*)	ρ	logLik	AICc
CW06							
Default	5.6 (0.4)	-66 (16)	-0.43(0.05)	5.2	0.49	-76	165
Simple	4.5(0.4)	_	-0.44(0.05)	6.2	0.64	-82	175
VR09	5.6(0.4)	-47(5)	-0.43(0.04)	0.1^{*}	_	_	
OLS	5.6(0.2)	-66(9)	-0.43(0.03)	5.2	_	-93	197
HadCRU temp	5.3(0.6)	-26(19)	-0.40(0.07)	6.4	0.65	-94	200
Smooth 5	5.0(0.4)	-27(13)	-0.42(0.05)	5.6	0.56	-80	173
Smooth 10	5.3(0.4)	-50(15)	-0.43(0.05)	5.3	0.52	-78	168
Smooth adaptive	5.4(0.3)	-52(12)	-0.42(0.04)	5.1	0.47	-75	162
No land-water corr.	4.4(0.5)	-62(19)	-0.48(0.07)	5.7	0.58	-79	172
Chao + Wada	5.1(0.4)	-68(16)	-0.42(0.05)	5.3	0.51	-77	166
Chao only	6.0(0.4)	-64(15)	-0.42(0.04)	5.1	0.48	-75	163
CW11							
Default	3.7(0.4)	-50(15)	-0.59(0.08)	5.4	0.44	-89	191
Simple	2.7(0.3)	_	-0.68(0.07)	5.9	0.55	-94	198
VR09	3.4(0.5)	-40(14)	-0.65(0.11)	0.2^{*}	_	-	-
OLS	3.6(0.2)	-50(9)	-0.59(0.05)	5.4	_	-103	217
HadCRU temp	3.6(0.4)	-39(13)	-0.58(0.09)	5.5	0.47	-89	192
Smooth 5	3.1(0.3)	-22(12)	-0.62(0.09)	5.7	0.50	-92	197
Smooth 10	3.4(0.3)	-38(14)	-0.60(0.08)	5.5	0.47	-90	193
Smooth adaptive	3.5(0.3)	-42(12)	-0.60(0.07)	5.3	0.44	-89	190
No land-water corr.	2.7(0.3)	-39(14)	-0.71(0.12)	5.3	0.42	-88	190
Chao + Wada	3.2(0.3)	-52(14)	-0.60(0.09)	5.3	0.44	-89	190
Chao only	4.1(0.4)	-48(15)	-0.56(0.07)	5.4	0.45	-89	192
JE08							
Default	6.6(0.8)	-98(42)	-0.43(0.10)	-	-	-595	1,198
Simple	5.2(0.6)	_	-0.43(0.07)	-	-	-598	1,202
VR09	5.8(0.9)	-67(40)	-0.47(0.12)	0.7^{*}	-	-	-
OLS	7.3(0.4)	-161(27)	-0.45(0.05)	23.8	-	-692	1,394
HadCRU temp	6.6(0.8)	-94(38)	-0.43(0.10)	-	-	-595	1,198
Smooth 5	5.2(0.7)	9(24)	-0.42(0.09)	-	-	-597	1,203
Smooth 10	5.9(0.8)	-5(34)	-0.42(0.09)	-	-	-597	1,202
Smooth adaptive	6.6(0.8)	-10(34)	-0.42(0.08)	-	-	-593	1,195
No land-water corr.	6.0(0.8)	-97(42)	-0.44(0.11)	-	_	-597	1,201
Chao + Wada	6.3(0.8)	-10(42)	-0.42(0.10)	-	-	-595	1,199
Chao only	6.9(0.8)	-96(42)	-0.43(0.09)	-	_	-595	1,198

The preferred parameter set is shown in bold. T_0 is given relative to the mean temperature for 1951–1980. For Church and White (2006) (CW06) and Church and White (2011) (CW11), there are two additional parameters for the AR1 error model: σ stands for the standard deviation (*indicates units of mm/year, otherwise expressed in mm) and ρ for the auto-correlation parameter. For the Jevrejeva et al. (2008) dataset, the observational error's covariance matrix is used unchanged (without further scaling). The log-likelihood (logLik) values and Akaike Information Criteria for small samples (AICc) are also shown, except for VR09 which uses a different estimation technique (Vermeer and Rahmstorf 2009)

data sets going back further in time, to a period of stable sea level (Jevrejeva et al. 2008; Kemp et al. 2011), are suited best to constrain T_0 , since for the shorter data sets T_0 is an extrapolated value outside the actual data range.

A notably lower estimate of T_0 is the main reason for the lower projections resulting from the CW11 data. A lower T_0 implies a smaller *a* and lesser modern acceleration of sea level rise compared to the other three data sets.

We argue that the projections based on the CW11 data are less plausible than the others. When comparing only the CW11 data with the older CW06 data, we note that the differences between them are not statistically significant given the reconstruction uncertainty (according to Church and White (2011)). However, the agreement of CW06 with the two longer data sets, in particular with respect to the value of T_0 constrained well by the latter (Fig. 9), makes the fit to CW06 more plausible. In addition the dual model fit is better for CW06 than for CW11 (especially for the last four decades, Fig. 6), with much smaller residuals. The statistical analysis performed in Vermeer and Rahmstorf (2009) suggests this is significant and very unlikely to be just a chance agreement.

6 Sensitivity to data smoothing

For the simple model Eq. 1, the best-fitting parameters found are only minimally affected by smoothing. Using the unsmoothed raw data in the integral form of Eq. 1, the parameter values (a, T_0) of (3.5 mm/year/°C, -0.49°C) are obtained, as compared to (3.4 mm/year/°C, -0.50°C) reported by R07 (without reservoir storage correction).

For the dual model there is a more significant parameter dependence on smoothing, because the *b*-term is a fastresponse term which will be fitted increasingly to shortterm variability if that is included in the analysis. This in turn affects also the value of a, due to the trade-off between a and b discussed earlier. Rahmstorf (2007b) and Vermeer and Rahmstorf (2009) used the SSAtrend filter with an 'embedding dimension' of 15 years (the 'embedding dimension' of the filter corresponds to its half-width) to smooth both temperature and sea level data. Rather than filtering the sea level data, in this paper we use an alternative as the default procedure, namely obtaining the parameters from the best fit to the sea level curve itself, rather than the rate of rise. The sea level curve is of course the primary quantity we are interested in, and it is also the quantity that is measured. It is inherently less noisy than the rate of rise. Using this procedure is simpler and requires no prior filtering of sea level data (the predictand) but only the temperature data (the predictor), as is common in statistical models.

Figure 10 shows the dependence of the model fit on this filter time scale. We consider the low smoothing values (<10 years half-width) as unrealistic, since the *b*-term is then fitted largely to short-term noise for which global temperature and sea level do not correlate (hence *b* goes to zero). High values (>20 years half-width) on the other hand start to smooth away important parts of the signal, considering that the major part of anthropogenic warming only started around 1980.

As may be expected, we find some compensating changes in a and b but practically no variation in T_0 , the model parameter that is measurable and has a direct physical meaning. For all filter widths, the sea level

projections for 2100 remain within ± 4 cm. We also tried the adaptive smoother of Mann (2004), which gives very similar results as the SSAtrend filter (Fig. 9).

7 Reservoir storage and groundwater pumping

Not all sea level changes are related to current climate changes. There are also solid-earth processes causing global-mean sea level change. In the modern era this effect is estimated as a downward trend of -0.3 mm/year due to an enlargement of the global ocean basins associated with glacial isostatic adjustment (GIA). This term is routinely subtracted from sea level data in order to obtain the "GIA-adjusted" sea level, which thus shows a slightly larger rise. This is a minor issue for semi-empirical projections since it is a small constant trend, so it does not affect estimates of the sea level sensitivity *a*, which only depend on *changes* in the trend. When using tide gauge data, local land movement at the sites of the gauges also needs to be corrected for.

Another non-climatic effect is sea level change due to direct anthropogenic changes in water storage on land. Both the building of artificial reservoirs (which lowers sea level) and the pumping of groundwater for irrigation purposes (which raises sea level) are time-varying contributions to sea level change which need to be removed from the data in order to isolate the climate-related sea level rise.

Fig. 10 Dependence of the model fit and projections on the halfwidth of the filter used to smooth the global temperature data. Note that sea level data are not smoothed at all in the 'default' case

Vermeer and Rahmstorf (2009) removed the reservoir storage effect as estimated by Chao et al. (2008), and they performed a sensitivity analysis for groundwater pumping since no time-dependent estimate for this was available at the time. In the meantime, two estimates of groundwater pumping have been put forth by Wada et al. (2010) and Konikow (2011), although the time series do not cover our full data period. To extend the range, we use the conclusion of Shiklomanov and Rodda (2003) that groundwater extraction for irrigation purposes approximately increases in proportion to global population. We fit the Wada et al. (2010) and Konikow (2011) groundwater extraction data to the global population curve and use these fits to estimate groundwater extraction both for the past and the future (Fig. 11). In the case labelled 'default' in Figs. 9 and 12 and Table 1, the sea level data were adjusted on the basis of the Chao et al. (2008) and Konikow (2011) data.

Including groundwater pumping has only a small influence on sea level projections (see Fig. 9), in agreement with the conclusions from the sensitivity study of Vermeer and Rahmstorf (2009). The reason for this is that it is not just the magnitude which counts, but also how well it correlates with temperature in the past. Even a large sea level contribution that correlates poorly with temperature will not strongly affect our estimate of the sea level sensitivity to temperature changes. The dam building correction, in contrast, coincides with late-twentieth century

Fig. 11 The groundwater pumping scenarios used in this study. It is assumed that the amount of groundwater pumping is proportional to the world population. The constant of proportionality is chosen to fit the data (*dots*) of Wada et al. (2010) and Konikow (2011), with for the latter case the additional constraint that the groundwater depletion is zero in 1850. The *dashed line* shows the extrapolation toward the future for groundwater extraction, based on the central UN population scenario. Dam building is assumed to have a negligible effect on future sea level. (The integral of the *blue curve* up to the present corresponds to ~3 cm of sea level.)

warming and has therefore a larger impact on the parameter estimation and the projections. Also, future groundwater extraction adds up to 10 cm to sea-level rise by 2100 (if Wada et al.'s (2010) large present-day estimation is correct); so the ongoing and growing groundwater mining automatically compensates some of the lowering impact of this correction term on the projections. Our assumption of groundwater mining increasing in proportion with the central UN population scenario is probably conservative, as the use of irrigation in agriculture could increase even more due to increasing affluence, increasing drought problems due to climate change and increased bio-energy production.

8 A scenario with greater warming

We repeated the projections with a temperature scenario based on the RCP 8.5 emissions scenario, to test the projection robustness under greater warming. Figure 12 shows a summary diagram that can be compared to Fig. 9. The projections are naturally higher, but the general pattern is similar. For the CW06 data, the projections remain within ± 8 cm (mean values) except for the case without any landwater correction. For the JE08 data the spread is somewhat larger, the sensitivity to land-water storage smaller, but overall the numbers are similar to those obtained with the CW06 data. The projections with the CW11 data are again significantly lower than the others. This difference is amplified for greater warming, since the sea level sensitivity to warming is found to be less from the CW11 data, as discussed above.

9 Simple estimates with reduced data input

As a simple back-of-envelope estimate of the sea level sensitivity *a*, we can use the Kemp et al. proxy data solely exploiting the fact that sea level was nearly stable during 1400–1800 AD, in combination with the twentieth century rate of rise. The global-mean temperature difference between these two time periods is $(T-T_0) = 0.32^{\circ}$ C (Mann et al. 2008), whilst the rate of sea level rise for 1900–2000 from tide gauge data is 1.7 ± 0.5 mm/year (IPCC 2007). From Eq. 1 this yields a sea level sensitivity *a* of 5.3 ± 1.6 mm/year/°C. With this, our RCP 4.5 temperature curve gives a sea level rise of 97 ± 29 cm for 2000–2100.

Alternatively we can use the recent rate of rise for 1993–2010 as determined by satellite altimeter data. The global-mean temperature difference between 1993 and 2010 versus 1400–1800 is $(T-T_0) = 0.79^{\circ}$ C (Mann et al. 2008), whilst the rate of sea level rise for 1993–2010 in the altimeter data is 3.2 ± 0.4 mm/year (Church and White 2011). From Eq. 1 this yields a sea level sensitivity of

Fig. 12 Summary of sea level projections for 2000–2100 for the RCP 8.5 warming scenario. The 90% uncertainty ranges (5–95 percentile) shown describe the parameter uncertainty for the mean sealevel projections (excluding random short-term variability) as described in the text, except for the VR09 case where the same approach has been taken as in that paper

 $a = 4.1 \pm 0.5$ mm/year/°C. With this, our temperature curve gives a sea level rise of 77 ± 9 cm for 2000–2100. Note that this estimate does not use any tide gauge data, nor does it use quantitative results from the sea level proxies—it only uses the qualitative finding of stable sea level from 1400 to 1800. Yet the projected numbers are consistent with those derived from the tide gauge data.

Some further tests illustrating the robustness of the method (using only half of the tide gauge data, as well as detrended data) were shown by (Rahmstorf 2007a).

10 Will the relationship hold in future?

Even though projections of future sea level rise with the semi-empirical method give robust results with respect to the choice of input data and analysis details, the question remains how well the empirical link between temperature and sea level found for the past will continue to hold in future. Two caveats have been discussed already in Rahmstorf (2007b) as well as in subsequent publications: (i) loss of glaciers may mean that this source of meltwater will be diminished in future, and (ii) a non-linear response of ice sheets may arise which is not captured during the calibration period of the method. The former might tend to make semi-empirical projections an overestimate while the latter would likely (but not necessarily) tend to make them an underestimate of the true future sea level rise.

Regarding the question of glaciers running out of ice, it has to be borne in mind that the empirical method does not treat mountain glaciers separately from ice sheets but considers all ice as a continuum. This continuum view is justified if we consider the extent of continental ice (i.e., its surface area, where melting may occur), as a function of annual air temperature at the location of the ice (Fig. 13). As temperatures rise, ice is lost at the warm end of this continuum. But as mountain glaciers dwindle, more and more ice of the big ice sheets gets subject to melting, gradually shifting the meltwater contribution from the small glaciers to the bigger ice sheets as it gets warmer.

At a given global-mean temperature, there is a roughly wedge-shaped (in the temperature vs. ice area graph) amount of ice that is subject to melting (highlighted in red in the graph). As the Earth and hence the temperature of the ice surfaces warms, this "wedge" is pushed towards the right into ever warmer temperatures. If we assume that melting rates per square meter of ice surface increase linearly with temperature (according to the widely-used "positive degree days" concept), and if ice did not disappear at the warm end of the wedge, integrated melting rates would not go up linearly with temperature but rather quadratically, as is readily derived. This is because both the amount of ice subject to melting and the melting rate at a given ice surface are increasing. On the other hand, if we assume that glacier retreat at the warm end keeps pace with warming, so that the tip of the wedge remains at the same temperature and the wedge merely gets steeper as ice gets pushed in from the left, the relation becomes linear again. Thus, the linear assumption in the semi-empirical formulas already accounts for glaciers retreating in step with

Fig. 13 Schematic histogram of synthermous continental ice surfaces, sorted by annual mean surface air temperature at the location of the ice. Note that melting can start at -20 to -15° C annual temperature, due to the daily and seasonal cycles and weather variability. A triangular "wedge" of ice surfaces (*red*) protrudes from about -15° C into warmer temperatures, which is not just made up of glaciers but at the colder end of increasing amounts of ice from Greenland and Antarctica. (Based on SeaRISE data provided by R. Winkelmann and A. Robinson and glacier inventory data provided by V. Radic (Radic and Hock 2010))

warming. Hence, we do not expect that glacier loss would cause first-order deviations from the semi-empirical projections.

Regarding the two major ice sheets in Greenland and Antarctica, (Rignot et al. 2011) found that the rate of sea level rise from these two sources has been increasing approximately linearly from 1992 to 2010 while global temperature has also been increasing linearly. Formally, this is consistent with the semi-empirical projections, since the total sea level rise in Eqs. 1, 2 can be split into components, each having their own value of *a*, *b* and T_0 denoted as a_i , b_i and $T_{0,i}$ for each component *i*. The total rate of rise will in this case still be of the form of Eqs. 1,2, with the sea level sensitivity $a = \sum a_i, aT_0 = \sum a_i T_{0,i}$ and $b = \sum b_i$. However, note that the semi-empirical model only requires that the sum of sea level rise follows Eq. 1 or 2, not that this necessarily applies to each component separately.

By extrapolating the observed linear increase in mass loss into the future, Rignot et al. estimated an ice sheet contribution of 15 cm and a total sea level rise of 32 cm during 2010–2050, right on top of the best estimate of Vermeer and Rahmstorf (2009) for the same period. Hence, at least until 2010 the observed ice sheet mass loss is fully consistent with the semi-empirical projections and shows no sign of an important non-linearity in its response to warming.

The semi-empirical approach could also reach its limits if in the future the regional patterns of warming start to deviate significantly from those seen in the past. IPCC projections to a reasonable approximation show stable patterns which are just scaled up in amplitude as the warming proceeds, but nonlinear phenomena (like a large change in thermohaline ocean circulation) could cause deviations.

To summarize this section: whilst we cannot be certain how well the semi-empirical approximation will continue to hold up in the future, we feel it represents a reasonable firstcut approximation. We also have no way of knowing at this point whether the semi-empirical projections are more likely to be an under- or an over-estimate of the true future sea level rise. It is thus vital to strengthen ongoing efforts to observe, physically understand and model ice sheet changes.

11 Conclusions

For the 1.8°C future global warming scenario considered here (corresponding to the moderate RCP 4.5 emissions scenario), a sea level rise over the period 2000–2100 of ~ 1 meter is obtained. Only two factors lead to deviations from this in excess of 20%:

- Disregarding the correction for water storage in artificial reservoirs lowers the projections by ~ 25 cm. However, we consider this an unphysical option. Although the exact magnitude of the correction may be debated, there is no question that it is a real effect that must be accounted for. We have shown that the effect of reservoir storage is by no means compensated by the effect of groundwater pumping.
- Using the CW11 data lowers the projections by ~ 30 cm as compared to the other three data sets. We find the results using the other three data sets more plausible, due to the high agreement between them, their better correlation to temperature data and the better constraint of T_0 from the longer data series.

Similar conclusions can be drawn from a test with a scenario of greater warming and sea-level rise, where again it is the issue of water storage and the CW11 data which cause substantial deviations from otherwise consistent projections.

Our preferred estimate is the one with the 'default' procedure based on the GISS temperature and CW06 sealevel data, with a = 5.6 mm/year/°C, b = -66 mm/°C and $T_0 = -0.43$ °C. This model version includes adjustments both for the reservoir storage and the most recent estimate of groundwater pumping, and it gives the best fit over the calibration period. The CW06 data are preferred over the CW11 data not only for their better fit but also in view of the tight constraint on T_0 provided by the proxy data, which is consistent with the CW06 results but not with the CW11 results. By coincidence, as the various differences in the analysis compensate, this preferred model is almost identical to the Vermeer and Rahmstorf (2009) model. Overall, we find that the semi-empirical method leads to robust future projections of sea level rise, regardless of the particular choices made in the analysis. However, since there is no guarantee that empirical connections found for the past continue to hold up in future, efforts to better understand and model the physical mechanisms leading to sea level rise are vital.

Acknowledgment We thank Katja Frieler, Jonathan Rougier and two anonymous reviewers for their helpful comments and discussions regarding this paper, and to Aslak Grinsted for providing the error covariance matrix for the JE08 data.

References

- Akaike H (1974) New look at statistical-model identification. IEEE Trans Automat Contr AC19(6):716–723
- Cazenave A, Nerem RS (2004) Present-day sea level change: observations and causes. Rev Geophys 42:20
- Chao BF, Wu YH, Li YS (2008) Impact of artificial reservoir water impoundment on global sea level. Science 320:212–214
- Christiansen B, Schmith T, Theill P (2010) A surrogate ensemble study of sea level reconstructions. J Clim 23(16):4306–4326. doi:10.1175/2010jcli3014.1
- Church JA, White NJ (2006) A 20th century acceleration in global sea-level rise. Geophys Res Let 33(1):L01602. doi:10.1029/ 2005GL024826
- Church JA, White NJ (2011) Sea level rise from the late 19th to the early 21st century. Surv Geophys. doi:10.1007/s10712-011-9119-1
- Gornitz V, Lebedeff S (1987) Global sea-level changes during the past century. In: Pilkey O, Howard J (eds) Sea-level fluctuation and coastal evolution. The Society for Sedimentary Geology, Tulsa, p 316
- Grinsted A, Moore JC, Jevrejeva S (2009) Reconstructing sea level from paleo and projected temperatures 200 to 2100 AD. Clim Dyn 34:461–472. doi:10.1007/s00382-008-0507-2
- Holgate S (2007) On the decadal rates of sea level change during the twentieth century. Geophys Res Lett 34:L01602
- Holgate SJ, Woodworth PL (2004) Evidence for enhanced coastal sea level rise during the 1990. Geophys Res Lett 31:L07305
- Horton R, Herweijer C, Rosenzweig C, Liu JP, Gornitz V, Ruane AC (2008) Sea level rise projections for current generation CGCMs based on the semi-empirical method. Geophys Res Let 35 (2):L02715. doi:10.1029/2007gl032486
- Houston J, Dean R (2011) Sea-level acceleration based on US tide gauges and extensions of previous global-gauge analysis. J Coast Res 27(3):409–417
- IPCC (2007) Climate change 2007: the physical science basis. In: Solomon S, Qin D, Manning M et al (eds) The fourth assessment report of the intergovernmental panel on climate change. Cambridge University Press, Cambridge
- Jevrejeva S Moore JC, Grinsted A, Woodworth PL (2008) Recent global sea level acceleration started over 200 years ago? Geophys Res Let 35(8):L08715. doi:10.1029/2008gl033611
- Jevrejeva S, Grinsted A, Moore JC, Holgate S (2006) Nonlinear trends and multiyear cycles in sea level records. J Geophys Res 111:C09012. doi:10.1029/2005JC003229
- Jevrejeva S, Grinsted A, Moore JC (2009) Anthropogenic forcing dominates sea level rise since 1850. Geophys Res Lett 36:L20706. doi:10.1029/2009GL040216
- Kemp A, Horton B, Donnelly J, Mann ME, Vermeer M, Rahmstorf S (2011) Climate related sea-level variations over the past two

millennia. Proc Natl Acad Sci USA. doi:10.1073/pnas.10156 19108

- Konikow LF (2011) Contribution of global groundwater depletion since 1900 to sea-level rise. Geophys Res Lett 38:5. doi: L1740110.1029/2011gl048604
- Mann ME (2004) On smoothing potentially non-stationary climate time series. Geophys Res Let 31 (7):L07214. doi:10.1029/2004 GL019569
- Mann ME, Zhang ZH, Hughes MK, Bradley RS, Miller SK, Rutherford S, Ni FB (2008) Proxy-based reconstructions of hemispheric and global surface temperature variations over the past two millennia. Proc Natl Acad Sci USA 105(36):13252–13257. doi:10.1073/pnas.0805721105
- Meinshausen M, Meinshausen N, Hare W, Raper SCB, Frieler K, Knutti R, Frame D, Allen MR (2009) Greenhouse-gas emission targets for limiting global warming to 2°C. Nature 458:1158– 1163
- Montoya M, Crowley TJ, Hv Storch (1998) Temperatures at the last interglacial simulated by a coupled ocean-atmosphere climate model. Paleoceanography 13:170–177. doi:10.1029/97PA02550
- Moore JC, Grinsted A, Jevrejeva S (2005) New tools for analyzing time series relationships and trends. Eos 86(24):226–232
- Moss RH, Edmonds JA, Hibbard KA, Manning MR, Rose SK, van Vuuren DP, Carter TR, Emori S, Kainuma M, Kram T, Meehl GA, Mitchell JFB, Nakicenovic N, Riahi K, Smith SJ, Stouffer RJ, Thomson AM, Weyant JP, Wilbanks TJ (2010) The next generation of scenarios for climate change research and assessment. Nature 463(7282):747–756. doi:10.1038/nature08823
- Overpeck JT, Otto-Bliesner BL, Miller GH, Muhs DR, Alley RB, Kiehl JT (2006) Paleoclimatic evidence for future ice-sheet instability and rapid sea-level rise. Science 311(5768):1747–1750. doi:10.1126/science.1115159
- Prandi P, Cazenave A, Becker M (2009) Is coastal mean sea level rising faster than the global mean? A comparison between tide gauges and satellite altimetry over 1993–2007. Geophys Res Lett 36:L05602. doi:10.1029/2008gl036564
- Radic V, Hock R (2010) Regional and global volumes of glaciers derived from statistical upscaling of glacier inventory data.J Geophys Res Earth Surf 115:F01010. doi:10.1029/2009 jf001373
- Rahmstorf S (2007a) Response to comments on "A semi-empirical approach to projecting future sea-level rise". Science 317 (5846). doi:10.1126/science.1141283
- Rahmstorf S (2007b) A semi-empirical approach to projecting future sea-level rise. Science 315(5810):368–370
- Rahmstorf S, Vermeer M (2011) Discussion of: Houston, J.R. and Dean, R.G., 2011. Sea-level acceleration based on U.S. tide gauges and extensions of previous global-gauge analyses. J Coast Res 27:784–787
- Rahmstorf S, Cazenave A, Church JA, Hansen JE, Keeling RF, Parker DE, Somerville CJ (2007) Recent climate observations compared to projections. Science 316:709
- Rignot E, Velicogna I, van den Broeke MR, Monaghan A, Lenaerts J (2011) Acceleration of the contribution of the Greenland and Antarctic ice sheets to sea level rise. Geophys Res Lett 38:L05503. doi:10.1029/2011gl046583
- Shiklomanov AI, Rodda J (2003) World water resources at the beginning of the 21st century. Cambridge University Press, Cambridge
- Trupin A, Wahr J (1990) Spectroscopic analysis of global tidal gauge sea level data. Geophys J Int 100:441–453
- Vermeer M, Rahmstorf S (2009) Global sea level linked to global temperature. Proc Natl Acad Sci USA 106:21527–21532
- Wada Y, van Beek LPH, van Kempen CM, Reckman J, Vasak S, Bierkens MFP (2010) Global depletion of groundwater resources. Geophys Res Lett 37:L20402. doi:10.1029/2010 gl044571