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Efficient Basin Scale Filtering of GRACE Satellite Products

M. Khaki^{a,1}, E. Forootan^b, M. Kuhn^a, J. Awange^a, L. Longuevergne^c, Y. Wada^{d,e,f,g}

^a*Department of Spatial Sciences, Curtin University, Perth, Australia.*

^b*School of Earth and Ocean Sciences, Cardiff University, Cardiff, UK.*

^c*CNRS Goscience Rennes, Universit de Rennes 1, Rennes, France.*

^d*Department of Physical Geography, Faculty of Geosciences, Utrecht University, Utrecht, The Netherlands.*

^e*NASA Goddard Institute for Space Studies, 2880 Broadway, New York, NY 10025, USA.*

^f*Center for Climate Systems Research, Columbia University, 2880 Broadway, New York, NY 10025, USA.*

^g*International Institute for Applied Systems Analysis, Laxenburg, Austria.*

Abstract

1 The Gravity Recovery And Climate Experiment (GRACE) satellite mission provides time-
2 variable gravity fields that are commonly used to study regional and global terrestrial total
3 water storage (TWS) changes. These estimates are superimposed by different error sources
4 such as the north-south stripes in the spatial domain and spectral/spatial leakage errors, which
5 should be reduced before use in hydrological applications. Although different filtering methods
6 have been developed to mitigate these errors, their performances are known to vary between
7 regions. In this study, a Kernel Fourier Integration (KeFIn) filter is proposed, which can sig-
8 nificantly decrease leakage errors over (small) river basins through a two-step post-processing
9 algorithm. The first step mitigates the measurement noise and the aliasing of unmodelled
10 high-frequency mass variations, and the second step contains an efficient kernel to decrease the
11 leakage errors. To evaluate its performance, the KeFIn filter is compared with commonly used
12 filters based on (i) basin/gridded scaling factors and (ii) ordinary basin averaging kernels. Two
13 test scenarios are considered that include synthetic data with properties similar to GRACE
14 TWS estimates within 43 globally distributed river basins of various sizes and application of
15 the filters on real GRACE data. The KeFIn filter is assessed against water flux observations
16 through the water balance equations as well as in-situ measurements. Results of both tests
17 indicate a remarkable improvement after applying the KeFIn filter with leakage errors reduced
18 in 34 out of the 43 assessed river basins and an average improvement of about 23.38% in leakage
19 error reduction compared to other filters applied in this study.

20

1. Introduction

21 Since 2002, the Gravity Recovery And Climate Experiment (GRACE) satellite mission
22 has been providing time-variable global gravity field solutions (Tapley et al., 2004). These
23 variations are primarily caused by temporal changes in the gravity field due to changes in
24 hydrology, ice masses of the cryosphere, or surface deformation, e.g., glacial isostatic adjustment
25 (GIA). Within a temporal and spatial resolution of respectively one day to one month and a
26 few hundred kilometers, GRACE products have proved to be very useful for various geophysical
27 and hydrological studies (see, e.g., Kusche et al., 2012; Wouters et al., 2014, for applications).
28 In particular, the so-called level 2 (L2) time-variable gravity fields are widely used to quantify
29 global (e.g., Rodell et al., 2004; Eicker et al., 2016; Kusche et al., 2016) and regional (e.g.,
30 Chen et al., 2009; Awange et al., 2014; Munier et al., 2014; Khaki et al., 2017a,b) terrestrial
31 total water storage (TWS) changes, i.e., the sum of changes in surface and sub-surface water
32 storage compartments. GRACE products are also applied to estimate changes of the terrestrial
33 water cycle (e.g., Ogawa et al., 2011; Eicker et al., 2016) or to validate the water cycle in
34 atmospheric reanalyses (e.g., Springer et al., 2014; Kusche et al., 2016; Forootan et al., 2017).
35 Combined with information observed from other monitoring techniques (e.g., GPS and satellite
36 altimetry) or simulations by land surface models, L2 products are applied to estimate surface
37 (e.g., lakes and rivers) and subsurface (e.g., soil moisture and groundwater) storage changes at
38 (river) basin scales (e.g., Syed et al., 2005; Longuevergne et al., 2010; Famiglietti et al., 2013;
39 Forootan et al., 2014b).

40 GRACE L2 products are provided in terms of potential spherical harmonic coefficients,
41 e.g., up to degree and order 60 or 90, which mainly represent the large- to medium-scale (e.g.,
42 few hundred km) time-variable gravity changes. However, the L2 potential coefficients contain
43 different types of errors. A part of these errors is related to colored/correlated noise due to the
44 anisotropic spatial sampling of the mission, instrumental noise (K-band ranging system, GPS,
45 and the accelerometer observations and star cameras), and temporal aliasing caused by the
46 incomplete reduction of short-term mass variations by models (Forootan et al., 2013, 2014a;
47 Dobslaw et al., 2016). These errors are manifested as north-south striping patterns in the
48 spatial domain (e.g., gridded TWS products). The application of smoothing techniques with

49 the primary aim of removing the stripes can lead to spatial leakages. The spatial averaging
50 introduced by the smoothing kernels such as the Gaussian Kernel in [Jekeli \(1981\)](#) or non-
51 Gaussian Kernels in [Kusche \(2007\)](#), results in spatial interference of mass anomalies. These
52 leakage errors do not allow for perfect separation of gravity anomalies, e.g., between land and
53 oceans, and limit the detection of small-scale hydrological signals. The accuracy of GRACE
54 TWS estimation is very important for hydrological applications especially at the basin scale,
55 e.g., to interpret redistribution of water storage or to indicate drought and flood patterns (e.g.,
56 [Yeh et al., 2006](#); [Longuevergne et al., 2010](#); [Awange et al., 2016](#)). Therefore, better post-
57 processing of GRACE data must be applied to improve consistencies between various types of
58 products that are usually used for studying the water cycle (e.g., [Eicker et al., 2016](#)).

59 Different filtering methods have been proposed to reduce north-south striping errors, such
60 as the isotropic Gaussian filter ([Jekeli, 1981](#)) and anisotropic filters (e.g., [Swenson and Wahr,](#)
61 [2006](#); [Kusche, 2007](#); [Klees et al., 2008](#)). A comprehensive review on filtering techniques has
62 been done e.g., by [Frappart et al. \(2016\)](#). The isotropic Gaussian filter [Jekeli \(1981\)](#) is a
63 degree-dependent filter in the spectral domain and bell-shaped filter in the spatial domain.
64 Anisotropic filters, on the other hand, are introduced to deal with the correlated errors between
65 the coefficients of L2 products (e.g., different marginal shapes in the north-south and the east-
66 west directions). In general, filtering techniques that spatially smooth the L2 signal contents
67 (e.g., [Wahr et al., 2006](#); [Kusche et al., 2009](#)) down-weight L2's higher degree and order potential
68 coefficients. Although these filters reduce noises, their main problem is that they also attenuate
69 the signals. In addition, the application of filtering moves gravity anomalies from one region to
70 another region. Generally speaking, after applying a smoothing kernel some parts of the signals
71 inside an area of interest leak out from it or alternatively signals from outside leak into the
72 area of interest (e.g., [Chen et al., 2007](#); [Baur et al., 2009](#)). These issues become more critical
73 for basin-scale studies, especially where the sizes of the basins are small in comparison to the
74 spatial resolution of GRACE (e.g., [Yeh et al., 2006](#); [Longuevergne et al., 2010](#)).

75 Several methods have been put forward to mitigate spatial leakage effects in TWS estima-
76 tions from L2 products. These methods can largely be categorised into the following three
77 groups (i) those that numerically estimate the leakages (leakage in and out) using the averaging
78 kernels (e.g., [Seo and Wilson, 2005](#); [Baur et al., 2009](#); [Longuevergne et al., 2010](#)), (ii) those
79 that are based on scaling factors derived from synthetic data (e.g., [Landerer and Swenson,](#)

80 [2012](#); [Long et al., 2015](#)), and (iii) those that use inversion for simultaneous signal separation
81 and leakage reduction (e.g., [Wouters et al., 2007](#); [Frappart et al., 2011](#); [Froootan et al., 2014b](#);
82 [Frappart et al., 2016](#)). From the first group, [Swenson and Wahr \(2002\)](#) developed an isotropic
83 kernel using a Lagrange multiplier filter to best balance signal and leakage errors over a basin of
84 interest. A non-isotropic Gaussian filter proposed by [Han et al. \(2005\)](#) to improve spatial resolu-
85 tion during the filtering process also belongs to this group. In another effort, [Harig and Simons](#)
86 [\(2015\)](#) used Slepian-function analysis to decrease leakage effects in Antarctica by maximizing
87 signal energy concentration within the area of interest. The second category uses synthetic
88 data, e.g., from land surface models (LSMs) or hydrological fluxes to derive scaling factors that
89 can be multiplied by GRACE filtered products to recover the lost signals. In this approach,
90 efforts are focused on the application of the same filtering techniques to the synthetic data
91 (that is close enough to the signal contents of GRACE products). Basin-averaged or gridded
92 scale factors are usually estimated as the solution of a least squares adjustment that compares
93 data before and after application of the filter. [Landerer and Swenson \(2012\)](#) estimated gridded
94 scaling factors for GRACE TWS anomalies to restore the signals lost after applying a regular
95 smoothing filter (a Gaussian smoothing kernel). A similar study that uses a different spatial
96 scale (basin averages) has been performed by [Long et al. \(2015\)](#) who estimated scale factors
97 using a global hydrological model over the Yangtze River Basin in China. A possible drawback
98 of this approach is its dependency on the reliability of the hydrological model used to estimate
99 the desired scale factors. The inversion techniques in (iii) also require a prior information about
100 mass changes within different storage compartments. The dependency of final signal separation
101 results on these information has not been reported yet.

102 To address the above problems arising from the application of filtering methods, the present
103 study proposes a new filtering method, Kernel Fourier Integration (KeFIn), which is designed
104 to reduce both types of above-mentioned errors using a two-step algorithm. In the first step,
105 the advantages of image processing techniques such as motion filters (e.g., [Hichri et al., 2012](#);
106 [Zhang et al., 2009](#)) are exploited to reduce the measurement noise and aliasing of unmodelled
107 high-frequency mass variations. This attempt is designed to keep as much of the higher fre-
108 quency information as possible. It should be mentioned here that, although the proposed KeFIn
109 filter has less effect on high-frequency signals compared to the existing methods, some signal
110 inferences still exist mainly due to the truncation of degree and order in L2 products. In the
111 second step of the KeFIn filter, the leakage problem is mitigated using an anisotropic kernel to

112 isolate the signals in the basin of interest. The main idea of this step is to combine the Fourier
113 transform and basin kernel functions to increase the strength of the attenuated signals. It will
114 be shown in the following that the KeFIn filter is suited to deal with basins of various shapes
115 and sizes.

116 The primary objectives of this study is developing a filter for (i) dealing with colored/correlated
117 noise of high-frequency mass variations (i.e., stripes); and (ii) reducing basin scale spatial leak-
118 age errors for hydrological applications. These objectives are addressed by introducing novel
119 methodologies discussed in Section 3.1.1 and 3.1.2, respectively. The performance of the intro-
120 duced filtering method (KeFIn) in terms of leakage reduction is compared with commonly used
121 methods that deal with leakage problem from the basin averaging kernel and the model-based
122 scaling factor groups. For this purpose, both real and synthetic data sets are employed. The
123 purpose of using synthetic data is to provide a more accurate evaluation of the newly proposed
124 method in comparison to existing methods (e.g., Seo and Wilson, 2005; Chen et al., 2009).
125 Therefore, we generate synthetic data in 43 globally distributed basins and use them to exam-
126 ine the performance of the proposed KeFIn and other commonly used filters. These filters are
127 further assessed using water flux observations in the context of the water balance equation (see
128 Equation 1 in Section 2.3), as well as by comparisons with in-situ measurements.

129 2. Data

130 2.1. GRACE

131 Monthly GRACE L2 products along with their full error information are computed at the
132 Technical University of Graz known as the ITSG-Grace2014 gravity field models (Mayer-Gürr
133 et al., 2014). We use these products and their full covariance errors up to degree and order 60
134 covering the period 2002–2013 ([https://www.tugraz.at/institute/ifg/downloads/gravity-field-
135 models/itsg-grace2014](https://www.tugraz.at/institute/ifg/downloads/gravity-field-models/itsg-grace2014)). Degree 1 coefficients are replaced with those estimated by Swenson et
136 al. (2008) to account for the movement of the Earth’s centre of mass. Degree 2 and order 0 (C20)
137 coefficients are replaced by those from Satellite Laser Ranging solutions owing to unquantified
138 large uncertainties in this term (e.g., Chen et al., 2007). We also account for the post glacial
139 rebound by incorporating the corrections provided by Geruo et al. (2013). The L2 gravity
140 fields are then converted to $1^\circ \times 1^\circ$ TWS fields following the approach of Wahr et al. (1998).

141 To evaluate the filtering techniques, no smoothing filter is applied at this stage on GRACE L2
142 products.

143 2.2. Synthetic data

144 In order to assess the efficiency of different filtering methods considered in this study, they
145 are applied on synthetic data whose advantage is the possibility to unambiguously estimate
146 leakage errors since the applied post-processing techniques must replicate the synthetic input
147 data. For this purpose, the world's 43 major river basins with diverse sizes and shapes located
148 at different places around the Earth are chosen (see Figure 1). A large number of signifi-
149 cantly different basins helps us to properly investigate the efficiency and reliability of the newly
150 proposed KeFIn filter.

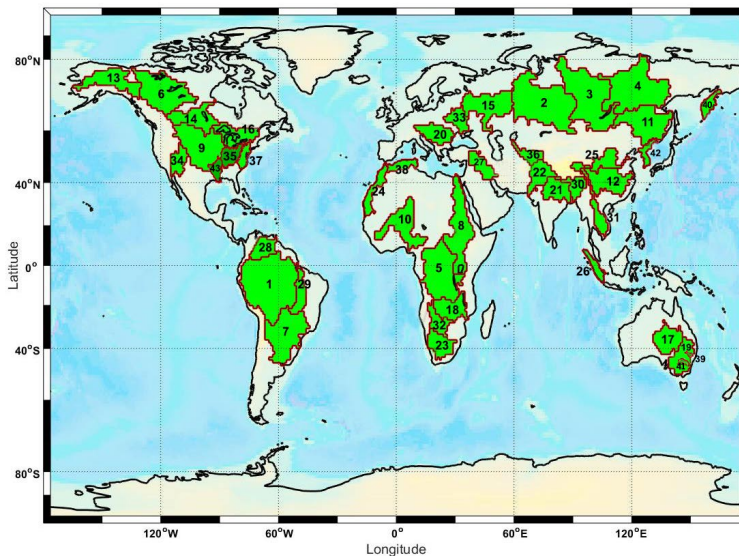


Figure 1: Shapes, sizes and locations of the world's 43 major river basins (red borders and green areas) used in this study.

151 For synthetic TWS data, a summation of monthly ($1^\circ \times 1^\circ$) soil moisture, snow, and the
152 canopy water storage from the Global Land Data Assimilation System (GLDAS) NOAH (Rodell
153 et al., 2004) over 2003 - 2013 is used (<http://giovanni.sci.gsfc.nasa.gov/>). Following Wang et al.
154 (2006), the TWS fields are converted to potential spherical harmonic coefficients up to degree
155 and order 120. Only those coefficients that are up to degree and order 60 are used to generate
156 similar spectral content as the real GRACE L2 products. These data are perturbed by north-

157 south striping errors using the full covariance matrix of ITSG-Grace2014 products. Using the
 158 Cholesky decomposition method, the monthly covariance matrices are split into their upper
 159 triangular and their conjugate transpose matrices. By multiplying each of the upper triangular
 160 matrices with a column of the unit random matrix, the GRACE-type realizations of monthly
 161 errors are generated (see, e.g., [Forootan and Kusche, 2012](#); [Kusche et al., 2016](#)). GLDAS TWS
 162 outputs are also used to compute model-derived scale factors using forward modelling following
 163 [Long et al. \(2015\)](#). These hydrological datasets have also been used to estimate gridded gain
 164 factors following [Landerer and Swenson \(2012\)](#). Results of these filters will be compared to the
 165 KeFIn filtering approach (see Section 4.1).

166 2.3. Auxiliary data sets

167 Recently developed Mass Concentration blocks (mascons) data (<http://grace.jpl.nasa.gov>)
 168 provided by Jet Propulsion Laboratory (JPL) are used to analyze their correlation to our esti-
 169 mation from L2 products as shown in the Appendix. The monthly JPL RL05M Mascon solution
 170 is post-processed liquid water equivalent thickness data using a Coastline Resolution Improve-
 171 ment (CRI) filter to separate the land and ocean portions of mass ([Wiese, 2015](#); [Watkins et
 172 al., 2015](#)). We apply land-grid-scaling coefficients provided with the data to water equivalent
 173 thicknesses in $1^\circ \times 1^\circ$ spatial resolution. These filtered data are compared with the results of
 174 filters applied in this study.

175 In addition, the temporal derivative of filtered GRACE data, known as total (hydrological)
 176 water fluxes (TWF) is compared with measured precipitation (P), Evapotranspiration (ET),
 177 and surface water discharge (or runoff, R) through the water balance equation below:

$$dS/dt = TWF = P - ET - R, \quad (1)$$

178 where the dS/dt represents TWF derived from the ITSG-Grace2014 products following the
 179 procedure in [Eicker et al. \(2016\)](#). The assessment in Equation 1 requires additional hydro-
 180 logical water flux measurements, which are not easily accessible globally. Eight river basins
 181 are selected to perform this assessment, i.e., the Amazon (South America), Mekong (Southeast
 182 Asia), Arkansas-White (North America), Ohio (North America), Lachlan (Australia), Namoi
 183 (Australia), Lower Mississippi (North America), and Macquarie-Bogan (Australia) basins. We
 184 use water fluxes data from both satellite remotely sensed and ground-based data. P is obtained
 185 from the Tropical Rainfall Measuring Mission (TRMM 3B43-v7, [Huffman et al., 2007](#), from

186 <http://pmm.nasa.gov/data-access/downloads/trmm>), and ET from Moderate the Resolution
187 Imaging Spectroradiometer (MODIS-MOD16; the University of Montana’s Numerical Terra-
188 dynamic Simulation group). In addition, in-situ water discharge data sets are provided from
189 different sources including the Global Runoff Data Centre (GRDC), the United States Geolog-
190 ical Survey (USGS), hydrological and biogeochemical alteration and material transfers in the
191 Amazon Basin (HYBAM, from <http://www.ore-hybam.org/>) that publish originally collected
192 data by Brazilian Water Agency (ANA, <http://www.snirh.gov.br/hidroweb/>), New South Wales
193 (NSW) Government for the Upper Murray river basin (from <http://waterinfo.nsw.gov.au/>), and
194 China Hydrology Data Project ([Henck et al., 2010](#); [Schmidt et al., 2011](#)).

195 Each dataset is associated with a level of uncertainty and varies for different basins due to
196 the diverse climatological condition. A number of studies has investigated the validity of above
197 observations over various basins, e.g., [Cai et al. \(2012\)](#), [Yan et al. \(2014\)](#), [Awange et al. \(2016\)](#)
198 for TRMM, as well as [Velpuri et al. \(2013\)](#), [Ramoelo et al. \(2014\)](#), and [Miralles et al. \(2016\)](#) for
199 MODIS products. Precipitation errors highly depend on temporal and spatial resolution ([Chen
200 et al., 2008](#)). Uncertainty in measuring precipitation over lands are smaller compared to oceans
201 since satellite data are merged with in-situ stations that are distributed over the continents.
202 The major source of uncertainty in MOD16 is the misclassification of landcover types from
203 the MODIS land cover products, scaling from flux tower to landscape, and other algorithm
204 limitations ([Ramoelo et al., 2014](#)). Evaluation of MODIS data in previous studies (e.g., [Zhang
205 et al., 2010](#); [Mu et al., 2011](#)) have shown a good agreement between the data and eddy flux
206 tower observations. The consideration of associated errors to the observation for imbalance
207 problem in water budget closure (using Equation 1) is beyond the scope of this study, and the
208 post-processing is restricted to filtering out the highly noisy measurements.

209 *2.4. In-situ Measurements*

210 Groundwater in-situ measurements are used to assess filters’ results. To this end, we
211 provide bore stations datasets over the Arkansas-White, Ohio, and Lower Mississippi basins
212 within the Mississippi Basin from USGS and Lachlan, Namoi, and Macquarie-Bogan basins
213 within the Murray-Darling Basin from New South Wales (NSW) Government. The distribu-
214 tion of groundwater in-situ stations is presented in Figure 2. Monthly well measurements are
215 acquired and time series of groundwater storage anomalies are generated. Generally, a specific
216 yield is required to convert well-water levels to variations in groundwater storage (GWS) in

217 terms of equivalent water heights (Rodell et al., 2007; Zaitchik et al., 2008). Following Strass-
218 berg et al. (2007), we use an average (0.15) of specific yields ranging from 0.1 to 0.3 (suggested
219 by Gutentag et al., 1984) over the Arkansas-White, Ohio, and Lower Mississippi basins, and
220 0.13 specific yield from the range between 0.115 and 0.2 (suggested by the Australian Bureau
221 of Meteorology (BOM) and Seoane et al., 2013) for the Lachlan, Namoi, and Macquarie-Bogan
222 basins.

223 Furthermore, we use in-situ soil moisture (SM) measurements obtained from the moisture-
224 monitoring network (<http://www.oznet.org.au/>), as well as International Soil Moisture Network
225 (<https://ismn.geo.tuwien.ac.at/>). These data provide long-term records of measured volumetric
226 soil moisture at various soil depths for distributed stations (cf. Figure 2). For each station and
227 each depth, soil moisture anomalies over the study period are calculated. Following Strassberg
228 et al. (2009), data for stations with shallow measurements are upscaled using soil moisture
229 data from deeper stations. We then calculate average soil moisture storage anomalies from
230 all stations within a $1^\circ \times 1^\circ$ cell. The same averaging process is done for groundwater mea-
231 surements. Afterwards, area-weighted anomaly of groundwater and soil moisture are used to
232 achieve GWS+SM. We use these GWS+SM, following Strassberg et al. (2009) and Longuev-
233 ergne et al. (2010), to evaluate the performance of different filters considered in this study. This
234 method does not account for snow water equivalent, canopy, and surface water storages due
235 to their small contribution in TWS over the Mississippi (less than 5%, e.g., Strassberg et al.,
236 2007) and Murray-Darling (less than 6%, e.g., BOM and Burrell et al., 2015) basins. In addi-
237 tion to GWS+SM, we also compare the results with only GWS by computing their correlation
238 coefficients (see details in Section 4.2).

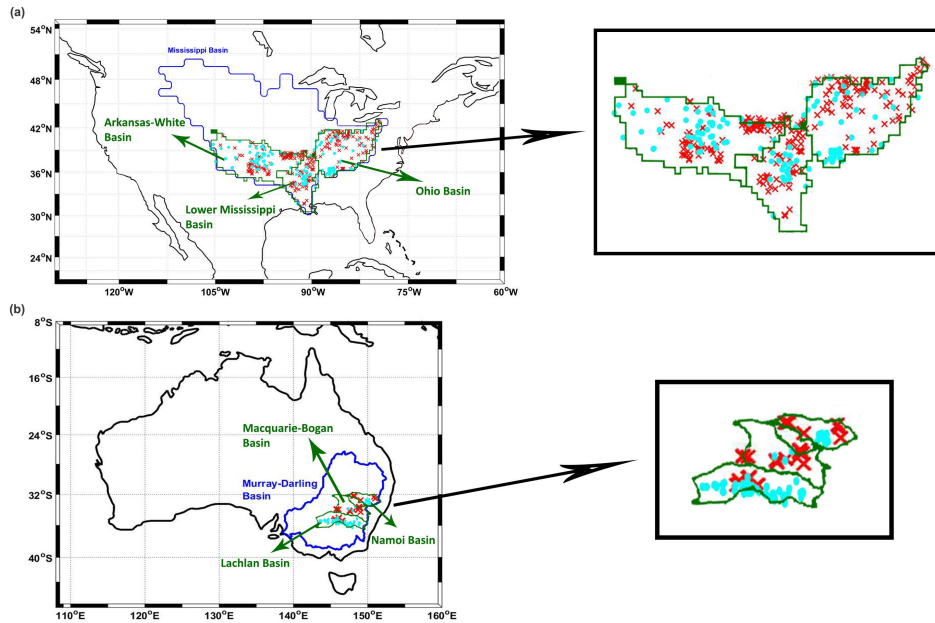


Figure 2: Distribution of groundwater (red crosses) and soil moisture (cyan circles) stations over the six selected river basins of Arkansas-White, Lower Mississippi, Ohio, Macquarie-Bogan, Namoi, and Lachlan basins.

239 3. Methods

240 In this section, first, details of the proposed KeFIn technique are discussed. Afterwards,
 241 the other implemented filters including four filters based on the basin averaging approach and
 242 two filters that use scale factors' are presented. These techniques are chosen due to their
 243 popularity in hydrological studies.

244 3.1. Kernel Fourier Integration (KeFIn) Filter

245 3.1.1. The KeFIn Method - First Step

246 The KeFIn approach follows a straight forward image processing technique, which has
 247 been widely applied to geophysical images to enhance their visual interpretation and geologi-
 248 cal understanding (Zhang al., 2005). The application of image enhancement methods is also
 249 beneficial for users that are less familiar with processing and filtering the standard GRACE L2
 250 products. The KeFIn includes two processing steps: (1) designing a 2D destriping filter in the
 251 spectral domain, and (2), defining an efficient averaging kernel to estimate basin average TWS

252 and at the same time decreasing the leakage-in and -out in the grid domain. A 2-D filter in the
 253 spectral domain (Hichri et al., 2012; Zhang et al., 2009) is defined as:

$$G(u, v) = F(u, v) \cdot H(u, v), \quad (2)$$

254 where $G(u, v)$ stands for a Fourier transform of the noisy TWS fields with u and v being spatial
 255 frequencies, F denotes a Fourier transform of the ideal (unperturbed) signal (here the ‘signal
 256 part’ or the ‘true’ TWS values), H is a Fourier transform of a 2-D smoothing kernel to suppress
 257 the ‘noise’ part of the observations, and the dot represents the matrix multiplication. Ideally,
 258 F can be estimated by applying an inverse filtering if G and H are known.

259 In general, however, the information on H does not exist, and its determination usually
 260 requires some trial-and-error procedures. Besides, noise in data sets can be amplified leading
 261 to the destruction of previous attempts made in reconstructing the TWSs. One solution for
 262 restoring F is to use the Wiener Filter (W_i) as $F = W_i \cdot G$, which allows to use an averaging
 263 kernel as H to estimate F . Here, a motion filter is used as an averaging kernel (H) to mit-
 264 igate the south-north stripping problem with different smoothing lengths, which provides us
 265 a convolutive filter with different averaging. More detail on creating the kernel with various
 266 smoothing lengths can be found e.g., in Bhagat and Gour (2013) (see Equation 5). The impact
 267 of smoothing length on the final TWS estimations is presented in Section 4.1.

268 Thereafter, F can be estimated using H and the Wiener Filter process as:

$$F(u, v) = \frac{|H(u, v)|^2 \cdot G(u, v)}{|H(u, v)|^2 \cdot H(u, v) + K}, \quad (3)$$

269 where K is a signal to noise ratio (Le Roux et al., 2010). A suitable estimate for K can be
 270 derived as:

$$K = S_G/S_F, \quad (4)$$

271 where S_G is estimated from the power spectral density of the noisy observed signal (G), and
 272 S_F is derived from the power spectral density of the ideal (unperturbed) signal (F). The main
 273 difference between the new filter and an ordinary Gaussian filter at this stage is the inclusion
 274 of the parameter K , which makes Wiener filter more robust and better suited to reduce high-
 275 frequency spatial patterns that likely correspond to high magnitude striping patterns. Besides,
 276 it introduces a reasonable trade off that minimizes errors of the smoothing process. In order to
 277 calculate K in Equation 4, S_G is derived from G . For S_F , where no information of ideal signal

278 F exists, one can estimate the power spectral density of TWS estimated from a hydrological
 279 model and use the mean/median of the estimated powers of S_F (see details in [Pitas, 1993](#)).
 280 Alternatively one can derive S_F by trial-and-error from a range of values (here [0 10]) to control
 281 the smoothness of the output, e.g., when the signal is very strong relative to the noise, selecting
 282 $K \approx 0$ yields less smoothed signals. Different values of K and their impacts on the smoothness of
 283 TWS estimations are discussed in Section 4.1. Here, we also use average model TWS estimates
 284 from GLDAS NOAH during the study period to compare with the value of K obtained through
 285 trial-and-error. The proposed scheme retains most of the high-frequency (spatial) changes that
 286 are usually over-smoothed by an ordinary smoothing process ([Sonka et al., 2001](#)).

287 3.1.2. The KeFIn Method - Second Step

288 In the second step of the KeFIn filter, we try to mitigate the problem that arose from
 289 the previous stage, i.e., leakage effects caused by spatial smoothing. In what follows, first,
 290 spatial averaging and the leakage problem are discussed, then a kernel is defined to reduce the
 291 leakage-in and leakage-out errors at the same time. Spatial averaging (Equation 5) is usually
 292 applied for improving surface mass anomalies within a specific area ([Swenson and Wahr, 2002](#);
 293 [Longuevergne et al., 2010](#); [Vishwakarma et al., 2016](#)),

$$F_R = \frac{1}{R} \int F h d\Omega, \quad (5)$$

294 where,

$$R = \int h d\Omega, \quad (6)$$

295 and F_R is the change in vertically integrated water storage averaged over the region of interest,
 296 shown by R , with the integrals done on a sphere. In both equations, h is a basin kernel with
 297 values 1 inside the basin and 0 outside of it as,

$$h(X) = \begin{cases} 1 & \text{if } X \in R \\ 0 & \text{if } X \in \Omega - R. \end{cases} \quad (7)$$

298 X refers to the positions on the surface of the Earth and Ω refers to the entire Earth's surface.
 299 Let us assume that \bar{F} is derived after applying a filter (that contains smoothing) in step 1. The
 300 smoothing moves signals both inside and outside of the basin. In the following, we start by
 301 separating the signal F inside and outside the basin and investigate the effects of smoothing
 302 leading to \bar{F} .

303 The whole water storage changes can be written as a summation of water storage signals
 304 inside and outside the basin following [Vishwakarma et al. \(2016\)](#) represented by the terms Fh
 305 and $F(1 - h)$, respectively, in Equation 8 as,

$$\begin{aligned} F &= Fh + F(1 - h), \\ &= F_R + F_{1-R}. \end{aligned} \quad (8)$$

306 This is equal to Equation 9 after applying the smoothing procedure from the first step, i.e.,

$$\bar{F} = \bar{F}_l + \bar{F}_l^*, \quad (9)$$

307 where \bar{F}_l is the smoothed signals inside the basin (with leakage out effects) and \bar{F}_l^* refers to
 308 the smoothed signals outside the basin (with leakage in effects). By multiplying both sides of
 309 Equation 9 by h (Equation 10) and $(1 - h)$ (Equation 11), we achieve the filtered water storage
 310 over the region R and outside of it $(1 - R)$.

$$\bar{F}_R = \bar{F}_{lR} + E_{leakage\ in}, \quad (10)$$

$$\bar{F}_{1-R} = \bar{F}_{l1-R}^* + E_{leakage\ out}. \quad (11)$$

311 Considering that \bar{F}_{lR} and \bar{F}_{l1-R} are the attenuated signals of F_R and F_{1-R} , [Longuevergne et](#)
 312 [al. \(2010\)](#) showed that they are related using a scaling factor s . For signals inside the basin
 313 (the same approach can be used for signals outside the basin), it can be shown that,

$$F_R = s \bar{F}_{lR}, \quad (12)$$

$$s = \frac{\int h d\Omega}{\int h \bar{h} d\Omega}, \quad (13)$$

314 with \bar{h} derived by smoothing h . Equation 10, thus, can be rewritten as,

$$F_R = s (\bar{F}_R - E_{leakage\ in}). \quad (14)$$

315 To be able to estimate F_R , one needs to calculate the leakage error ($E_{leakage\ in}$) first. To this
 316 end, we developed a kernel to account for both leakage in and leakage out errors. The proposed
 317 method looks for stronger anomalies outside the basin (for leakage in) and inside the basin
 318 (for leakage out). The definition starts by creating a kernel expressed in terms of spherical
 319 harmonics as:

$$\begin{pmatrix} v_{lm}^c \\ v_{lm}^s \end{pmatrix} = \sum_{\theta} \sum_{\phi} \psi(\theta, \phi) \tilde{P}_{lm}(\cos(\theta)) \begin{pmatrix} \cos(m\phi) \\ \sin(m\phi) \end{pmatrix} \sin(\theta). \quad (15)$$

320 In Equation 15, \tilde{P}_{lm} are the normalized associated Legendre functions, v_{lm}^c, v_{lm}^s represent the
 321 spherical harmonic coefficients and the summation covers the entire surface of the Earth. The
 322 definition of the mask filter ψ is very important and different literatures have found various
 323 methods to implement this. For example, Seo and Wilson (2005) use a Gaussian filter to smooth
 324 mentioned kernel inside a basin (for B_1 and B_2 in their study). Swenson and Wahr (2003)
 325 applied Lagrange multiplier rather than a Gaussian filter. Here, we use a different definition
 326 and instead of simply having a value 1 inside a basin, the method tries to maximize signals
 327 concentrated in different regions while decreases their effects on the surrounding signals. For
 328 the leakage in effect, ψ contains values outside the basin with special focus on strong anomalies
 329 while for the leakage out effect, it considers values inside the basin again with a concentration
 330 on strong anomalies. Accordingly, the mask filter ψ is defined through the following procedure.
 331 Note that in the following, we consider \bar{F} (the smoothed signal from step 1) as a 2D matrix
 332 and apply an image processing procedure (as follow) to extract strong signals.

333 A: The calculated \bar{F} in the first part of the filtering process is used to create \tilde{F} as a measure
 334 of spatial variability of GRACE TWS.

$$\tilde{F} = \left(\frac{\bar{F} - \min(\bar{F})}{(\max(\bar{F}) - \min(\bar{F}))} \right). \quad (16)$$

335 Then, the 2D intensity matrix (I),

$$I = \begin{cases} 1 & \text{if } \tilde{F} > S_b \\ 0 & \text{if } \tilde{F} < S_b, \end{cases} \quad (17)$$

336 can be used to identify strong anomalies using the normalised \bar{F} (given by \tilde{F}). The
 337 threshold S_b in Equation 17 is chosen to be a value within [0 1]. Often the median
 338 of \tilde{F} can be a good choice for S_b . A smaller S_b yields a smoother intensity matrix that
 339 controls the mass anomalies being considered in the averaging, and which is less weighted.
 340 Different values of S_b are tested in this study and their results are reported in Section 4.1.

341 B: A high pass filter, e.g., Laplacian filter (Gonzalez and Woods, 1992, 2002) using Equa-
 342 tion 18, is applied to intensify strong anomalies (found in [A]) and reduce their effects on
 343 surrounding anomalies.

$$L = \frac{1}{\sin\theta} \frac{\partial}{\partial\theta} \left(\sin\theta \frac{\partial I}{\partial\theta} \right) + \frac{1}{\sin^2\theta} \frac{\partial^2 I}{\partial\phi^2}. \quad (18)$$

344 C: Convolve the filtered matrix L with a Gaussian filter (W in Equation 19), which can
 345 be applied with different averaging radii. Smoothing is applied because converting the
 346 basin kernel from spatial to spectral domain introduces short-wavelength errors due to the
 347 Gibbs effect and introduces artificial fluctuations around the high contrast edges (Zeng
 348 and Allred, 2009).

$$\bar{L} = \int W(\theta, \phi, \theta', \phi') L(\theta', \phi') d\Omega', \quad (19)$$

349 In Section 4.1, the impact of the smoothness on the final averaging values is assessed. It should
 350 be mentioned here that this step is not restricted to the application of a Gaussian filter, and
 351 one can use anisotropic filter such as the DDK smoothing filters proposed by Kusche et al.
 352 (2009). Nevertheless, in the following we only discuss the application of Gaussian smoothing
 353 for the sake of simplicity.

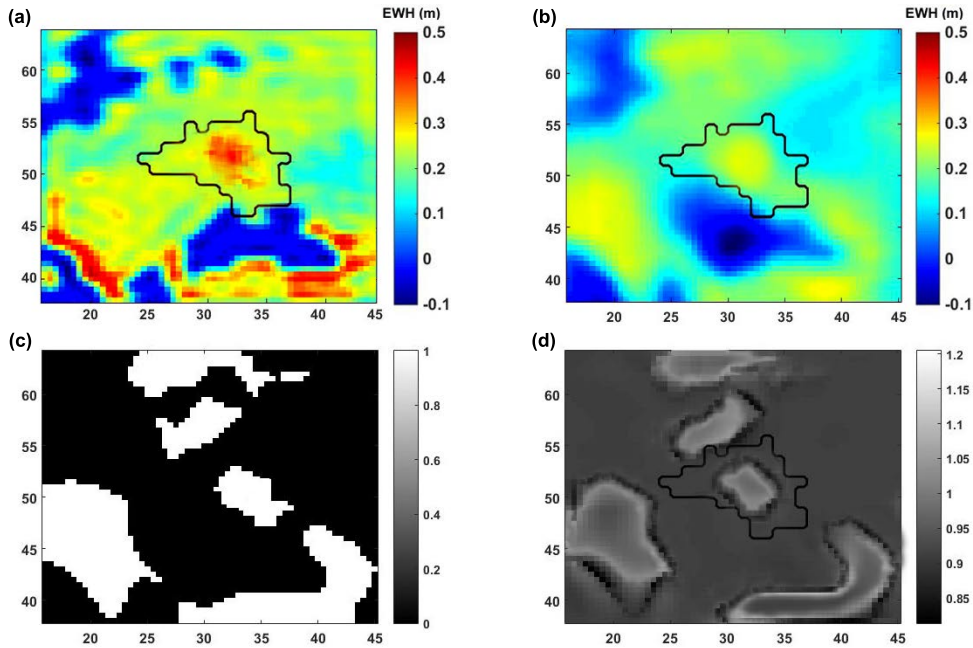


Figure 3: A schematic view of the steps for preparing ψ in [A]-[C] described above. (a) shows the initial unperturbed signal, (b) represents the smoothed signal from the first step of the filter (applied with the motion length of 60), (c) is I in step [A] using $S_b = 0.5$, and (d) depicts the kernel ψ created by $r = 300$ km.

354 The mask filter ψ is then calculated by $\psi = 1 + \bar{L}$, which can be used in Equation 15 to
 355 estimate v_{lm}^c and v_{lm}^s . Figure 3 illustrates a schematic performance of the three steps above.

356 The final form of the basin kernel (v) is built as,

$$v(\theta, \phi) = \frac{1}{4\pi} \sum_{l=0}^{\infty} \sum_{m=0}^l \{v_{lm}^c \cos(m\phi) + v_{lm}^s \sin(m\phi)\}. \quad (20)$$

357 The created kernel is multiplied by the smoothed field from the first step to estimate F_N using,

358

$$F_N = \bar{F} \circ v, \quad (21)$$

359 where the operator \circ performs a pixel-wise multiplication. Once F_N is computed, it is used
 360 rather than F to estimate leakage in and leakage out (Equations 22 and 23). To estimate the
 361 leakage in, we only consider F_N outside the basin and apply smoothing to capture its effect
 362 inside. A similar process can be done to compute the effect of leakage out by only considering
 363 anomalies inside the basin. The smoothing in these procedures can be done by applying either
 364 the same smoothing procedure as the first step of the proposed filter or using a Gaussian filter,
 365 e.g.,

$$E_{leakage\ in} = \frac{h(\theta, \phi)}{4\pi} \int W(\theta, \phi, \theta', \phi') (1 - h(\theta', \phi')) F_N(\theta', \phi') d\Omega', \quad (22)$$

$$E_{leakage\ out} = \frac{1 - h(\theta, \phi)}{4\pi} \int W(\theta, \phi, \theta', \phi') h(\theta', \phi') F_N(\theta', \phi') d\Omega'. \quad (23)$$

366 The estimated $E_{leakage\ in}$ is used in Equation 14 to obtain the averaged water storage over the
 367 region of interest. The example of the KeFIn filter performance in the second step is presented
 368 in Figure 4. Synthetic signals are produced in the spatial domain (Figure 4a) and are smoothed
 369 using an ordinary Gaussian filter (Figure 4b). The application of the KeFIn with two different
 370 sets of parameters are shown in Figures 4c and 4d. The effects of the filter are clearly visible
 371 from the reduction of signals interferences caused by leakage. Implementing the filter with
 372 various Gaussian filter sizes (r) and different S_b (as in Equation 17) yields different results.
 373 Detailed results that indicate the filter's sensitivity to different parameters are presented in
 374 Section 4.1. Figure 5 provides a flowchart that summarizes the filter process using the KeFIn
 375 algorithm.

376 3.2. Basin Averaging Kernel Methods

377 Averaging using basin functions or basin kernels is a common approach for estimating
 378 basin scale TWS (see e.g., Swenson and Wahr, 2002). The kernel h (cf. Equation 7) can
 379 be expanded in terms of spherical harmonic coefficients and subsequently combined with L2

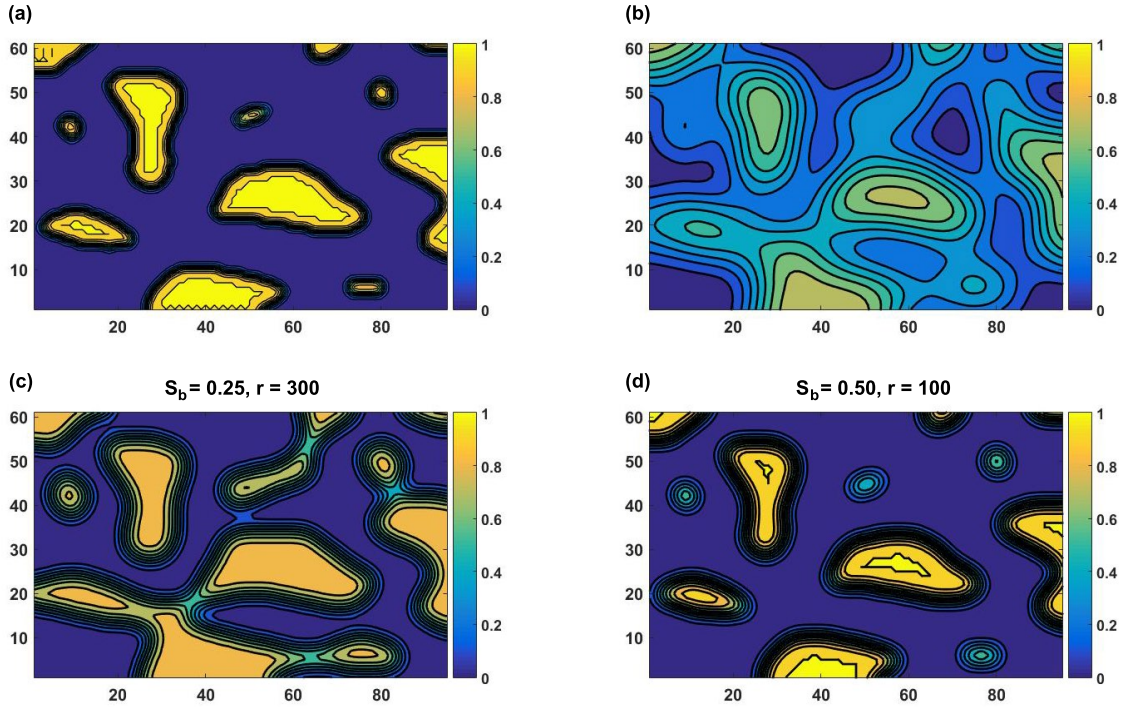


Figure 4: Performance of the second step of the KeFIn filter based on synthetic data. (a) Initial TWS anomalies, (b) smoothed TWS using a Gaussian filter with the half-width radius of 500 km. (c) and (d) represent the performance of the KeFIn filter with different factors of S_b and r (half width radius in kilometre). In this figure, we show how the KeFIn filter tries to reproduce the signals in (a) based on the smoothed signal (b), which result in (c) and (d).

380 potential coefficients to obtain basin averaged GRACE TWS estimates (see e.g., [Swenson and](#)
 381 [Wahr, 2003](#), and more details in Section 3.1). Different kernel averaging methods will likely
 382 result in different signal attenuation and displaced mass anomalies based on the shape and size
 383 of the basins ([Werth et al., 2009](#)). [Swenson and Wahr \(2002\)](#) introduced the spatial averaging
 384 kernel for regional studies that try to minimize leakage errors coming from outside into the area
 385 of interest by isolating the signals inside the area (see also [Swenson and Wahr, 2003](#)). Their
 386 approach reduces short wavelength effects using a smooth averaging kernel with less power on
 387 short wavelengths using Lagrange multiplier rather than applying a Gaussian filter. For the
 388 Lagrange Multiplier method, we apply a smoothing radius of 300 km. Furthermore, we use
 389 a time-dynamic filter proposed by [Seo and Wilson \(2005\)](#). Here we use filter number three
 390 (from four types of their filters), which can be directly applied to GRACE L2 products. This
 391 is a dynamic filter that scales spherical harmonic coefficients using the ratio of signal variance

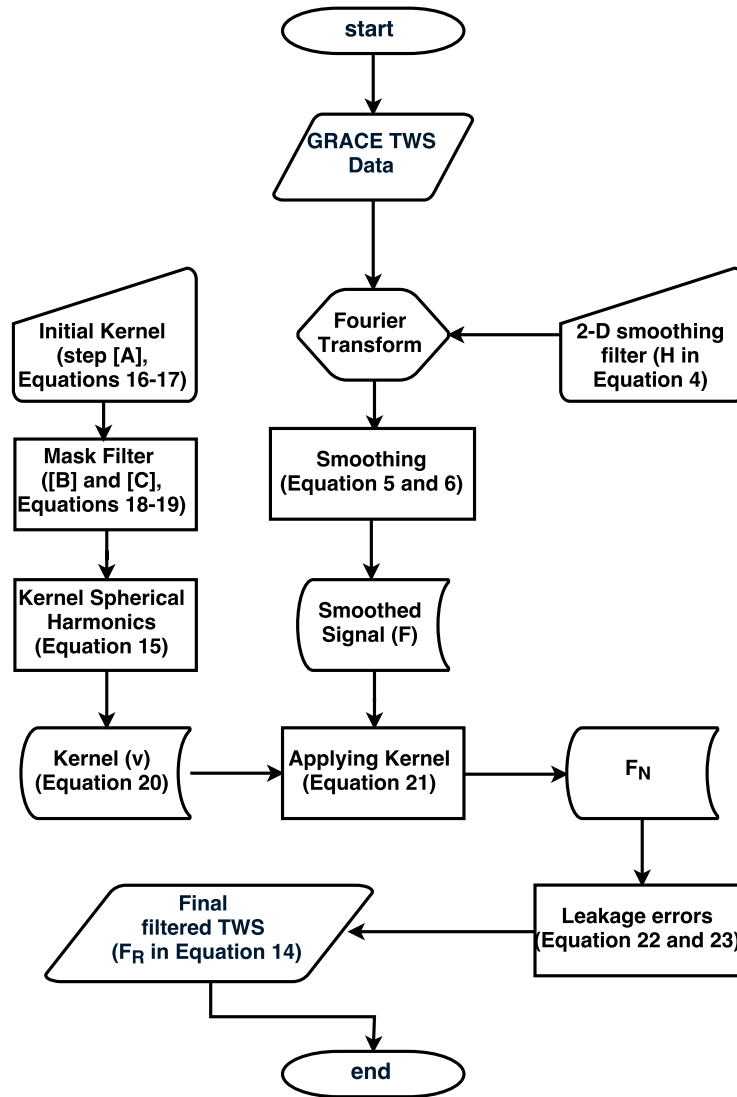


Figure 5: Flowchart of the proposed KeFIn filtering process.

392 and signal plus noise variance that employs a least squares optimum approach. The method is
 393 based on the Lagrange Multiplier Method (Swenson and Wahr, 2003) while assuming that the
 394 root-mean-square (RMS) of the signal over the target basin is known from GLDAS model (for
 395 more details, see Seo and Wilson, 2005; Seo et al., 2006). Here we use GLDAS NOAH for this
 396 purpose.

397 In a different approach, [Han and Simons \(2008\)](#) tried to maximize the ratio of the energy
 398 of the function within the target region (h) by constraining regional contributions to global
 399 spherical harmonics spectra based on [Simons and Hager \(1997\)](#). They argued that the resulted
 400 localized coefficients increase the signal-to-noise ratio. This method is also applied in the present
 401 study with the spectrum band-limited to spherical harmonic degree and order of 25. We also
 402 use a data-driven approach recently introduced by [Vishwakarma et al. \(2016\)](#), where leakage in
 403 and out are separately solved using a catchment mask and a filter kernel. A Gaussian filter of
 404 half width radius of 350 km (following [Vishwakarma et al., 2016](#)) is used to suppress the noise
 405 before implementing this approach in the present study. The data-driven filter is sensitive to
 406 basin sizes in a way that noise increases as the catchment size decrease (see [Vishwakarma et](#)
 407 [al., 2016](#), for more details).

408 *3.3. Scaling Factor Methods*

409 [Landerer and Swenson \(2012\)](#) suggested the use of a scaling (gain) factor, which can
 410 be multiplied with filtered GRACE TWS estimates. In this study, monthly simulations of the
 411 GLDAS NOAH are used as synthetic input TWS (a summation of snow water equivalent, canopy
 412 water storage, soil layers, and surface water) to estimate scaling factors following [Landerer and](#)
 413 [Swenson \(2012\)](#) as in Equation 24, where the goal is to find the scaling factor α by minimising
 414 the quadratic sum of difference M between original (ΔS_T) and filtered (ΔS_F) GLDAS TWS
 415 fields, i.e.,

$$M = \sum (\Delta S_T - \alpha \Delta S_F)^2. \quad (24)$$

416 Following [Landerer and Swenson \(2012\)](#) and [Long et al. \(2015\)](#), synthetic TWS data is
 417 converted to spherical harmonics and truncated at degree and order 60. We then apply the
 418 destriping procedure after [Swenson and Wahr \(2006\)](#) and a 300 km Gaussian filter to smooth
 419 high-degree and order noises. The model-derived TWS estimates before (ΔS_T) and after (ΔS_F)
 420 filtering are used to calculate scaling factors. In this study, two methods of scaling factors at
 421 grid points and basin scale are computed and used for comparison with the newly developed
 422 KeFIn and other filtering techniques. All filters used in this study are presented in Table 1.

Table 1: A summary of the implemented GRACE leakage filtering methods, which are used in this study for comparison with the proposed KeFIn filter.

Study	Method	Case Study	Evaluation Method	Abbreviation *
Swenson and Wahr (2002)	Lagrange multiplier method	Mississippi River Basin	Using synthetic GRACE data	F_1
Han and Simons (2008)	Localization of Global Geopotential Fields	Java/Sunda trench	Using seismic model based data	F_2
Seo and Wilson (2005)	$B_1, B_2, B_3,$ and B_4	Amazon, Mississippi, Lena, Huang He and Oranje Basins	Using synthetic GRACE data	F_3
Landerer and Swenson (2012)	Gridded gain factor	46 globally distributed basins	GLDAS data	F_4
Landerer and Swenson (2012)	Single gain factor	46 globally distributed basins	GLDAS data	F_5
Vishwakarma et al. (2016)	Data-driven approach	32 globally distributed basins	Closed-loop environment using monthly GLDAS fields	F_6
The present study	Kernel Fourier Integration (KeFIn)	43 globally distributed basins	Using synthetic data and soil moisture + groundwater data	$KeFIn$

* In the last column, the abbreviations are assign to the filters we use in the present study.

423 3.3.1. Application Example of the Proposed KeFIn Filter

424 First, the performance of the KeFIn filter with respect to both leakage-in and leakage-
425 out errors is assessed, for which two tests are performed that correspond to each type of error
426 (leakage-in and leakage-out). Setup (i), the signal is only introduced inside a basin and GRACE-
427 like TWS noise is added as described in Section 2.2. A 300 km half width radius Gaussian filter
428 (Jekeli, 1981) is then applied to smooth the introduced signals and noises, which causes signal
429 leakage outside the basin. Setup (ii), TWS signals are introduced only outside a basin to assess
430 the leakage-in effects. The KeFIn filter is applied to post process both scenarios as shown in
431 Figure 6. In Figure 6a bottom, the blue line represents the introduced synthetic TWS while
432 the green lines show the signal after the application of a Gaussian filter. In Figure 6a, the
433 results correspond to a cross section at $3^\circ S$ that passes the Amazon basin, South America, and
434 in Figure 6b, they correspond to a cross section at $41^\circ N$ crossing the Huang He Basin, China.
435 The results clearly indicate that the Gaussian filter attenuates the original signal and causes
436 leakage-out and leakage-in effects shown in Figures 6a and 6b, respectively. The smoothed
437 signals of the KeFIn filter are shown by the red lines, which in both cases better follow the
438 initial TWS (blue lines). It is worth mentioning that if there was no striping noise added to
439 the signal, the red curve (KeFIn) would have closely reproduced the true signal (blue curve).

440 Therefore, we avoid showing a close-loop or a noise free assessment of the KeFIn’s performance.

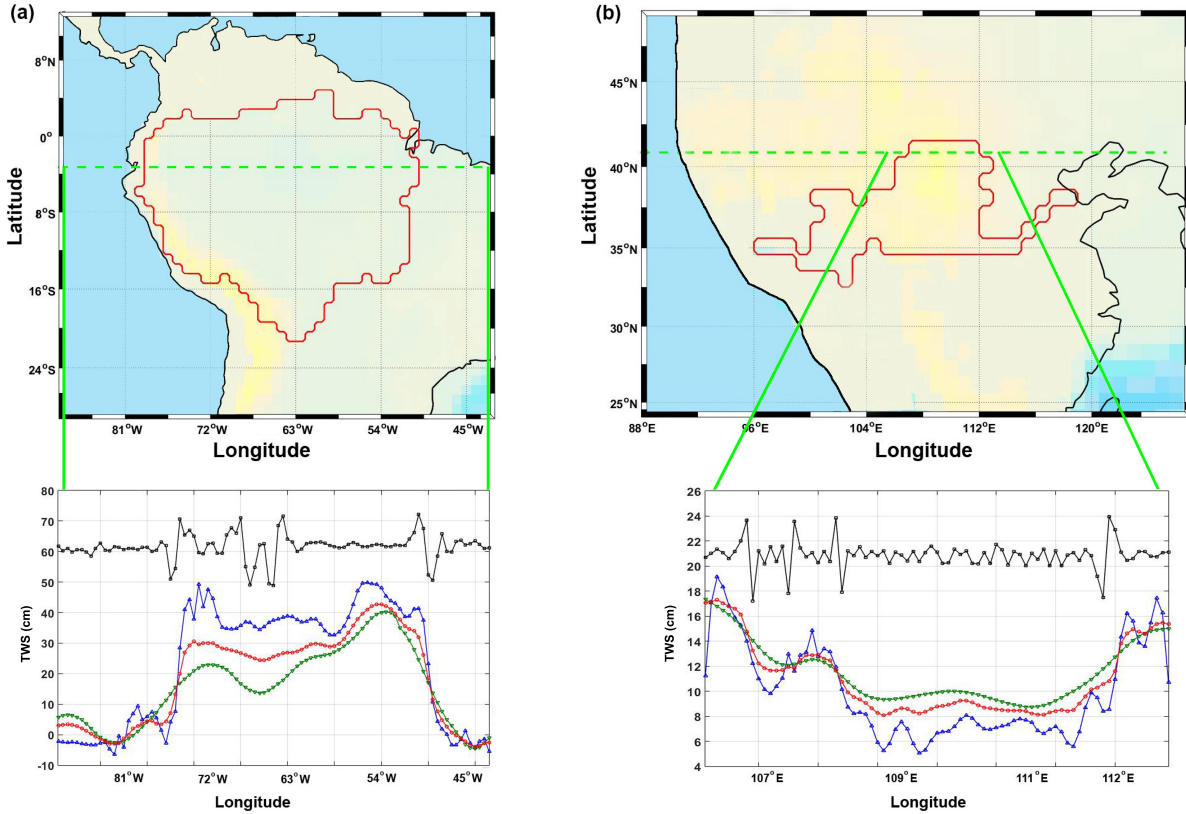


Figure 6: Assessing the performance of two filtering techniques on synthetic GRACE-like TWS examples with realistic noise. (a) TWS is introduced in the Amazon River Basin, South America, and (b) TWS is introduced outside of the Huang He River Basin, China. The line plots indicate the TWS after application of Gaussian filter with 300 km radii (green) and the KeFIn filter (red), estimated using the motion length of 60, $S_b = 0.5$, and $r = 300$ km. Note that the line plot of kernel (black) is also shown in these figures, which are shifted for better visual demonstration. The initial synthetic TWS is represented by the blue lines. Units are in cm.

441 Further, to better demonstrate how the proposed KeFIn filter operates, the results of its
 442 application over two basins with different shape and sizes (e.g. Colorado, USA, basin number
 443 34 and Congo, Africa, basin number 5) out of the 43 basins in Figure 1 are shown in Figure 7. In
 444 this figure, each row of a and b corresponds to one specific basin, where the first column is the
 445 initial unperturbed signals (before applying the Gaussian filter), the second column represents
 446 the perturbed signals (after applying the Gaussian filter) using the synthetic data sets (see
 447 Section 2.2), and the third column contains the filtered signals. The Root-Mean-Square-Errors
 448 (RMSE) time series of the filters performances using the synthetic data over the basins is

449 calculated and their averages are shown in Figure 7c. This is done to compare the results of
450 the KeFIn filter with other methods (F_1 to F_6 in Table 1). It is clearly visible in Figure 7 that
451 the KeFIn filter works properly in both basins. RMSE values over the Colorado Basin (Figure
452 7c) suggest that the application of the KeFIn filter (i) successfully decreases leakage error, and
453 (ii) improved results in relation to other filters. We find approximately 34% RMSE reduction
454 compared to the unperturbed signals by implementing the KeFIn filter. By comparing RMSE
455 values in the Congo basin, again, smaller errors are found for those associated with the KeFIn
456 filter compared to the other six filters applied in this study. This indicates that the KeFIn filter
457 successfully decreased leakage effects based on the GRACE-like artificial data, especially over
458 smaller basins.

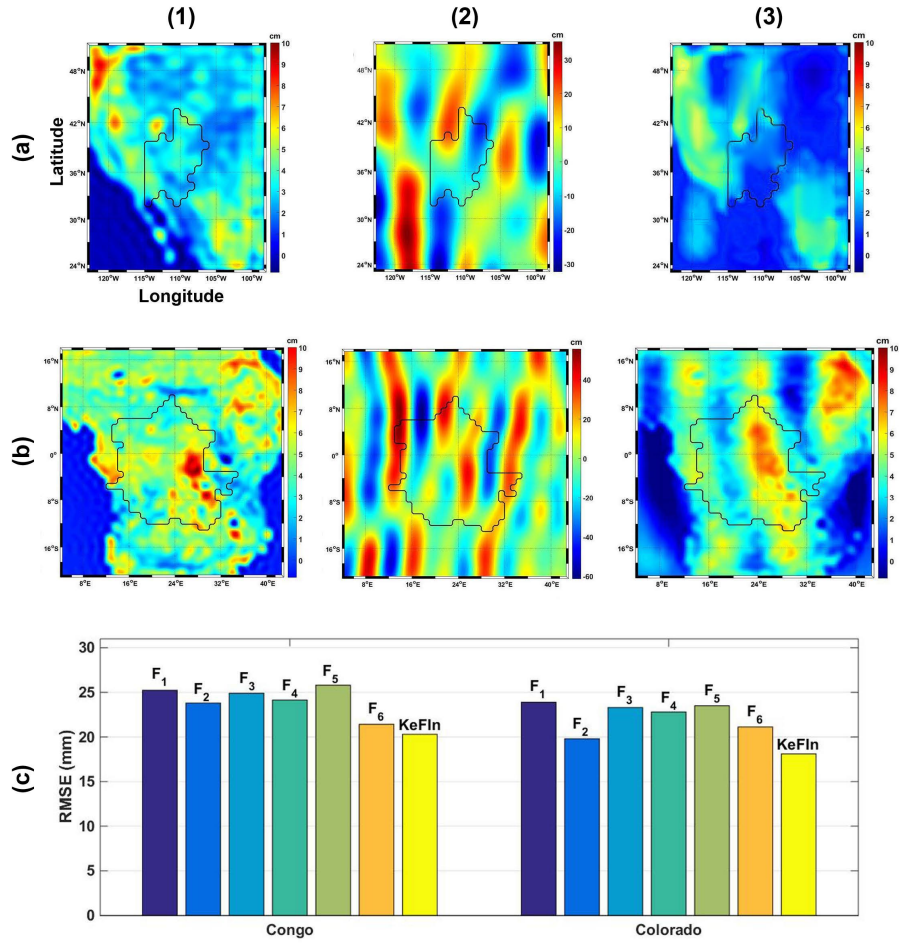


Figure 7: The KeFin filter operation over the Colorado (a) and Congo (b) basins using synthetic GRACE-like TWS signals and noise. In column (1), the unperturbed water storages are shown; in column (2), the corresponding perturbed water storages are shown, and the results of the KeFin filtered TWS estimates are presented in column (3). Panel (c) shows the average RMSE results within both basins for the filters listed in Table 1.

459 4. Results

460 In Section 4.1, various filtering techniques (cf. Table 1) are tested on the synthetic TWS
 461 data while in Section 4.2, the results from filtering the real GRACE data are assessed against
 462 direct observations of water fluxes through the water balance equation (Equation 1), as well as
 463 in-situ groundwater measurements.

464 *4.1. Filter Results Based on Synthetic Data*

465 There are two effective factors in each step of the proposed KeFIn filter, which potentially
 466 change the final filtering outcomes. The main aim here is to find out which choice yields an
 467 optimum performance of the filter in terms of leakage error reduction. Figure 8a contains
 468 the results of applying the first step of KeFIn while considering different sizes for the motion
 469 filter (controlling the smoothing of north-south stripping error) and K to mitigate the signal
 470 attenuation. Each scenario (using Equations 3 and 4) is applied separately to the basins and
 471 the average errors for all basins and are represented in Figure 8a. From our investigations,
 472 using K from GLDAS provides the best results with $\sim 14.76\%$ higher leakage error reduction
 473 with different filter lengths. Considering K as a constant can lead to a promising result with
 474 the value of 1 with 58 mm average error. On the other hand, motion filters with bigger windows
 475 better decrease errors, where the optimum value in this study is derived from the 75 degree
 476 motion filter size. As mentioned, the first part of the filter deals with colored/correlated noise
 477 of high-frequency mass variations (i.e., stripes). In order to investigate the performance of this
 478 step of the filter, we compare its results with the widely used destriping algorithm by Swenson
 479 and Wahr (2006) and DDK smoothing filter following Kusche (2007) and Kusche et al. (2009).
 480 We apply these filters over all basins and illustrate the average results in Table 2. Note that we
 481 apply the KeFIn method with best cases of K and motion filter for the comparison presented
 482 in Table 2. Based on these results, the first step of the KeFIn filter performs comparable to
 483 other filters in terms of RMSE reduction. The level of RMSE reduction, as well as correlation
 484 improvements for the KeFIn filter are larger in most of the cases, particularly compared to
 485 Gaussian with 250 km radii and DDK3.

Table 2: Average statistics derived after applying different filtering methods over the world’s 43 major river basins using synthetic data (after removing seasonal effects) in comparison with the unperturbed synthetic data (F_0). Note that the first step of the KeFIn filter is used in this table.

	Gauss (250 km)	Gauss (350 km)	Gauss (500 km)	DDK1	DDK2	DDK3	KeFIn
RMSE (mm)	78.54	54.13	60.91	57.87	53.19	62.67	52.73
Correlation	0.73	0.81	0.78	0.83	0.80	0.76	0.81

486 In addition, we used the same experiment this time for the second part of the filter (cf.
 487 Equations 6 and 8) while applying diverse values of S_b and selecting various smoothing radii
 488 (half-width radius, r) for the Gaussian filter. Using the best cases of K and motion filter length,
 489 we analyze the effects of different S_b and r on errors (Figure 8b). In general, results indicate
 490 that a higher S_b needs lower r to derive better results. Nevertheless, applying the second part
 491 of the KeFIn filter with $S_b = 0.5$ and $r = 300$ km performed better in most of the cases.

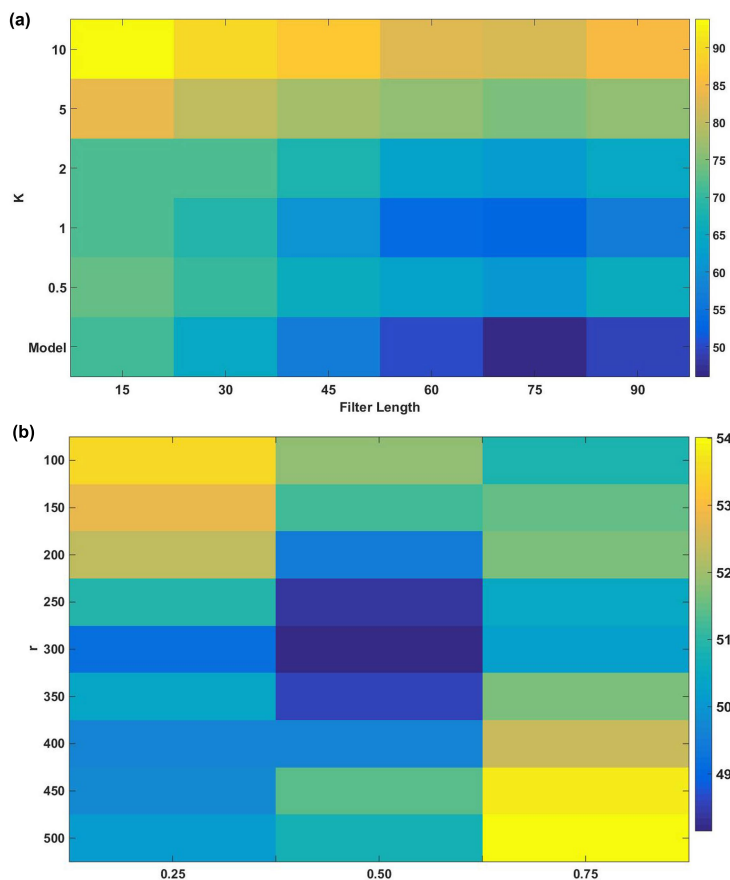


Figure 8: Average error (mm) derived after applying the KeFIn filter with different values of K and the motion filter length (a) for the first step of the filter as well as different scenarios that contain S_b and r for the second step of the filter (b). (a) indicates that the filter length of larger than 30 km and K between 0 to 2 yield smaller errors, while (b) indicates S_b of 0.5 and $r = 300$ km yield the smallest errors.

492 For comparison, all the filters of F_1 , F_2 , F_3 , F_4 , F_5 , and F_6 (cf. Table 1) as well as the
 493 KeFIn filter are then applied on the GRACE-like synthetic TWS fields. A summary of these
 494 results is presented in Table 3. For every basin, we estimate F_R (averaged signals inside the

495 basin) and F_{1-R} (averaged signals outside the basin) using each filter and compare the results
 496 to initial unperturbed TWS values inside and outside the basins by calculating the RMSE and
 497 correlation coefficients. Note that for a better assessment, seasonal variations are removed from
 498 time series. The average results for the study period, i.e. 2002–2013, and for all the 43 basins
 499 (cf. Figure 1) is given in Table 3. Note that detailed RMSE values for each individual basin
 500 can be found in the Appendix. From Table 3, it can be seen that higher correlations, both
 501 inside and outside the basin, can be found by applying the KeFIn filter. Estimated measures
 502 indicate that the KeFIn filter is more successful in recovering the spatial distribution of the
 503 synthetic TWS estimates. Overall, the KeFIn filter performs better both inside and outside the
 504 basins with an average of 73.6% TWS recovery from the perturbed synthetic data (cf. Table 3).
 505 Our results further indicate that the KeFIn filter works well over smaller river basins such as
 506 the Colorado, Ohio, Lachlan, and the Namoi basins, showing maximum $\sim 81\%$ TWS recovery
 507 from noisy data. We also found that in 35 out of the 43 basins, the proposed filter provides
 508 the lowest RMSE (cf. Appendix). Nevertheless, in the other 8 cases, the KeFIn approach still
 509 demonstrates a promising performance in terms of RMSE reduction. Overall, Table 3 suggests
 510 that the proposed filter performs better in more than 80% of the basins.

Table 3: Average statistics derived after applying different filtering methods over the world’s 43 major river
 basins using synthetic data in comparison with the unperturbed synthetic data (F_0). Averaged signals inside
 and outside of the basins are calculated using $C_R = \int F_0 h d\Omega$ and $C_{1-R} = \int F_0 (1 - h) d\Omega$, respectively.

Method	Inside the Basin		Outside the Basin		TWS improvement (%)	
	Correlation	RMSE (mm)	Correlation	RMSE (mm)	$(F_R - \bar{F}_R) / C_R$	$(F_{1-R} - \bar{F}_{1-R}) / C_{1-R}$
F_1	0.77	32.02	0.68	49.52	19.25	11.32
F_2	0.83	28.71	0.77	44.08	21.14	13.81
F_3	0.79	31.03	0.72	47.84	20.13	12.44
F_4	0.88	29.12	0.87	37.26	22.67	19.53
F_5	0.82	30.86	0.84	39.95	19.09	18.20
F_6	0.85	28.17	0.83	41.30	21.18	16.79
<i>KeFIn</i>	0.91	27.25	0.89	34.65	24.41	22.36

511 4.2. Filter Results Based on GRACE Data

512 4.2.1. Comparisons with Hydrological Total Water Flux

513 We further assess the performance of the filters, using independent data sets such as
 514 water fluxes. Therefore, TWS changes are evaluated through the water balance equation (cf.
 515 Equation 1) using TRMM 3B43-v7 precipitation, AVHRR data to account for evaporation
 516 products, and in-situ discharge data over the Amazon, Mekong, Arkansas-White (basins 1 and
 517 31 in Figure 1, respectively), Ohio, Lachlan, Namoi, Lower Mississippi, and Macquarie-Bogan
 518 basins (cf. Figure 2).

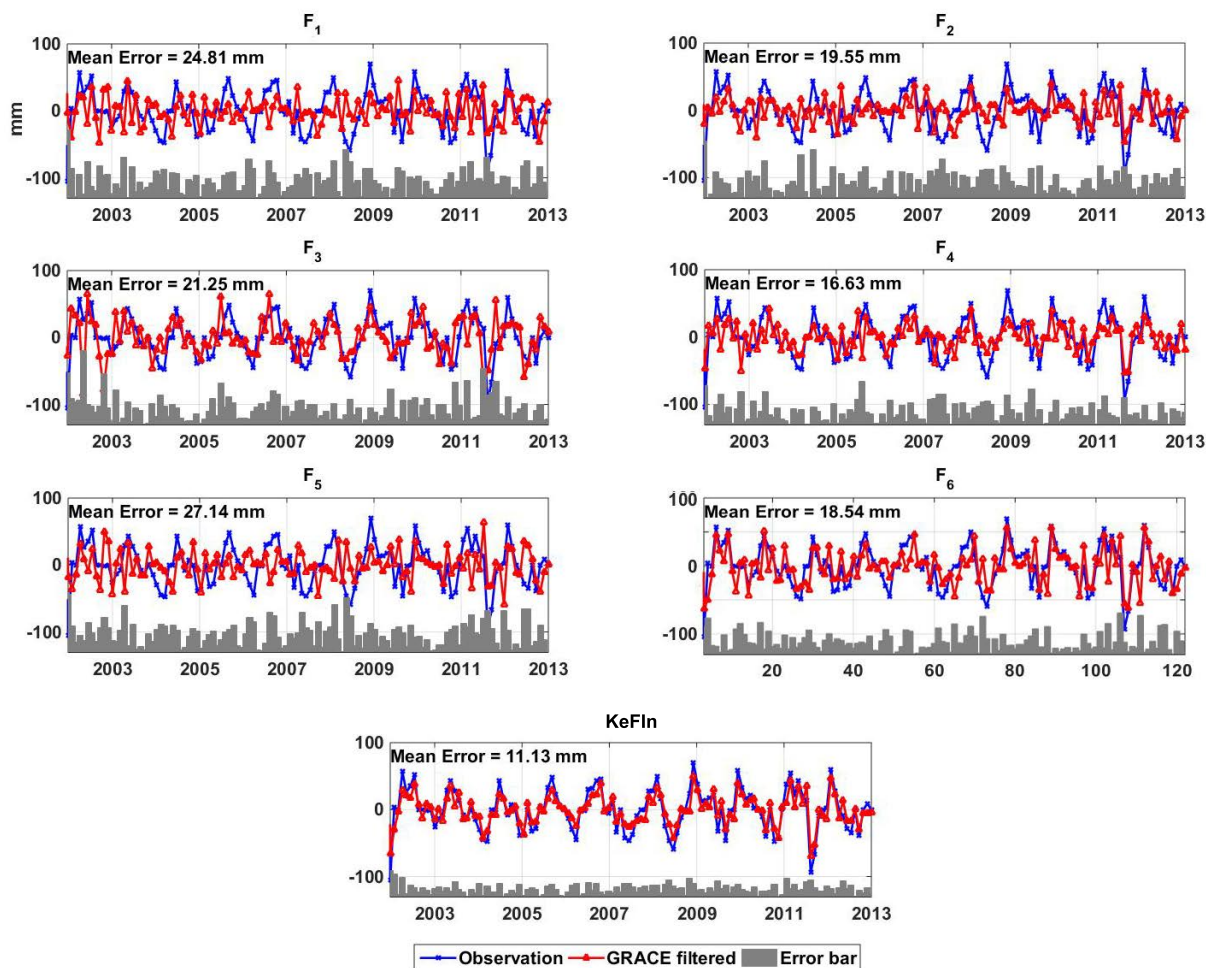


Figure 9: Comparison between the derivative of filtered TWS (red) and TWF from observations (blue) within the Namoi Basin. Each sub-figure corresponds to one filter and also contains error bars that is computed as the absolute value of difference between GRACE derivatives and the observed TWF.

519 To this end, we calculate TWF (from Equation 1) over each basin (see Section 2.3). Figure
520 9, for example, shows the results of this comparison within the Namoi Basin. The figure also
521 contains error bars for every filter representing the differences between the observed TWF and
522 those derived by estimating the temporal derivative of filtered TWS change. It can be seen that
523 the results of the KeFIn filter are much closer to the observed TWF with the smallest average
524 error of 11.13 mm and overall 13% higher correlation in comparison with the other filters.

525 Average error estimates within different basins corresponding to each filter are illustrated
526 in Figure 10. Errors after applying the KeFIn filter are found to be the smallest in all the
527 assessed basins. We find F_2 , F_4 , and to a lesser degree F_6 to be efficient in most of the cases,
528 especially over the Ohio Basin. More details on results can be found in Table 4, in which
529 correlations between the TWFs (estimated as precipitation minus evaporation minus runoff)
530 and the derivatives of TWS changes that are filtered by all implemented filtering methods are
531 represented. Maximum correlations are calculated for the proposed filter with 0.89 average
532 correlation. A higher correlation is achieved from all the filters over the Amazon and Mekong
533 basins, which can be due to their stronger signals compared to other basins. Results from F_2 ,
534 F_3 , and F_6 are found to have larger correlations to TWFs than those from F_1 and F_5 .

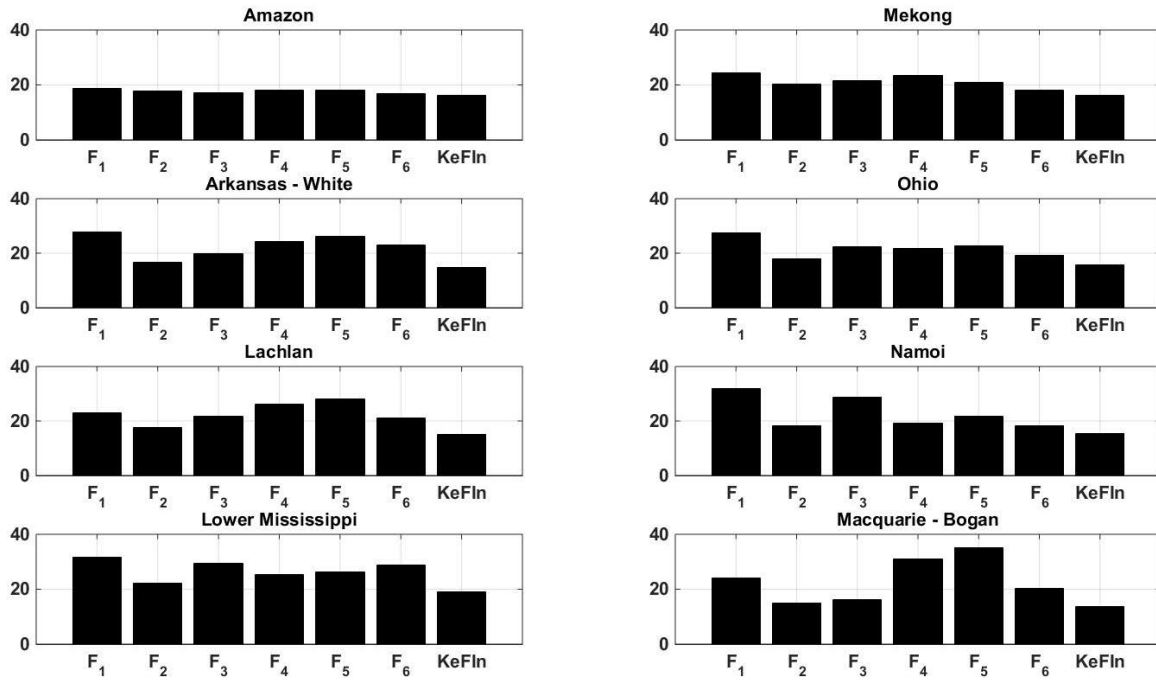


Figure 10: The temporal average of errors defined as derivative of filtered TWS minus observed TWF. Each error bar is estimated after applying the F_1 to F_6 and KeFln filters over 8 selected river basins (units are mm).

Table 4: Correlations between the TWFs as precipitation minus evaporation minus runoff, and the derivatives of TWS changes from each applied filter. The correlation coefficients have been computed at the 95% confidence level.

Basin	F_1	F_2	F_3	F_4	F_5	F_6	<i>KeFln</i>
Amazon	0.92	0.93	0.94	0.92	0.91	0.95	0.95
Mekong	0.85	0.92	0.88	0.88	0.89	0.91	0.93
Arkansas-White	0.78	0.82	0.81	0.75	0.73	0.75	0.88
Ohio	0.76	0.82	0.74	0.82	0.81	0.78	0.85
Lachlan	0.80	0.86	0.82	0.73	0.75	0.84	0.89
Namoi	0.72	0.87	0.78	0.80	0.82	0.81	0.91
Lower Mississippi	0.77	0.78	0.79	0.81	0.80	0.78	0.84
Macquarie-Bogan	0.79	0.85	0.81	0.78	0.74	0.69	0.92

535 *4.2.2. Comparisons with Groundwater and Soil Moisture*

536 We further assess the results of the different filters against groundwater measurements
537 as mentioned in Section 2.4. TWS estimates after implementing each filter and a summation

538 of groundwater storage (GWS) and soil moisture contents (GWS+SM) are compared in the
539 following basins: Arkansas-White, Ohio, Lachlan, Namoi, Lower Mississippi, and Macquarie-
540 Bogan (cf. Figure 2), where access to in-situ data is provided. For each basin and each
541 filtering method, basin averaged values are compared with GWS+SM. For this purpose, absolute
542 differences between the filtered results and in-situ measurements are illustrated in Figure 11.
543 Similar to the previous section, the minimum errors are found after using the KeFIn filter for
544 these basins. It can be seen from the distribution of error points that the KeFIn results obtain
545 errors with less magnitudes and variances. This indicates the smaller deviations of these results
546 compared to in-situ measurements. Among the other filters, in general, smaller errors are found
547 for F_2 and F_6 . F_2 and F_5 depict less errors over the Ohio Basin and Lachlan Basin. In summary,
548 the KeFIn filter and F_2 better decrease errors over these basins, respectively 38% and 22% (on
549 average) better than the other filters. These show the higher capability of the two filters for
550 reducing errors within smaller basins. For a better comparison, the average errors in Figure 11
551 for all the basins are shown in Figure 12.

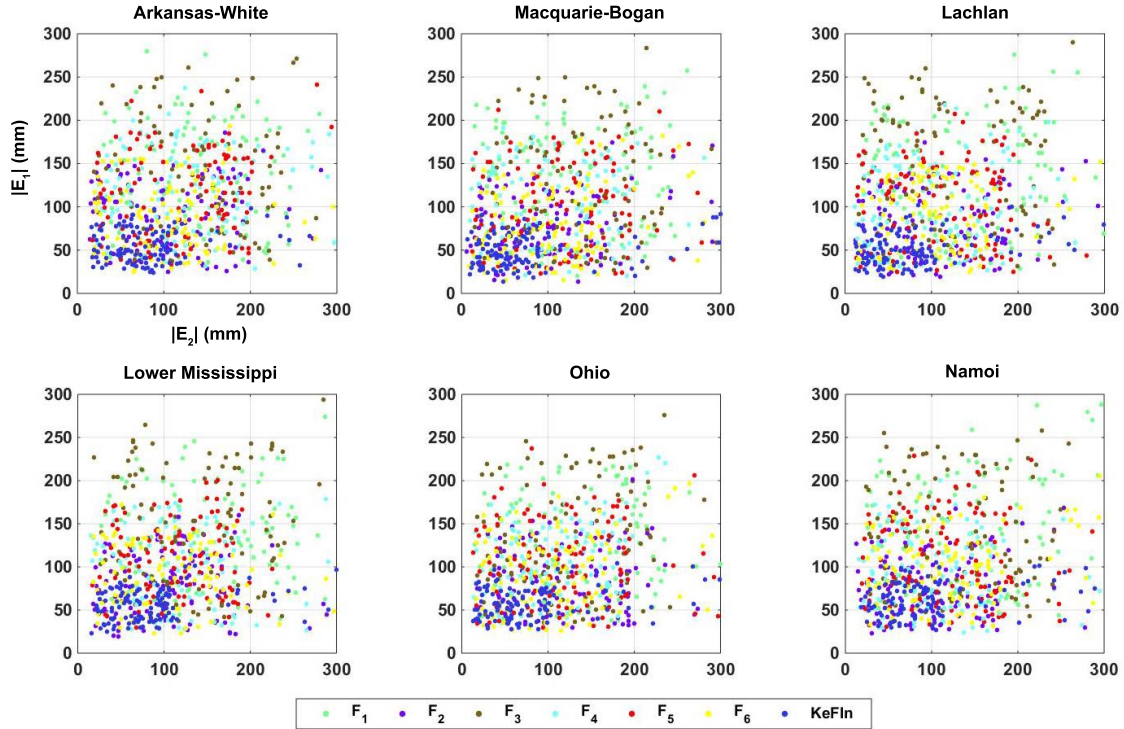


Figure 11: Errors estimated at each epoch after applying the assessed filters F_1 – F_6 and KeFIn on the Ohio (basin number 35, with blue circles) and Lachlan (basin number 41, with red triangles) basins. These values are calculated as differences between in-situ measurements (GWS+SM) and filtered TWS before (E_1) and after (E_2) removing seasonal effects. The average absolute error is indicated in each sub-figure and for each basin.

552 Figure 12 illustrates that the proposed KeFIn filter in all the cases has the minimum error
 553 (24.13 mm on average). Similar to the two basins discussed earlier in this section, using F_2 ,
 554 F_3 and to a lesser degree F_3 lead to a higher agreement with observations compared to the
 555 other methods (except the KeFIn filter). The results of these filters are much closer to those
 556 of the proposed filter in Arkansas–White and Macquarie–Bogan Basins. F_4 seems to have an
 557 approximately constant effect on different basins (37.58 mm on average) except for the Ohio
 558 Basin. The summary of comparisons between different filtered TWS and in-situ groundwater
 559 time series measurements are presented in Table 5. This is performed to show each filter’s
 560 performance independent against direct observations without incorporating model estimates.
 561 Higher correlations are reported between the KeFIn filter results and in-situ data, which indi-
 562 cates 19.31%, 6.67%, 10.57%, 8.41%, 18.52%, and 6.33% improvements in comparison to F_1 ,
 563 F_2 , F_3 , F_4 , F_5 , and F_6 , respectively. F_3 , F_6 , and F_4 results are also in good agreement with the

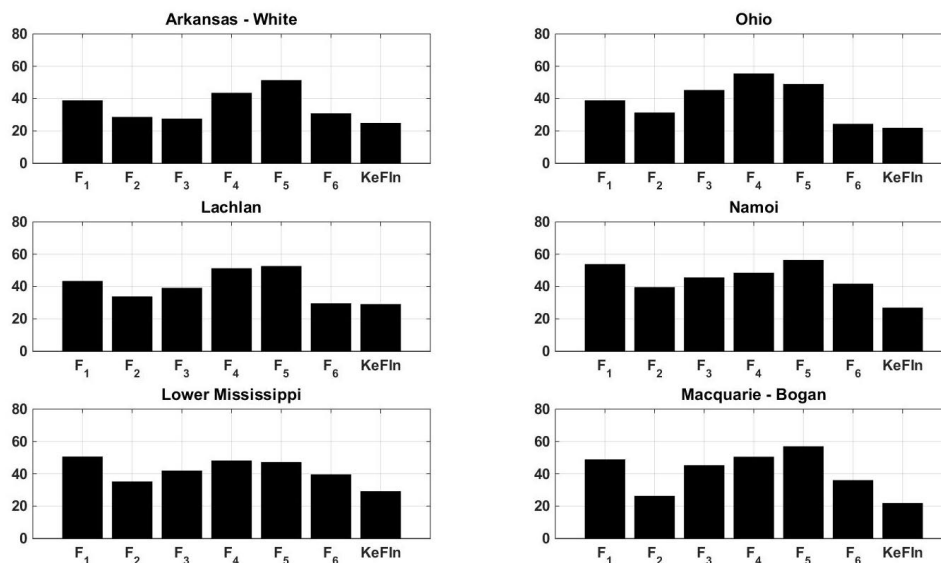


Figure 12: Average differences between GRACE TWS and observed groundwater plus soil moisture content within 6 river basins. GRACE data are processed using 7 filtering techniques (F_1 to F_6 and KeFin filters) over 6 selected river basins (units are mm).

Table 5: Correlations between the filtered results and in-situ measured groundwater time series.

Basin	F_1	F_2	F_3	F_4	F_5	F_6	<i>KeFin</i>
Arkansas-White	0.78	0.76	0.73	0.69	0.63	0.75	0.81
Ohio	0.76	0.82	0.73	0.63	0.69	0.84	0.85
Lachlan	0.69	0.71	0.75	0.67	0.68	0.78	0.83
Namoi	0.59	0.74	0.64	0.75	0.58	0.66	0.80
Lower Mississippi	0.54	0.78	0.73	0.66	0.67	0.72	0.78
Macquarie-Bogan	0.77	0.85	0.81	0.76	0.73	0.82	0.88

565 5. Discussion

566 Evaluation of the proposed KeFin filter against common techniques (cf. Table 1) using
 567 different datasets suggests that this filter successfully removes striping and reduces leakage er-
 568 rors over basins of different shapes and sizes. Other filters show a different level of improvements
 569 within the world’s major 43 basins (Figures 9, 11, and 12). We find here that those filters based

570 on the averaging kernel, especially F_2 (Han and Simons, 2008) and F_3 (Seo and Wilson, 2005),
571 deal better with leakage errors over smaller basins compared to those based on scaling factor
572 (F_4 and F_5 ; Landerer and Swenson, 2012). Nevertheless, in general, F_2 , F_6 (Vishwakarma et
573 al., 2016), F_3 , and F_4 perform better than F_1 and F_5 in most of the cases. The grid-based F_4 is
574 found to better reduce leakage errors in comparison to the single gain factor F_5 . Between basin
575 average kernel methods, in general, F_6 and F_2 perform better compared to F_1 . The results
576 confirm that F_6 reduces leakage errors better than other basin average techniques when it is
577 applied over larger basins as mentioned in Vishwakarma et al. (2016). This approach is, how-
578 ever, found to be sensitive to the basin size in a way that noise increases when the catchment
579 size decreases.

580 Over smaller basins (e.g., Lachlan and Namoi basins), F_2 works significantly better than
581 F_3 and F_4 . This confirms the findings of Han and Simons (2008) that this filter is designed
582 to address leakage errors over basins with a small area (cf. Table 4). In summary, our results
583 indicate that the KeFIn filter and F_2 are likely better suited to deal with the leakage in small
584 river basins. F_3 , designed by Seo and Wilson (2005) and tested over the Mississippi Basin,
585 shows reliable results over this basin with fewer similar performance in other basins. This likely
586 indicates that filters must be extensively tested over different basins that are of different shapes
587 and sizes with different magnitude and distribution of TWS signals.

588 We find that the proposed KeFIn filter reduces the leakage errors over $\sim 82\%$ of the basins
589 with an area less than 1 million km^2 , thus, we conclude it is suitable for leakage error reduction
590 over basins with various sizes and shapes. Comparison with water flux observations indicates
591 that in addition to the KeFIn filter, the recently developed F_6 and F_4 that use a hydrologi-
592 cal model to recover GRACE smoothed signals (on a gridded basis), better approximate the
593 derivatives of TWS changes than the other filters. Over the larger basins (e.g., Amazon and
594 Mekong basins), the results of the F_1 and F_5 filters are found to be better than those in the
595 smaller basins. Overall, more consistent leakage reduction within different basins is achieved
596 by the KeFIn filter, F_2 , F_6 , and F_4 considering the results of Figure 10 and Figure 12, as well
597 as Table 3.

598 **6. Conclusion**

599 In this study, a new GRACE post-processing technique, the so-called KeFIn filtering
600 method, is proposed and its performance in reducing GRACE TWS errors in higher spatial
601 frequencies as well as leakage (in/out) errors is investigated. The KeFIn filtering method suc-
602 cessfully mitigates the existing problems with other leakage filtering methods, e.g., the high
603 sensitivity of them to prior models in the scale factor approaches. To demonstrate the benefit
604 of using the KeFIn filtering method, two different test scenarios are considered over the 43 river
605 basins of different shapes and sizes. First, all the filtering methods are compared using gener-
606 ated synthetic data with properties similar to real GRACE TWS data within the 43 globally
607 distributed river basins. In addition, we assessed the performance of the filters against water
608 storage changes from water fluxes observation, as well as a summation of observed groundwater
609 storage and soil moisture content over the selected basins. The results show that the KeFIn
610 filter successfully (i) mitigates the amplitude damping caused by smoothing, and (ii) increases
611 flexibility towards a variety of basins (shapes and sizes of basins as well as the magnitude of
612 TWS). It is worth mentioning here that we do not claim that the KeFIn method is able to re-
613 duce all possible artificial features appearing in the two steps of the post processing algorithm.
614 Therefore, further investigations will be done to optimize parameters that are used to define
615 the shape of the KeFIn filter.

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625 8. Appendix

626 The following table shows the basin averaged RMSE values calculated by each filtering
627 technique. The results in the table are temporally averaged (between 2002 and 2013), and
628 indicate that the KeFIn filtering method works better compared to other filters in 35 out of the
629 43 basins, especially over smaller basins.

Table A1: Summary of RMSE (mm) estimated using the unperturbed basin averaged synthetic TWS and the perturbed TWS after using different filtering methods over the 43 river basins. Note that the basins are sorted according to their area.

Basin	Area (million km^2)	F_1	F_2	F_3	F_4	F_5	F_6	$KeFln$
1 (Amazon)	6.97	31.25	31.83	31.19	30.98	30.88	31.06	30.69
2 (Ob)	4.40	26.64	24.25	28.77	27.64	28.55	22.93	23.79
3 (Yenisey)	4.09	29.76	23.17	26.10	21.94	21.11	19.44	17.63
4 (Lena)	3.99	31.94	36.15	27.56	32.99	33.70	30.71	29.57
5 (Congo)	3.81	25.24	23.52	24.96	24.19	25.60	21.59	20.47
6 (Mackenzie)	2.88	24.60	29.23	31.42	26.63	28.56	23.86	22.18
7 (Parana)	2.64	37.97	31.83	38.18	30.27	32.71	26.97	26.68
8 (Nile)	2.48	34.17	34.01	33.86	34.15	33.45	37.36	32.79
9 (Mississippi)	2.35	42.93	38.52	37.51	38.22	43.37	39.83	37.20
10 (Niger)	2.11	34.56	33.01	29.34	34.93	33.38	27.84	27.78
11 (Amur)	1.85	52.03	49.35	46.19	50.33	50.24	47.73	48.52
12 (Yangtze)	1.81	39.90	36.93	38.56	40.20	41.81	36.68	35.75
13 (Yukon)	1.58	37.91	40.27	38.63	38.10	39.67	37.14	36.69
14 (Nelson)	1.43	31.50	24.22	30.43	22.99	26.21	24.12	21.41
15 (Volga)	1.38	30.00	34.84	31.33	32.01	33.71	28.22	28.93
16 (St. Lawrence)	1.27	39.53	39.97	33.82	36.02	37.68	34.14	32.65
17 (Lake Eyre)	1.12	24.10	26.49	24.94	17.51	29.60	19.45	16.45
18 (Zambezi)	1.12	29.54	28.10	31.67	34.98	33.10	29.05	27.67
19 (Murray Darling)	1.01	46.66	41.51	38.89	40.94	43.42	38.72	37.84
20 (Danube)	0.93	36.67	35.97	37.39	39.31	41.72	31.40	29.20
21 (Ganges, Brahmaputra)	0.92	28.92	17.77	33.88	26.03	25.19	29.75	28.25
22 (Indus)	0.91	41.31	33.39	36.57	32.04	34.04	35.50	33.69
23 (Orange)	0.90	18.71	14.96	21.82	13.01	16.08	11.67	7.94
24 (North West Coast)	0.80	16.85	17.97	18.81	22.10	17.58	19.39	16.39
25 (Huang He)	0.78	33.86	28.70	30.77	23.09	27.11	24.98	23.30
26 (Sumatra)	0.76	32.46	27.08	28.43	34.61	34.38	28.03	26.19
27 (Euphrates and Tigris)	0.74	35.91	22.20	19.75	22.00	24.36	19.08	17.53
28 (Orinoco)	0.73	42.57	35.90	34.65	38.94	35.99	32.69	32.42
29 (Tocantins)	0.71	25.32	15.02	16.05	18.99	20.29	22.72	20.65
30 (Ayeyarwady)	0.69	34.75	38.21	36.09	34.17	35.64	35.74	33.97
31 (Mekong)	0.68	34.46	35.78	32.27	33.06	36.82	38.03	31.78
32 (Kalahari Stampriet)	0.67	36.01	34.75	37.51	32.32	39.25	35.16	34.29
33 (Dnieper)	0.65	24.25	23.18	29.80	25.14	25.59	24.09	22.84
34 (Colorado)	0.63	23.12	19.32	23.05	22.95	23.87	21.79	18.05
35 (Ohio)	0.52	23.31	22.54	25.06	21.82	26.96	23.38	20.46
36 (Sirdaryo)	0.51	32.56	27.98	30.35	25.47	25.63	29.40	24.74
37 (Central East Coast)	0.49	40.21	42.51	37.21	38.64	39.23	41.20	36.31
38 (Western Mediterranean)	0.45	31.64	28.42	28.59	32.44	36.54	37.91	27.06
39 (Namoi)	0.43	21.80	12.80	14.33	17.09	25.31	19.53	12.43
40 (Kamchatka)	0.40	43.06	33.69	33.62	40.80	37.73	38.89	32.90
41 (Lachlan)	0.08	34.05	32.42	28.11	25.79	32.05	28.41	24.46
42 (Yalu)	0.03	13.07	12.33	11.40	12.76	18.40	14.73	8.82
43 (Lower Mississippi)	0.01	23.64	18.79	20.24	25.13	28.42	21.13	18.49

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