Calibration and Assimilation in Hydrodynamic Model of a Micro-Tidal Estuary and Comparison with Lagrangian Drifter Data

MOHAMMADREZA KHANARMUEI\(^{(1)}\), KABIR SUARA\(^{(2)}\) & RICHARD J BROWN\(^{(3)}\)

\(^{(1,2,3)}\) Environmental Fluid Mechanics Group, Queensland University of Technology (QUT), QLD, 4000, Australia

m.khanarmuei@qut.edu.au; \(^{2}\)k.suara@qut.edu.au; \(^{3}\)richard.brown@qut.edu.au

ABSTRACT

Deployment of Lagrangian drifters in water systems can provide a larger spatial coverage and an additional insight into horizontal motion of particles than Eulerian techniques. This feature has provided an opportunity to assimilate Lagrangian data into hydrodynamic models to enhance their accuracies. Numerical models suffer from both systematic and random errors. Conventional data assimilation methods were designed to reduce the stochastic errors, and systematic errors can negatively affect the assimilation systems. Therefore, a calibration process, which is an effective way to reduce systematic errors and consequently biases in the numerical models, is required to be performed before implementation of data assimilation techniques. In this study, D-Flow FM, a hydrodynamic model, was set up for simulating the essential processes in a micro-tidal estuary in Queensland, Australia. To calibrate the model, bathymetry and bed roughness were selected as calibration parameters, while most studies in estuarine application have only considered the bed roughness as the calibration parameter. Evaluation of model performance in terms of correlation and root mean square error between model outputs and observations for both water level and velocity showed that calibration of bathymetry is important. Herein model outputs are validated with Lagrangian drifter velocity data for different environmental conditions. The results showed that calibration with the consideration of bed roughness and bathymetry reduced the systematic errors and increase the correlation between model outputs and Lagrangian drifter data. This is an important step prior to assimilation of Lagrangian data to reduce stochastic errors.

Keywords: Lagrangian drifter; calibration; estuary; bathymetry; data assimilation.

1 INTRODUCTION

Shallow water systems, such as estuaries and rivers, are critical natural resources for human society by providing environments for species populations and agriculture purposes, fish production, transportation, economic development and ecological processes. During the coming decades, population growth and urbanisation will have significant impact on these water bodies and increase the risk of pollution in these systems. Therefore, monitoring and managing shallow water systems are increasingly becoming a challenging area. Estuaries and rivers are characterised by complex non-linear interactions of physical, biological and chemical processes. Particle transport plays an important role in estuaries and one of the most imperative challenges in this area is to provide reliable predictions of material transport, including pollutant and sediment. Numerical modelling provides forecast estimates and it is also used to study the hydrodynamics and particle transport of the estuarine and riverine systems. Compared to field observations, models can provide a large spatio-temporal coverage. However, numerical model outputs are associated with several uncertainties which cause divergence from observations. These uncertainties can result from imperfect knowledge about physical processes, discretization errors and uncertainties in initial and boundary conditions. Improvement of the output flow fields of hydrodynamic models is especially important where numerical models are used to simulate dynamics of particles and sediment (Cea & French, 2012).

Depth-averaged two dimensional models are widely used to study the hydrodynamics of riverine and estuarine systems. These models are based on the St. Venant equations and they deal with two major categories of uncertainties, which are systematic and stochastic uncertainties. The systematic uncertainties can be reduced by improving the knowledge of the system and to this end, calibration methods can be used to tune a set of parameters that are fixed in time. Bed roughness is usually considered as the main calibration parameter, while bathymetry also has a significant impact on the estuarine and riverine flow fields. However, the number of studies about the incorporation of the uncertainty of bathymetry into the calibration process is limited, whereas it has been shown that by calibrating bathymetry, model performance can be improved noticeably especially for estimation of depth-averaged currents (Cea & French, 2012; Wang, et al., 2009). Errors in bathymetric data can result from either uncertainties in bathymetry surveys (Cea & French, 2012), random errors due to measurement precision, inaccuracies in datum and geographical positioning, or errors that are associated with hydrodynamic modelling (Wang, et al., 2009). These errors include those from the sensitivity of...
the model to the spatial density of the bathymetric data and interpolation scheme for mapping bathymetric data into the model mesh nodes. The errors associated with bathymetric data have been quantified in several studies, which are reported in the order of ±0.5 m (List, et al., 1997; Van Der Wal & Pye, 2003), and 1 m or more in (Burningham & French, 2011) depending on the technology and operational post processing parameters.

Stochastic errors are related to the existing noise in the system and can be reduced by periodically updating model outputs with observed data (Bates, et al., 2004). Data assimilation (DA) is an effective approach to enhance model estimates through incorporating reliable data (observations) into the numerical models. Moreover, estimating model parameters and quantifying uncertainties of the model are other applications of the DA (Toye et al., 2017). DA methods can be categorized into two techniques: variational and sequential DA. Variational schemes, such as 3 and 4-dimensional variational, are based on optimal control which assimilate observations into a hydrodynamic model via optimizing of the best model trajectory that fits the time series of experimental data. Sequential or statistical approaches such as the Kalman filter (KF), ensemble Kalman filter (EnKF) and particle filter (PF), update model states once observation are available (Bertino, et al., 2002).

Data assimilation algorithms either in the variational or sequential framework are developed to optimally reduce random errors by incorporating observations into the model. Indeed, assimilation systems are generally bias-blind and systematic errors, biases, can adversely affect their performances (Dee, 2005). Therefore, as DA suffers from imperfect models, first it requires to reduce the systematic errors as possible in the model during calibration.

To investigate the hydrodynamics of the shallow waterways, either Eulerian (fixed frame) or Lagrangian (moving frame) frameworks can be employed. During recent decades, the experimental deployment of Lagrangian sensors, such as drifters and floats, has been increased because of their advantages, namely low cost, portability, and more importantly providing larger spatial coverage compared to Eulerian techniques (Strub, et al., 2009). While Lagrangian instruments have been used in many studies related to oceanography, there are significantly less studies that employed Lagrangian observations in the estuarine application. As Lagrangian observations are measured in a moving coordinate system that are different from model sates computed in a fixed frame, assimilation of this type of data is challenging and it opens-up potential research opportunities.

This research is targeted to develop and implement robust approach for Lagrangian data assimilation into hydrodynamic modelling shallow waters to reduce both systematic and stochastic errors in the model. However, given the above discussion, this article focuses first on reducing the systematic errors within hydrodynamic modelling to enhance its representation of tidal propagation and estimation of the horizontal velocity fields for a micro-tidal estuary. This is to eventually provide a reasonable level of perfection for the DA process in which a DA technique can be employed to mitigate the random errors by integrating either Lagrangian or Eulerian observations into the model. To this end, bathymetry and bed friction are used as calibration parameters for D-Flow FM, as a hydrodynamic model, and improve its accuracy to represent the essential processes in the domain of interest. Model performance is evaluated in terms of correlation and calibration statistics between model outputs and observations. Model outputs are validated with high-resolution Lagrangian drifter velocity for different environmental conditions in a micro-tidal system.

This article is organized as follows: In Section 2, the field of study and observation datasets are presented. In Section 3, details regarding the hydrodynamic modelling are described. Section 4 provides the calibration procedure. Results are discussed in Section 5. Finally, conclusion is given in Section 6.

2 STUDY REGION AND OBSERVATIONS

The region of study is Eprapah Creek, which is a micro-tidal estuary in south east Queensland, Australia (Long. 153.293° E, Lat. 27.574° S). As can be seen in Figure 1, this estuary consists of straight and meandering channels, which are characterised by irregular bathymetry with a maximum depth between 3 and 4 m. The estuarine length is around 3.8 km and due to the existence of mangroves, it is mostly sheltered from the wind. Eprapah Creek is connected to the ocean and hence tidal forcing is the main driving force in this estuary.

Summary of instrumentation is presented in Table 1. The following list is the available data that were obtained from a field experiment during a spring tide in July 2015. Full description of the field study and data analysis are presented in detail in (Suara, et al., 2017; Suara, et al., 2018):

- Lagrangian measurements were obtained from deployment of the low and high-resolution drifters in fairly straight part of the estuary during the experiment (Figure 1). Low and high-resolution drifters were sampled at 1 and 10 Hz with the position accuracy of 1-2 m and 2 cm, respectively (Suara et al., 2015). By using a finite difference approach, velocity data has been derived from the successive drifter positions. Note that only high-resolution drifter data is used in this study.

- Eulerian measurements were obtained from acoustic Doppler current profiler (ADCP) and two acoustic Doppler velocimeters (ADV) were deployed close to upstream and measured water current. The water velocity is used to estimate time series of discharge as upstream boundary condition for the hydrodynamic modelling. Moreover, Surface water velocity obtained from ADCP is used for calibration of model.

- Water level was manually collected and its time series provide information to the downstream boundary.

-
A 2D sonic anemometer (ANE) was deployed to collect the time series of wind velocity near the water surface. However, in present study, the effect of wind is not considered in the hydrodynamic modelling.

Bathymetry was obtained from LiDAR data with a resolution of 5 m and a vertical accuracy of 0.3 m from the Geoscience Australia. Moreover, a survey of bathymetry was performed at different cross sections of the estuary. The locations of surveyed cross sections are shown in Figure 1.

**Figure 1.** (a) The experimental region, including surveyed cross sections (Y and Z); drifters were deployed at cross section Y, and ADVs and Sonic ANE were deployed at cross section Z. (b) Aerial view of the experimental test section. (c) Dimensional sketch of low-resolution (LR) and high-resolution (HR) drifters. Reproduced from (Suara, et al., 2018).

### 3 HYDRODYNAMIC MODEL

#### 3.1 Model description

In this study, D-Flow Flexible Mesh (FM) is used to perform hydrodynamic modelling of the estuary. D-Flow FM is an unstructured hydrodynamic model developed by Deltares. Using finite volume techniques on a staggered scheme, it solves the unsteady Shallow Water Equations in 2 dimensional depth-averaged or in 3 dimensional modes, which are derived from three dimensional Navier-Stokes equation (Deltas, 2019). A Boussinesq assumption is applied to this model. By using a flexible mesh, D-Flow FM can be applied to the
complex geometries such as meandering estuaries. D-Flow FM has been widely used in modelling flows in shallow water systems (Bomers, et al., 2019; Symonds et al., 2017; Thanh, et al., 2017).

Table 1. Instrument description

<table>
<thead>
<tr>
<th>Instrument</th>
<th>Instrument description</th>
<th>Measured parameter</th>
<th>Sample location</th>
<th>Sample frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADCP</td>
<td>Nortek AquaDopp Profiler P27759 upward looking</td>
<td>Water level and Eulerian velocity</td>
<td>0.1 m above the bed centre of channel at transect 32 downstream ADV1 location, Bin size= 10 cm</td>
<td>1 Hz</td>
</tr>
<tr>
<td>ADV1</td>
<td>Sontek 3D-sideloooking microADV A813F (16MHz)</td>
<td>Eulerian velocity</td>
<td>0.08 m above the bed 7.4 m from the left bank</td>
<td>50 Hz</td>
</tr>
<tr>
<td>ADV2</td>
<td>Sontek 2D-sideloooking microADV A641F (16MHz)</td>
<td>Eulerian velocity</td>
<td>0.18 m above the bed 7.4 m from the left bank</td>
<td>50 Hz</td>
</tr>
<tr>
<td>HR drifter</td>
<td>High resolution GPS-tracked drifters</td>
<td>Lagrangian velocity</td>
<td>Floating with Pseudo-Lagrangian motion</td>
<td>10 Hz</td>
</tr>
<tr>
<td>LR drifter</td>
<td>Low resolution Holux-GPS-tracked drifters</td>
<td>Lagrangian velocity</td>
<td>Floating with Pseudo-Lagrangian motion</td>
<td>1 Hz</td>
</tr>
<tr>
<td>ANE</td>
<td>Sonic 2D anemometer</td>
<td>Wind velocity</td>
<td>0.5 m above water level at high tide</td>
<td>4 Hz</td>
</tr>
<tr>
<td>LiDAR</td>
<td>5 m horizontal resolution and 0.3 m vertical accuracy, obtained from Geoscience Australia</td>
<td>Bathymetry</td>
<td>Bathymetry of Eprapah Creek</td>
<td>n/a</td>
</tr>
<tr>
<td>Measuring staff</td>
<td>Water level</td>
<td>Manual sampling</td>
<td>Every 15 minutes</td>
<td></td>
</tr>
</tbody>
</table>

3.2 Model setup

In the present study, the hydrodynamic simulation is performed in two dimensional depth-averaged mode. Performing a mesh independency experiment, a spatially variable unstructured mesh with the average 3 m resolution was obtained to be suitable for the model. Higher resolution grids were defined for the meandering parts of estuary to realistically model the flow in these regions. The number of cells in width and length of the estuary are 25 and 716, respectively. The width of the modelled flow domain varies from 46 to 178 m from upstream to the downstream. Time-varying water level and discharge are used as downstream and upstream boundary conditions, respectively. The simulation period is 4 days, of which the first two days were used as the spin-up time for model. The modelled domain is presented in Figure 2. This figure also shows the bathymetry relative to Australian Height Datum (AHD), which was interpolated onto the model grids. A spatially constant bed roughness was adopted to this model.
3.2 Model calibration

The main aim of this study is to reduce the systematic uncertainties within hydrodynamic modelling of a microtidal estuary to improve its estimates for horizontal velocity fields. Therefore, at first, the model is calibrated to ensure that the model is capable of representing the hydrodynamics of the Eprapah Creek. As was mentioned, bathymetry is provided from LiDAR data with global vertical accuracy of 0.3 m then interpolated onto the mesh nodes. However, some offsets were observed between bathymetric data obtained from LiDAR and those manually measured in different cross sections along the estuary. This difference could result from measurement precision, regional errors due to use of different datum that can be introduced by LiDAR, the time difference between field work and LiDAR survey, and also uncertainties from interpolation algorithm which is used in model. Since errors in bathymetric data can affect the performance of hydrodynamic modelling significantly, and eventually the model cannot provide a realistic representation of the environmental processes, bathymetry was considered as a calibration parameter as well as bed friction. In this regard, the present study uses MATLAB to perform a sensitivity analysis on these parameters. To perform a calibration study, a range of constant offset throughout the domain was considered as a global error ($\Delta z$) in the bathymetric data, and a range of Manning’s $n$ roughness coefficient was tested. The offset $\Delta z$ varied from zero to an optimum point, while the roughness coefficient varied from 0.016 to 0.030.

To evaluate the performance of the model, root mean square error (RMSE) and the Nash-Sutcliff Efficiency (NSE) between model outputs and observations are employed. The time series of water level and velocity obtained from ADCP are selected as evaluation variables. NSE is the ratio of the error variance to the variance of observations. RMSE and NSE can be calculated based on following equations:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (S_i - O_i)^2}{n}}, \quad [1]$$

$$NSE = 1 - \frac{\sum_{i=1}^{n} (S_i - O_i)^2}{\sum_{i=1}^{n} (O_i - \bar{O})^2}, \quad [2]$$

where $S$ and $O$ are the simulated and observed states, respectively, $\bar{O}$ is the time average of observations, $i$ is the time step index, and $n$ is the number of time step.

4 RESULTS AND DISCUSSION

4.1 Calibration

It was observed that considering bathymetry as calibration parameter can significantly improve model performance for representing the tidal propagation through the model, which default value was used for roughness ($n=0.023$). However, to improve the model estimation for Eulerian velocity, both bathymetry and bed roughness are required to be considered in calibration process. Therefore, further calibration was performed to determine a proper roughness for the model. Figure 3 shows the improvement of the model performance in terms of dimensionless RMSE between modelled and observed velocity by considering bathymetry offset in calibration process. From this figure, it is shown that the calibration of bathymetry reduced the RMSE by about
20% compared with the peak velocity. The optimum dimensionless bathymetry offset ($\Delta z/\max(\z_{\text{observed}})$) was found to be 0.32. It worth note that RMSE of water level converged into an asymptote at $\Delta z/\max(\z_{\text{observed}})<0.3$. Therefore, there is need to combine both water level and velocity as parameters for selecting the optimum bathymetry offset in a calibration procedure. The results demonstrate that model performance can be more improved by using $n=0.018$ as bed roughness. Simulated and observed water level and current velocity are compared in Figure 4. Moreover, the calibration statistics RMSE and NSE for the combination of calibration parameters and tidal phase are presented in Table 2. In panel (a), the time series of water level show good agreement between model and observations in terms of amplitude and phase. Although there are some deviations between modelled and observed Eulerian velocity, panel (b) and error statistics in Table 2 indicate that the model has reasonable level of improvement in calibration (with $R>0.98$). As can be seen from Table 2, calibration improved Eulerian velocity in terms of NSE. It is worth noting that the difference between the modelled and observed velocity was larger during the flood tides, where the model underestimated the flow velocity, than ebb tide phase. The model has better performance in ebb tides with the RMSE about 0.03 m/s. These differences could be related to the random errors in boundary conditions and effect of wind forcing in field observations. Furthermore, scatter plot of modelled and observed current velocity (panel (c)) illustrates that calibrated model is highly correlated with observations.

![Figure 3](image_url)  
*Figure 3. Model performance vs. bathymetry offset as the global error in bathymetric data. RMSE and $\Delta z$ are normalized by using maximum observed Eulerian velocity and bathymetry, respectively.*
Figure 4. Calibrated model performance. (a) Time series of water level and three experiment periods for deployment of drifters (E1, E2 and E3). (b) Time series of Eulerian velocity for 48 hours simulation during spring tide. (c) Scatter plot of modelled and observed current velocity.

Table 2. Statistics of RMSE and NSE for water level and current velocity between measurements and calibrated model

<table>
<thead>
<tr>
<th>Calibration parameter</th>
<th>RMSE</th>
<th>NSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water level (m)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-calibrated</td>
<td>0.154</td>
<td>0.9342</td>
</tr>
<tr>
<td>Bathymetry and roughness</td>
<td>0.067</td>
<td>0.9841</td>
</tr>
<tr>
<td>Calibrated- flood tides</td>
<td>0.082</td>
<td>0.9787</td>
</tr>
<tr>
<td>Calibrated- ebb tides</td>
<td>0.051</td>
<td>0.9879</td>
</tr>
<tr>
<td>Eulerian velocity (m/s)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-calibrated</td>
<td>0.119</td>
<td>0.7413</td>
</tr>
<tr>
<td>Bathymetry and roughness</td>
<td>0.045</td>
<td>0.9381</td>
</tr>
<tr>
<td>Calibrated- flood tides</td>
<td>0.058</td>
<td>0.9209</td>
</tr>
<tr>
<td>Calibrated- ebb tides</td>
<td>0.031</td>
<td>0.9545</td>
</tr>
</tbody>
</table>

4.2 Validation
In order to validate the model, a comparison between Lagrangian velocity of drifters and the velocities of the model is performed. During 48 hours field work, three experiments were carried out to deploy drifters. Two experiments were carried out in flood conditions with the tidal range of 1.75 and 2.25 m, and third experiment was performed during slack water with tidal range of 1.7 m (Figure 3). More information about the environmental conditions, including wind speed and direction and average water surface velocity, during the different experiments are presented in Table 3. It should be noted that wind direction was measured clockwise from positive streamwise direction downstream. Using a finite difference approach, Lagrangian velocity data was derived from the successive drifter positions. To compare the Eulerian velocity of the model with Lagrangian velocity, modelled velocity is linearly interpolated to the drifter positions.

Table 3. Environmental conditions of field during drifter deployment

<table>
<thead>
<tr>
<th>Experiment (E)</th>
<th>Tidal type</th>
<th>Experiment duration (minutes)</th>
<th>Tidal range (m)</th>
<th>Wind speed (m/s)</th>
<th>Average wind speed (m/s)</th>
<th>Wind direction (deg.)</th>
<th>Average water surface velocity (m/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>E1</td>
<td>Flood</td>
<td>183</td>
<td>1.75</td>
<td>0-1.76</td>
<td>0.31</td>
<td>137</td>
<td>0.48</td>
</tr>
<tr>
<td>E2</td>
<td>Flood</td>
<td>210</td>
<td>2.25</td>
<td>0-4.43</td>
<td>0.65</td>
<td>10</td>
<td>0.57</td>
</tr>
<tr>
<td>E3</td>
<td>Slack</td>
<td>93</td>
<td>1.7</td>
<td>0-3.05</td>
<td>0.59</td>
<td>70</td>
<td>0.19</td>
</tr>
</tbody>
</table>
Figure 4. Scatter plot of Lagrangian velocity of drifters and Eulerian velocity of model

The scatter plot of Lagrangian velocity obtained from drifters and Eulerian velocity computed by D-Flow FM for three experiments are illustrated in Figure 4. Moreover, the RMSE between model and drifter velocity is calculated. Generally, these results show a reasonable agreement between model and Lagrangian observations (panel (a)). Level of the correlation as well as the RMSE between the model and the drifter data varied with the phase of the tide that experiment was carried out. It can be observed from panels (b) and (c) that the Eulerian velocity obtained from model and Lagrangian drifter velocity are highly correlated \( R \approx 0.87 \) during experiments 1 and 2. However, correlation coefficient decreased \( R \approx 0.58 \) for experiment 3 which was performed during slack (panel (c)). Model underestimated the Eulerian velocity during this slack water experiment. This reduction in regression can be explained by the combination of environmental factors during this experiment. In Table 3, the average water surface velocity was small during slack, while wind speed was significant. Moreover, Eprapah Creek is a semi-enclosed estuary and it is surrounded by mangroves which caused a strong spatio-temporal variability of wind in this area. This variability of wind can impose variation into the flow and, especially during slack, effect of wind on drifter motion could be noticeable (Suara, et al., 2018). In addition, resonance which is the reflection of tidal signal between landmarks have been reported to be significant in Eprapah Creek (Suara, et al., 2019). Therefore, resonance can impose rapid fluctuation particularly in the direction of surface flow experienced by these drifters. Although the model might be able to capture resonance inherent in time series of discharge at upstream boundary, there would be lower correlation between model outputs and Lagrangian drifter velocity at slack tide because wind as a driven force is not accounted in hydrodynamic model. Finally yet importantly, lower accuracy of the instrument at very low velocity like those experiments at slack tides can contribute to this difference. In this regard, limitations of drifters used in this study are comprehensively discussed in (Suara, et al., 2015). In addition to the aforementioned factors, some other sources of uncertainties, such as imperfect knowledge about physics of the system, discretization errors, and errors in initial and boundary conditions, result in stochastic errors that can lead to divergence of the model outputs from observations. By employing DA, these uncertainties can be significantly reduced further.
4 SUMMARY and CONCLUSION

In this study, D-Flow FM, as a hydrodynamic model, was employed to simulate the tidal flow of a micro-tidal estuary with complex geometry in a 2D depth-average mode. Inputs for hydrodynamic modelling were obtained from a 48 hours field work in which both Eulerian and Lagrangian instruments were deployed and model was forced by tide. To realistically represent the physical processes of the system, model was calibrated by using bathymetry and bed friction as the calibration parameters. Evaluation of model performance demonstrated that errors in bathymetric data can significantly affect model outputs in such a way that they deviate from observations. Considering bathymetry as a calibration parameter leaded to significant improvement in model performance in terms of RMSE and NSE statistics between model outputs and observations for time series of water level. However, there was still differences between modelled and observed Eulerian velocity. Better performance was indicated after model calibration by considering both bathymetry and bed roughness. The high correlation, around 0.985, was obtained for simulated and observed Eulerian velocity. Model had better performance for ebb tides than flood tides. Model were validated using velocity data obtained from Lagrangian drifters. Validation was performed for three experiments with different environmental conditions. The results showed that performance of the model in comparison to the Lagrangian drifter velocity varied as the function of tidal phase. Generally, Eulerian velocity obtained from model has good agreement with Lagrangian drifter velocity especially during flood tides where tidal force was dominant driven force. However, the lower correlation was during slack tides. Using bathymetric data in addition to bed friction for calibration process and also validating model Eulerian velocity with Lagrangian velocity obtained from high-resolution drifters could be highlights from this study. The main aim of present study was to reduce the systematic errors in the model. Therefore, in the next step a data assimilation method will be used to incorporate the Lagrangian drifter data into the model to enhance its accuracy as well as study the effect of different environmental forcings, such as wind and diffusion, on model estimations in both 2D and 3D simulation modes.

ACKNOWLEDGEMENTS

The authors would like to thank the Geoscience Australia for providing the bathymetry information. This project is supported through Australia Research Council Linkage grant LP1501072.

REFERENCES


