Kidney Cancer

Estimated Glomerular Filtration Rate Decline at 1 Year After Minimally Invasive Partial Nephrectomy: A Multimodel Comparison of Predictors

Fabio Crocerossa\textsuperscript{a,b}, Cristian Fiori\textsuperscript{c}, Umberto Capitanio\textsuperscript{d}, Andrea Minervini\textsuperscript{e}, Umberto Carbonara\textsuperscript{a,f}, Savio D. Pandolfo\textsuperscript{a}, Davide Loizzo\textsuperscript{a}, Daniel D. Eun\textsuperscript{g}, Alessandro Larcher\textsuperscript{d}, Andrea Mari\textsuperscript{e}, Antonio Andrea Grosso\textsuperscript{e}, Fabrizio Di Maida\textsuperscript{e}, Lance J. Hampton\textsuperscript{a}, Francesco Cantiello\textsuperscript{b}, Rocco Damiano\textsuperscript{b}, Francesco Porpiglia\textsuperscript{c}, Riccardo Autorino\textsuperscript{a,}\textsuperscript{*}

\textsuperscript{a}Division of Urology, VCU Health, Richmond, VA, USA; \textsuperscript{b}Department of Urology, Magna Graecia University, Catanzaro, Italy; \textsuperscript{c}Division of Urology, San Luigi Hospital, University of Turin, Orbassano, Italy; \textsuperscript{d}Unit of Urology, Division of Experimental Oncology, Urological Research Institute, IRCCS Ospedale San Raffaele, Milan, Italy; \textsuperscript{e}Department of Experimental and Clinical Medicine, Unit of Oncologic Minimally-Invasive Urology and Andrology, Careggi University Hospital, University of Florence, Florence, Italy; \textsuperscript{f}Department of Urology, Andrology and Kidney Transplantation Unit, University of Bari, Bari, Italy; \textsuperscript{g}Department of Urology, Lewis Katz School of Medicine, Temple University, Philadelphia, PA, USA

Article info

Article history:
Accepted February 11, 2022

Associate Editor:
M. Carmen Mir

Keywords:
Partial nephrectomy
Robotics
Laparoscopy
Kidney neoplasms
Treatment outcomes

Abstract

\textbf{Background:} Long-term renal function after partial nephrectomy (PN) is difficult to predict as it is influenced by several modifiable and nonmodifiable variables, often intertwined in complex relations.

\textbf{Objective:} To identify variables influencing long-term renal function after PN and to assess their relative weight.

\textbf{Design, setting, and participants:} A total of 457 patients who underwent either robotic (\(n = 412\)) or laparoscopic PN (\(n = 45\)) were identified from a multicenter international database.

\textbf{Outcome measurements and statistical analysis:} The 1-yr estimated glomerular filtration rate (eGFR) percentage loss (1YPL), defined as the eGFR percentage change from baseline at 1 yr after surgery, was the outcome endpoint. Predictors evaluated included demographic data, tumor features, and operative and postoperative variables. Bayesian multimodel analysis of covariance was used to build all possible models and compare the fit of each model to the data via model Bayes factors. Bayesian model averaging was used to quantify the support for each predictor via the inclusion Bayes factor (BF\textsubscript{incl}). High-dimensional undirected graph estimation was used for network analysis of conditional independence between predictors.

\textbf{Results and limitations:} Several models were found to be plausible for estimation of 1YPL. The best model, comprising postoperative eGFR percentage loss (PPL), sex, ischemia technique, and preoperative eGFR, was 207 times more likely than all the others.

\* Corresponding author. Division of Urology, VCU Health, West Hospital, 1200 East Broad Street, Richmond, VA 23298, USA. Tel. +1 804 8273099; Fax: +1 804 8282157. E-mail address: ricautor@gmail.com (R. Autorino).
other models regarding relative predictive performance. Its components were part of the top 44 models and were the predictors with the highest $BF_{\text{incl}}$. The role of cold ischemia, solitary kidney status, surgeon experience, and type of renorraphy was not assessed.

**Conclusions:** Preoperative eGFR, sex, ischemia technique, and PPL are the best predictors of eGFR percentage loss at 1 yr after minimally invasive PN. Other predictors seem to be irrelevant, as their influence is insignificant or already nested in the effect of these four parameters.

**Patient summary:** Kidney function at 1 year after partial removal of a kidney depends on sex, the technique used to halt blood flow to the kidney during surgery, and kidney function at baseline and in the early postoperative period.

© 2022 The Author(s). Published by Elsevier B.V. on behalf of European Association of Urology. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

1. **Introduction**

Partial nephrectomy (PN) is the standard treatment for T1 renal masses [1]. In comparison to radical nephrectomy, PN is associated with a lower incidence of chronic kidney disease (CKD) while maintaining similar oncologic and safety outcomes [2]. Preservation of kidney function is critical in patients with pre-existing comorbidities, solitary renal malignancies, or bilateral cancers, as it can influence the risk of mortality from other causes [3].

Immediate and long-term renal function after PN is affected by several modifiable and nonmodifiable variables, including demographic, disease-related, intraoperative, and postoperative factors, often intertwined in complex relations [4].

In this study we sought to identify which variables influence long-term renal function and to assess their relative weight in determining the percentage change in estimated glomerular filtration rate (eGFR) at 1 yr after minimally invasive PN.

A Bayesian multimodel comparison was applied to objectively compare the predictive performance of all possible combinations of predictors while balancing estimation errors and overfitting risks. Using Bayesian model averaging, it was possible to weight each predictor across all models and give information on its overall predictive performance and plausibility.

2. **Patients and methods**

2.1. **Patient population**

An international, multicenter, institutional review board–approved, retrospective study including patients undergoing laparoscopic or robot-assisted PN at five academic institutions (three from Europe and two from USA) between 2013 and 2019 was conducted. Inclusion criteria were (1) adult patients diagnosed with a localized renal tumor (T1 or T2); (2) undergoing robotic or laparoscopic PN; and (3) with a complete description of preoperative and postoperative characteristics, including up to 1-yr follow-up data. The following exclusion criteria were applied: (1) patients undergoing radical nephrectomy or nonsurgical treatments; (2) pediatric patients; and (3) patients with a transplanted kidney or a history of multiple PNs on the same kidney.

2.2. **Data collection**

Demographic data and baseline characteristics included age, sex, ethnicity, hypertension, diabetes mellitus status, body mass index, American Society of Anesthesiologists score, solitary kidney status, preoperative hemoglobin. eGFR was calculated using the CKD-Epidemiology Collaboration equation. Hypertension was defined as systolic blood pressure of $\geq 140$ mm Hg or diastolic blood pressure of $\geq 90$ mm Hg or taking anti-hypertensive medication. Information on tumor and operative details included pathologic tumor size, Radius, Endophytic, Nearness to collecting system, Anterior/posterior, and Location (RENAL) score, surgical approach, clamping technique, warm ischemia time (WIT), operative time, estimated blood loss (EBL), and intraoperative complications. Postoperative data included eGFR at discharge, length of stay, and postoperative complications. eGFR postoperative percentage loss (PPL) was calculated as the percentage difference between baseline eGFR and eGFR at discharge: (preoperative eGFR – postoperative eGFR) $\times$ 100 / preoperative eGFR.

The functional outcome endpoint was the 1-yr eGFR percentage loss (1YPL), defined as the eGFR percentage change from baseline at 1 year after surgery: (eGFR at 1 yr – preoperative eGFR) $\times$ 100 / preoperative eGFR.

2.3. **Statistical analysis**

To predict 1YPL, analysis of covariance (ANCOVA) with multiple continuous and categorical variables was performed. To objectively identify models that balance estimation errors and overfitting risk, a Bayesian multimodel comparison was used. In Bayesian statistics, the prior beliefs (prior distribution of the model and the parameter probability) are updated with inclusion of the likelihood of data in the posterior beliefs (posterior distributions). The likelihood of data is the relative support from data for alternative hypotheses and is quantified using Bayes factors (BFs). With Bayesian multimodel ANCOVA it is possible to overcome the uncertainty derived from the use of only one model by comparing the predictive performance of all possible combinations of predictors and calculating the relative plausibility of each model relative to the others. Furthermore, Bayesian model averaging can be used to weight each predictor across all models and give information on its overall predictive performance and plausibility [5]. In the first step, we performed a Bayesian model comparison and calculated the posterior model probability $P(M|\text{data})$ to evaluate the relative plausibility of each model across the entire model space; we used the model BF ($BF_{\text{m}}$) as an indicator of model predictive performance, or model likelihood, which measures how many times the data were more likely to occur under a specific model than all the others averaged across the space. $BF_{\text{m}}$ was used to
represent the relative predictive performance (likelihood) of the best model with respect to the model considered [6]. For the model prior probability P(M), we chose a uniform model prior and imposed that all models were equally likely before seeing the data [7]. In the second step, we used a Bayesian model averaging approach to choose which variable is useful in predicting 1YPL and quantified the support for each predictor as its posterior inclusion probability P(incl|data), which is the probability of including it in a model after observing the data. P(incl|data) is the sum of P(M|data) for the models including a given variable. We compared the predictive performance of predictors in terms of BFexcl, which is the ratio between the likelihood of models excluding a predictor and models including it. In this way, the data are BFexcl times more likely to occur under the models that do not include a predictor than the models that include it. BFexcl represents the reciprocal of BFincl. The percentage error was used to quantify the proportional error associated with BF estimation and reflects the percentage accuracy in predicting the value of each BF. We also reported the model-averaged effect size for each parameter (regression coefficient β) to assess the weight of each predictor in estimating 1YPL. The mean β was calculated by averaging the β values assumed for the predictor across all models and weighted by the P(M|data). Standard deviation (SD) and the 95% credible interval for estimates are also reported. We chose the Jeffrey-Zellner-Siow distribution as its posterior inclusion probability P(incl|data), which is the probability that 1YPL was highly dependent on PPL and moderately dependent on preoperative eGFR and EBL; inverse dependence was observed between 1YPL and male sex (Fig. 1).

The analysis showed that several models of varying complexity are plausible for estimation of 1YPL (Table 2). The best model, comprising sex, preoperative eGFR, ischemia technique, and PPL, was 207 times more likely than all the others averaged across the model space. For all the predictors in this model, the likelihood increased after seeing the data. The second-best model includes the same predictors with the addition of age (BFM 122.6). The relative predictive performance of the third-best model (comprising ischemia technique, PPL, and preoperative eGFR) is 81 times higher than the average performance of the other models. The components of this model (ischemia technique, PPL, and preoperative eGFR) are part of the top 44 models with the highest P(M|data) values.

Comparison between the group of models not including PPL and the group of models including PPL showed that the data were extremely less likely (BFexcl 4.441E-16) to occur under the former (Table 3). The data were less likely to occur under the group of models not including preoperative eGFR (BFexcl 0.02), ischemia technique (BFexcl 0.034), and sex (BFexcl 0.458). The other variables (preoperative hemoglobin, hypertension, diabetes, tumor size, RENAL score, WIT, and EBL) were all worse predictors than those mentioned above.

Mean β coefficients supported the importance of PPL, preoperative eGFR, sex, and ischemia technique in predicting 1YPL: specifically, the 95% credible interval for the regression coefficient did not include 0 for any of these variables (Supplementary Table 1). For sex, the 95% credible interval ranged from −4.0 to −0.4, demonstrating that male sex is a protective factor for renal function because it reduces the extent of 1YPL. The 95% credible interval for all the other variables included the null effect.

Network analysis of conditional independence showed that 1YPL was highly dependent on PPL and moderately dependent on preoperative eGFR and EBL; inverse dependence was observed between 1YPL and male sex (Fig. 1).

3. Results

Data were collected for 1359 patients. Six patients were excluded because of pediatric age, and 896 were excluded because of incomplete preoperative, postoperative, or follow-up data. A total of 457 patients undergoing robotic (n = 412) or laparoscopic PN (n = 45) were thus included in the study cohort. Demographic data and baseline characteristics are shown in Table 1. There were no differences in available characteristics between the included and excluded patients. No violation of model assumptions for ANCOVA was observed (Supplementary Fig. 1).

The analysis showed that several models of varying complexity are plausible for estimation of 1YPL (Table 2). The best model, comprising sex, preoperative eGFR, ischemia technique, and PPL, was 207 times more likely than all the others averaged across the model space. For all the predictors in this model, the likelihood increased after seeing the data. The second-best model includes the same predictors with the addition of age (BFM 122.6). The relative predictive performance of the third-best model (comprising ischemia technique, PPL, and preoperative eGFR) is 81 times higher than the average performance of the other models. The components of this model (ischemia technique, PPL, and preoperative eGFR) are part of the top 44 models with the highest P(M|data) values.

Comparison between the group of models not including PPL and the group of models including PPL showed that the data were extremely less likely (BFexcl 4.441E-16) to occur under the former (Table 3). The data were less likely to occur under the group of models not including preoperative eGFR (BFexcl 0.02), ischemia technique (BFexcl 0.034), and sex (BFexcl 0.458). The other variables (preoperative hemoglobin, hypertension, diabetes, tumor size, RENAL score, WIT, and EBL) were all worse predictors than those mentioned above.

Mean β coefficients supported the importance of PPL, preoperative eGFR, sex, and ischemia technique in predicting 1YPL: specifically, the 95% credible interval for the regression coefficient did not include 0 for any of these variables (Supplementary Table 1). For sex, the 95% credible interval ranged from −4.0 to −0.4, demonstrating that male sex is a protective factor for renal function because it reduces the extent of 1YPL. The 95% credible interval for all the other variables included the null effect.

Network analysis of conditional independence showed that 1YPL was highly dependent on PPL and moderately dependent on preoperative eGFR and EBL; inverse dependence was observed between 1YPL and male sex (Fig. 1).

4. Discussion

This study demonstrates that several models are plausible for predicting renal loss at 1 yr after minimally invasive

| Variable | Result a |
|----------|----------|
| Age (yr) | 61 (17)  |
| Body mass index (kg/m²) | 26.1 (5.11)  |
| Preoperative hemoglobin (g/dl) | 14.3 (1.9)  |
| Preoperative eGFR (ml/min/1.73 m²) | 87.36 (25.34)  |
| eGFR at discharge (ml/min/1.73 m²) | 76.52 (33.22)  |
| PPL (%) | 9.11 (25.41)  |
| eGFR at 1 yr (ml/min/1.73 m²) | 71.78 (23.59)  |
| PPL at 1 yr (%) | 1038 (15.04)  |
| RENAL score | 6 (3)  |
| Tumor size (cm) | 2.8 (1.9)  |
| Operative time (min) | 144 (63)  |
| Warm ischemia time (min) | 16 (10)  |
| Length of stay (d) | 5 (3)  |
| Sex | Male 286 (62.6), Female 171 (37.4)  |
| Race (Black) | Yes 29 (6.3), No 428 (93.7)  |
| Hypertension b | Yes 166 (36.3), No 291 (63.7)  |
| Diabetes mellitus | Yes 46 (10.1), No 411 (89.9)  |
| Solitary kidney | Yes 19 (4.1), No 438 (95.8)  |
| Partial nephrectomy approach | Robot-assisted 404 (88.4), Laparoscopic 53 (11.6)  |
| Ischemia technique | Clampless 47 (10.3), Selective 107 (23.4), Full 303 (66.3)  |

PPL = postoperative percentage eGFR loss; eGFR = estimated glomerular filtration rate.

a Results are presented as mean (SD) for continuous variables and n (%) for categorical variables.

b Defined as systolic blood pressure of ≥140 mm Hg or diastolic blood pressure of ≥90 mm Hg or taking antihypertensive medication.
PN. We found that the best model includes sex, preoperative eGFR, ischemia technique, and PPL. All the models containing these four variables exhibited an increase in probability after seeing the data and showed greater predictive performances than the models including all or some of the remaining variables. Model averaging and network analysis of conditional independence confirmed these results. Several points regarding these findings deserve more detailed consideration.

Unlike most studies in the literature, we chose percent-age eGFR loss to evaluate functional loss after minimally invasive PN. Several previous models used the ultimate eGFR or progression to stage III CKD as the endpoint [9–12]. Choice of a similar criterion might lead to deceptive results because the dependent variable is directly calculated from the same variables (ie, age, sex, or serum creatinine) that it is tested against. This always results in identification of those variables as important predictors of the outcome. Other studies evaluated predictors of significant eGFR loss, defined as a reduction of >25% from baseline eGFR [13–15]. This endpoint resolved the above-mentioned limitation, as it is not necessarily influenced by variables used in eGFR formulas. Nonetheless, those studies chose only a subset of predictors to build a model containing the covariates considered relevant. Consequently, inference in all previous studies was carried out without taking into account the uncertainty derived from the use of only one model among all possible models; furthermore, the weight of each predictor was specific to a particular model and cannot give information on its overall predictive performance (likelihood) provided by the data [5]. This process can ultimately lead to overestimation of model precision and may provide biased estimates.

We took account of model space uncertainty by using Bayesian model averaging, in which the full range of models contribute to estimates and predictions. In this way, a
summary of the importance and consistency of each predictor can be provided. Regression coefficients that have a mean value close to zero will have very limited importance in predicting the independent variable; furthermore, predictors with a 95% credible interval that includes the null effect will influence the outcome in an opposite way, depending on the model considered, thus proving to be inconsistent. Specifically, calculation of the posterior mean and the 95% credible interval for the regression coefficients showed that PPL, preoperative eGFR, and sex retained their predictive performance throughout the entire model space: possible values for their regression coefficients were all of opposite signs.

Previous studies tested the use of the acute kidney injury (AKI) categories of the Acute Dialysis Quality Initiative as predictors of long-term renal failure after PN. The Risk, Injury, Failure, Loss, and End-stage (RIFLE) criteria define AKI as an abrupt loss of kidney function resulting in a >25% reduction in eGFR from baseline [16]. It has been shown that AKI increases the risk of mortality and CKD development in patients with underlying medical conditions [17,18] but it was not thought to affect these outcomes when occurring in patients undergoing PN [19,20]. However, recent studies showed that both the presence and duration of AKI increase the risk of long-term renal failure in this type of patient as well [14,21]. Nonetheless, the RIFLE criteria may be inappropriate for patients undergoing renal surgery; in these patients the increase in eGFR may be due to both surgical excision and ischemic damage, with relative contributions that are difficult to differentiate diagnostically and prognostically [18].

We did not use a cutoff value to define AKI in our study; instead, we evaluated acute renal failure in terms of PPL. This choice might offer some benefits, including avoiding the negative consequences of dichotomization such as loss of effect size and the risk of misclassification, allowing comparison with other continuous covariates of long-term eGFR and yielding a more detailed prediction of functional recovery [22].

We not only confirmed that PPL has noticeable repercussions for long-term function but also demonstrated that PPL is the most important factor affecting 1YPL. Unlike AKI, PPL seems to be useful for predicting long-term functional deterioration even when the percentage eGFR loss is <25%; moreover, it is essential to precisely quantify the extent of PPL as a continuous variable, as it is linearly related to the outcome (Supplementary Fig. 2). An interesting difference between our study and the current literature is that PPL is a better predictor than all the other surgical variables tested, including WIT, tumor size, RENAL score, and EBL. In addition, all these variables showed little support from the data, because models that do not include them are more likely than models that use them as predictors. Finally, it should be considered that renal function decline related to postoperative acute injury could be influenced by consequent hypertrophy of the remnant healthy kidney parenchyma. Studies with longer follow-up have shown that the impact of these modifiable parameters has a progressively lower influence on functional outcomes, while other comorbidities or de novo vascular diseases may have a significant impact on long-term outcomes [13,23].

Several studies found that WIT was a crucial factor in predicting eGFR change [24–27]. Other studies downgraded its role and concluded that as long as WIT is below a safe threshold (25–30 min) its duration does not significantly affect long-term eGFR [10,28–30].

A large body of literature has focused on the percentage of parenchymal mass preserved (PPMP) as the key determinant of remaining renal function, with WIT playing only a minor role [28,31]. For instance, both Simmons et al [10] and Ginzburg et al [15] found that PPMP and baseline eGFR, but not WIT, were independently associated with long-term renal function after PN. Other authors found that inclusion of PPMP in multivariable linear regression led to loss of significance for WIT in predicting eGFR at 3 mo [31] or later [32]. It must be noted that PPMP assessment is not immediate and requires dedicated three-dimensional rendering software to compare preoperative and postoperative renal computed tomography scans performed with intravenous contrast.

WIT and PPMP are closely related and difficult to decouple [33]. Large and complex tumors are usually associated with great parenchymal excision, extensive devascularization, and secondary damage due to reconstruction [9,34,35]. All of these factors are associated with longer WIT and smaller PPMP, which in turn are strongly related to PPL [35–37], thus causing multicollinearity between all
these variables. This is clearly shown by analysis of the network structure for variable dependence. Specifically, each node in the network graph represents a single variable and each edge represents the conditional dependence of two variables given all the others. Two variables initially found to be correlated (i.e., marginally dependent) can become conditionally independent (no direct edge between the two nodes) when their correlation is explained by a third variable that is strongly related to both. For instance, after introducing PPL into the model, WIT and 1YPL become conditionally independent, because WIT influences the outcome via PPL. In addition, when conditionally independent predictors are added to a model already containing conditionally dependent variables, they are unlikely to increase model predictivity. In our analysis, models containing both WIT and PPL performed worse than models containing only PPL because the influence of WIT on 1YPL is already nested in the PPL effect.

Our database does not have complete data for PPMP, so we did not evaluate this variable. However, PPMP should not add any benefit to our models; when several variables related to PPMP, including pathological size, RENAL score, and tumor stage [35], were added to a model containing PPL, the derived models did not have higher likelihood. In other words, these variables related to PPMP are unable to explain the residual variance, achieving a worse overall predictive performance. This does not mean that WIT and PPMP are not important in determining long-term renal function, but most of their effect is mediated by PPL, which represents the best predictor of eGFR at 1 yr after surgery.

Age, hypertension, body mass index, and diabetes mellitus have all been identified as risk factors for CKD onset and could also be involved in greater long-term functional loss [9,11,31]. Contrasting results have been found for the role of sex [11,31,38]. We believe that these findings may be strongly influenced by the study design and choice of endpoint, as they are all associated with lower baseline renal function. We evaluated the role of clinical variables including age, diabetes, obesity, hypertension, and preoperative hemoglobin in determining 1YPL. Model averaging analysis showed that only age was clearly related to 1YPL; its effect is largely mediated by PPL and it retains a marginal effect if it is added as an independent predictor.

Some studies suggest that selective clamping of artery branches [39] or the zero-ischemia approach [40] gives a significantly higher chance of parenchymal sparing compared to hilar clamping. Our results indicate that ischemia technique is a useful predictor of 1YPL as shown by its BF_{incl} of 29.4, which means that its inclusion increased the predictive performance of models nearly 30-fold.

Several reports found no significant difference in the reduction in eGFR between surgical approaches [31,38,41]. Our study confirms these findings by demonstrating that the data were less likely to occur under the group of models including surgical technique as a predictor.

Our study is characterized by several limitations. It is a retrospective study and thus selection and detection biases cannot be excluded. Our population came from high-volume centers and all PNs were performed by highly experienced surgeons; therefore, our findings may not apply to other health care settings. In this study, data for 1359 patients were collected, with 896 excluded owing to incomplete data. This is largely because of the strict inclusion criteria applied; a large proportion of these patients lacked 1-yr follow-up data and no statistical inference for these patients is possible; This might introduce a selection bias and impact the generalizability of the findings. We were not able to draw any conclusions regarding the role of cold ischemia, solitary kidney status, surgeon experience, or renorraphy techniques; the likelihood and magnitude of long-term functional loss may be affected by each of these.

5. Conclusions

Several models are plausible for predicting renal loss at 1 yr after minimally invasive PN. Our analysis suggests that the best model should include sex, ischemia technique, preoperative eGFR, and PPL. All the predictive models containing these four variables had higher probability and showed greater predictive performance than models including all or some of the remaining variables. Compared to other tools, these predictors are immediate and readily available. PPL is useful for predicting long-term functional decline even when the percentage loss is less than 25%, since it is linearly related to 1YPL. Other predictors seem to be irrelevant, as their influence is insignificant or already nested in the effect of these four parameters.

Author contributions: Fabio Crocerossa and Riccardo Autorino had full access to all the data in the study and take responsibility for the integrity of the data and the accuracy of the data analysis.

Study concept and design: Crocerossa, Autorino.
Acquisition of data: Crocerossa, Fiori, Capitanio, Larcher, Mari, Carbonara.
Analysis and interpretation of data: Crocerossa, Carbonara.
Drafting of the manuscript: Crocerossa, Carbonara, Autorino.
Critical revision of the manuscript for important intellectual content: Crocerossa, Fiori, Capitanio, Larcher, Mari, Grosso, Di Maida, Minervini, Eun, Carbonara, Pandolfi, Loizzo, Cantiello, Damiano, Hampton, Porpiglia, Autorino.
Statistical analysis: Crocerossa.
Obtaining funding: None.
Administrative, technical, or material support: None.
Supervision: Crocerossa, Autorino.
Other: None.

Financial disclosures: Riccardo Autorino certifies that all conflicts of interest, including specific financial interests and relationships and affiliations relevant to the subject matter or materials discussed in the manuscript (e.g., employment/affiliation, grants or funding, consultancies, honoraria, stock ownership or options, expert testimony, royalties, or patents filed, received, or pending), are the following: None.

Funding/Support and role of the sponsor: None.
Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.euros.2022.02.005.

References

[1] Ljungberg B, Bhansali K, Canfield S, et al. EAU guidelines on renal cell carcinoma: 2014 update. Eur Urol 2015;67:915–24. https://doi.org/10.1016/j.eururo.2015.01.005.

[2] Bradshaw AW, Autorino R, Simone G, et al. Robotic partial nephrectomy vs minimally invasive radical nephrectomy for clinical T2a renal mass: a propensity score-matched comparison from the ROSULA (Robotic Surgery for Large Renal Mass) collaborative group. BJU Int 2020;126:114–23. https://doi.org/10.1111/bju.13964.

[3] Larcher A, Capitanio U, Terrone C, et al. Elective nephron sparing surgery decreases other cause mortality relative to radical nephrectomy only in specific subgroups of patients with renal cell carcinoma. J Urol 2016;196:1008–13. https://doi.org/10.1016/j.juro.2016.04.093.

[4] Swavely NR, Anele UA, Porpiglia F, Mir MC, Hampton LJ, Autorino R. Optimization of renal function preservation during robotic partial nephrectomy 1756287218815819. Ther Adv Urol 2019;11. https://doi.org/10.1177/1756287218815819.

[5] Claeskens G, Hjort NL. Model selection and model averaging. Cambridge, UK: Cambridge University Press; 2008. 00031305.1999.10474443.

[6] Simmons MN, Hillyer SP, Lee BH, Fergany AF, Kaouk J, Campbell SC. Surgery decreases other cause mortality relative to radical nephrectomy 1756287218815819. Ther Adv Urol 2019;11.https://doi.org/10.1177/1756287218815819.

[7] Zabih R, Isharwal S, Yue S, et al. Acute kidney injury after partial nephrectomy of solitary kidneys: impact on long-term stability of renal function. J Urol 2018;200:1295–301. https://doi.org/10.1016/j.juro.2018.07.042.

[8] Zhang Z, Zhao J, Dong W, et al. Acute kidney injury after partial nephrectomy: role of parenchymal mass reduction and ischemia and impact on subsequent functional recovery. Eur Urol 2016;69:745–52. https://doi.org/10.1016/j.eururo.2015.10.023.

[9] Zabih R, Isharwal S, Yue S, et al. Acute kidney injury after partial nephrectomy. Eur Urol 2019;76:398–403. https://doi.org/10.1016/j.eururo.2019.04.040.

[10] Perrone L, Zabih R, Yue S, et al. The huge package

[11] Clark MA, Shikanov S, Raman JD, et al. Chronic kidney disease predictive model of new-onset chronic kidney disease after on-clamp partial nephrectomy in patients with T1 renal tumors. Int J Learn Res 2012;13:1059–62. https://doi.org/10.1080/1009212519.

[12] Arellano-Valle RB, Bolfarine P. Bayesian inference for censored regression models using MCMC sampling. J R Stat Soc Ser B Stat Methodol 2012;74:195–213. https://doi.org/10.1111/j.1467-9868.2011.00797.x.

[13] Aron M, Gill IS, Campbell SC. A nonischemic approach to partial nephrectomy is optimal. J Urol 2016;195:387–90. https://doi.org/10.1016/j.juro.2011.10.092.

[14] Mari A, Tellini R, Antonelli A, et al. A nomogram for the prediction of immediate, early and late functional results, and its relationship with cardiovascular outcome after partial nephrectomy. J Urol 2016;196:1008–13. https://doi.org/10.1016/j.juro.2016.12.021.

[15] Zabih R, Isharwal S, Yue S, et al. Acute kidney injury after partial nephrectomy during volume averaging: a tutorial. Stat Sci 1999;14:382–401. https://doi.org/10.1214/ss/1009212519.

[16] Thompson RH, Lang B, Loth CM, et al. Every minute counts when the renal hilum is clamped during partial nephrectomy. Eur Urol 2010;58:340–5. https://doi.org/10.1016/j.eururo.2010.05.047.

[17] Thompson RH, Lane BR, Loth CM, et al. Renal function after partial nephrectomy for localized renal tumors: a prospective multicenter observational study (RECORd2 project). Eur Urol Focus In press. https://doi.org/10.1016/j.euf.2021.09.012.

[18] Thompson RH, Lane BR, Loth CM, et al. Acute kidney injury after partial nephrectomy: Effect of warm ischemia relative to quality and quantity of preserved kidney. Urology 2012;79:356–60. https://doi.org/10.1016/j.urology.2011.10.031.

[19] Afshar A, Blute ML, Cifuentes V, et al. Acute kidney function after partial nephrectomy: a collaborative review of the literature. Eur Urol 2015;68:61–74. https://doi.org/10.1016/j.eururo.2015.01.025.

[20] Thompson RH, Lang B, Loth CM, et al. A nomogram for the prediction of immediate, early and late functional results, and its relationship with cardiovascular outcome after partial nephrectomy: results from a prospective clinical trial. BJU Int 2016;117:766–74. https://doi.org/10.1111/bju.13192.

[21] Thompson RH, Lane BR, Loth CM, et al. Comparison of cold and warm ischemia during partial nephrectomy in 660 solitary kidneys reveals predominant role of nonmodifiable factors in determining ultimate renal function. J Urol 2011;185:421–7. https://doi.org/10.1016/j.juro.2010.09.099.

[22] Thompson RH, Lane BR, Loth CM, et al. Acute kidney injury after partial nephrectomy in 660 solitary kidneys reveals predominant role of nonmodifiable factors in determining long-term renal function after partial nephrectomy. J Urol 2017;198:927–32. https://doi.org/10.1016/j.juro.2017.11.065.

[23] Thompson RH, Lane BR, Loth CM, et al. Differential contribution of the factors determining long-term renal function after partial nephrectomy. J Urol 2016;195:387–90. https://doi.org/10.1016/j.juro.2016.08.036.

[24] Thompson RH, Lane BR, Loth CM, et al. Every minute counts when the renal hilum is clamped during partial nephrectomy. Eur Urol 2010;58:340–5. https://doi.org/10.1016/j.eururo.2010.05.047.

[25] Thompson RH, Lane BR, Loth CM, et al. Renal function after partial nephrectomy for localized renal tumors: a prospective multicenter observational study (RECORd2 project). Eur Urol Focus In press. https://doi.org/10.1016/j.euf.2021.09.012.

[26] Thompson RH, Lane BR, Loth CM, et al. Acute kidney injury after partial nephrectomy: Effect of warm ischemia relative to quality and quantity of preserved kidney. Urology 2012;79:356–60. https://doi.org/10.1016/j.urology.2011.10.031.

[27] Thompson RH, Lane BR, Loth CM, et al. Acute kidney injury after partial nephrectomy: Effect of warm ischemia relative to quality and quantity of preserved kidney. Urology 2012;79:356–60. https://doi.org/10.1016/j.urology.2011.10.031.

[28] Thompson RH, Lane BR, Loth CM, et al. Acute kidney injury after partial nephrectomy: Effect of warm ischemia relative to quality and quantity of preserved kidney. Urology 2012;79:356–60. https://doi.org/10.1016/j.urology.2011.10.031.

[29] Thompson RH, Lane BR, Loth CM, et al. Acute kidney injury after partial nephrectomy: Effect of warm ischemia relative to quality and quantity of preserved kidney. Urology 2012;79:356–60. https://doi.org/10.1016/j.urology.2011.10.031.

[30] Thompson RH, Lane BR, Loth CM, et al. Acute kidney injury after partial nephrectomy: Effect of warm ischemia relative to quality and quantity of preserved kidney. Urology 2012;79:356–60. https://doi.org/10.1016/j.urology.2011.10.031.
[38] Shum CF, Bahler CD, Cary C, et al. Preoperative nomograms for predicting renal function at 1 year after partial nephrectomy. J Endourol 2017;31:711–8. https://doi.org/10.1089/end.2017.0184.

[39] Desai MM, de Castro Abreu AL, Leslie S, et al. Robotic partial nephrectomy with superselective versus main artery clamping: a retrospective comparison. Eur Urol 2014;66:713–9. https://doi.org/10.1016/j.eururo.2014.01.017.

[40] Gill IS, Patil MB, de Castro Abreu AL, et al. Zero ischemia anatomical partial nephrectomy: a novel approach. J Urol 2012;187:807–14. https://doi.org/10.1016/j.juro.2011.10.146.

[41] Eggener SE, Clark MA, Shikanov S, et al. Impact of warm versus cold ischemia on renal function following partial nephrectomy. World J Urol 2015;33:351–7. https://doi.org/10.1007/s00345-014-1315-4.