

1 A comparison of game-play characteristics between elite youth and senior Australian National Rugby  
2 League competitions

3

4 **Woods T. Carl<sup>1\*</sup>, Robertson Sam<sup>2</sup>, Sinclair H. Wade<sup>1</sup>, Till Kevin<sup>3</sup>, Pearce Leesa<sup>1</sup>, Leicht S. Anthony<sup>1</sup>**

5

6 <sup>1</sup>Discipline of Sport and Exercise Science, James Cook University, Townsville, Queensland, Australia

7 <sup>2</sup>Institute of Sport, Exercise & Active Living (ISEAL), Victoria University, Melbourne, Australia

8 <sup>3</sup>Institute for Sport, Physical Activity and Leisure, Leeds Beckett University, Leeds, West Yorkshire,  
9 United Kingdom

10

11 \*Corresponding Author

12 Carl Woods, Discipline of Sport and Exercise Science, James Cook University, Townsville, Queensland,  
13 Australia.

14 Ph: +61 08 4781 6550 Mob: +61 421254329 Email: [carl.woods@jcu.edu.au](mailto:carl.woods@jcu.edu.au)

1 **Abstract**

2 *Objectives:* To compare game-play characteristics between elite youth and senior Australian National  
3 Rugby League (NRL) competitions.

4 *Design:* Longitudinal observational.

5 *Methods:* The dataset consisted of 12 team performance indicators (e.g., 'all runs', 'offloads' and  
6 'tackles') extracted from all 2016 national under 20 (U20) competition (elite youth; n = 372  
7 observations) and National Rugby League (NRL) (elite senior; n = 378 observations) matches. Data  
8 was classified according to competition (Two levels: U20 and NRL) and modelled using two  
9 techniques. Firstly, non-metric multidimensional scaling resolved multivariate competition  
10 (dis)similarity, visualised using a two-dimensional ordination. Secondly, a conditional interference  
11 (CI) classification tree was grown to reveal the performance indicators most capable of explaining  
12 competition level.

13 *Results:* Non-metric multidimensional scaling revealed high competition dissimilarity, with U20 and  
14 NRL teams orienting distinctive positions on the first dimension of the ordination surface. Five team  
15 performance indicators were retained within the CI tree ('all runs', 'tackle breaks', 'tackles', 'missed  
16 tackles', and 'kicks'), which correctly classified 79% of the U20 observations and 93% of the NRL  
17 observations.

18 *Conclusions:* Multivariate differences between elite youth and senior rugby league competitions  
19 were identified. Specifically, NRL game-play was classified by a greater number of 'all runs', and  
20 'tackles' and a lower number of 'missed tackles' relative to the U20 competition. Given the national  
21 U20 competition is purported to assist with the development of prospective NRL players, junior  
22 coaches may consider training interventions that primarily aid the tackling capacities of players. This  
23 may subsequently assist with talent development and player progression in Australian rugby league.

24

25 *Key words:* Performance analysis; talent development; classification tree; multidimensional scaling

## 1 **1. Introduction**

2 Developing talent is a complex and typically non-linear process,<sup>1</sup> influenced by a range of  
3 intrapersonal, environmental and situational catalysts.<sup>2</sup> In an attempt to positively augment this  
4 process, it is common for national sporting organisations to establish talent development academies  
5 or 'pathways', intended to offer longitudinal player development opportunities for talent identified  
6 juniors.<sup>3,4</sup> The unifying goal of these development pathways is often to bridge performance  
7 discrepancies between junior and senior competitions, creating an expedited developmental  
8 transition for participants towards the elite senior level.<sup>5</sup>

9 Talent development in team sports, such as rugby league, is often further complicated given their  
10 innate multidimensionality (i.e., physical, technical and perceptual requisites).<sup>6-9</sup> Accordingly, it is  
11 unsurprising to note the quantity of work that has investigated a range of performance qualities  
12 discriminant of developmental level specific to rugby league.<sup>8,10-12</sup> Till et al.<sup>8</sup> identified the  
13 anthropometric and physical fitness characteristics of English academy rugby league players in  
14 relation to their career attainment (professional or academy). Their results demonstrated  
15 differences (lower body strength) and changes (10 m momentum) in the physical characteristics of  
16 players as they progressed through the academy according to career attainment level, with these  
17 observations being of use for the establishment of training interventions assistive with talent  
18 development.<sup>8</sup>

19 In Australia, the premier youth rugby league competition is the national under 20 (U20) competition;  
20 currently referred to as the Holden Cup. Fundamentally, the premise of this competition is to  
21 provide talent identified youths with a pathway into the elite senior competition, the National Rugby  
22 League (NRL). Accordingly, each of the 16 NRL teams has a representative U20 team who competes  
23 within a 26-week competition. Although statistics regarding player progression from the U20 to the  
24 NRL competition are not available, it is widely known within the NRL community that this national  
25 youth competition offers a critical developmental environment for prospective NRL players.

1 However, despite this, the game-play characteristics (e.g., ball carries and tackles) between  
2 competitions has yet to be compared. Resolving this competition difference would likely provide  
3 coaches at the U20 level with an objective basis to minimise performance gaps between the U20 and  
4 NRL competitions and aid player progression and development within Australian rugby league.

5 Given the multidimensional dynamicity of rugby league match play,<sup>13</sup> singular linear statistical  
6 approaches may not adequately reveal multivariate patterns within a dataset,<sup>14</sup> constraining the  
7 practical utility of the observations.<sup>15</sup> Given this, recent research in rugby league has adopted  
8 machine learning approaches to assist with the explanation of match outcomes using a diverse range  
9 of performance indicators.<sup>16</sup> As such, it would seem appropriate to consider machine learning  
10 approaches when examining differences between elite junior and senior rugby league competitions  
11 to assist with the resolution of non-linear interactions between diverse datasets.

12 The aim of this study was to compare game-play characteristics between elite youth (national U20)  
13 and senior (NRL) Australian rugby league competitions. The subsequent results of this work will offer  
14 coaches at the U20 level with objective guidance with respect to the establishment of targeted  
15 training interventions intended to expedite talent development and player progression in rugby  
16 league.

## 17 **2. Methods**

18 Team performance indicators from the 2016 Holden Cup and NRL seasons were extracted from a  
19 publicly available source (<http://www.nrl.com/stats>) (Supplementary Table 1). These 12 indicators  
20 were chosen owing to their relevance in the explanation of rugby league match outcomes,<sup>17</sup> as well  
21 as their availability at the time of analysis. Both competitions consisted of 26-rounds, equating to  
22 372 observations in the U20 competition (n = 186 games) and 378 observations in the NRL (n = 189  
23 games). The observational differences were due to the number of match-free rounds ('byes')  
24 integrated within both competitions. The absolute game-times were the same across both

1 competitions. The relevant Human Ethics Committee provided ethical approval prior to data  
2 acquisition.

3 All of the following analyses were performed using the computing environment *R*, version 3.2.5.<sup>19</sup>  
4 Prior to modelling, data was classified according to competition (Two levels: U20 and NRL). A  
5 correlation matrix was built to assess the level of collinearity between each team performance  
6 indicator. Descriptive statistics (mean  $\pm$  standard deviation) were calculated for each team  
7 performance indicator relative to developmental level. A multivariate analysis of variance  
8 (MANOVA) was then used to test the main effect of competition (Two levels: U20 and NRL) on each  
9 team performance indicator, with the Type-I error being set at  $P < 0.05$ . Additionally, the effect size  
10 and subsequent 90% confidence interval of competition was calculated using Cohen's *d* statistic<sup>20</sup> in  
11 the 'MBESS' package,<sup>21</sup> with interpretations being in accordance with established  
12 recommendations.<sup>22</sup>

13 To reveal the level of competition dissimilarity, non-metric multidimensional scaling (nMDS) was  
14 used. This is an indirect gradient analysis that produces an ordination based on a dissimilarity  
15 matrix.<sup>23</sup> This matrix is resolved via isotopic regression, which is a non-parametric form of regression  
16 that iteratively searches for a least squares fit based on the ranked dissimilarities.<sup>23</sup> It is the  
17 preferred ordination technique when no assumptions are made about the underlying distribution of  
18 the data.<sup>23</sup> Aggregates of each team performance indicator were used across the season for this  
19 analysis. Further, teams across both competitions were sorted according to their ladder position at  
20 the conclusion of the season. This enabled insights into the dissimilarity of dominant and less  
21 dominant teams across both competition levels. The team performance indicators were used to  
22 build a dissimilarity matrix using the Bray-Curtis measure in the 'vegan' package via the *metaMDS*  
23 function.<sup>24</sup> This dissimilarity matrix was then plotted in two-dimensions using generalised additive  
24 models employing an isotopic smoother via thin-plate regression splines.<sup>23</sup> On the ordination  
25 surface, competition was colour coded and teams were labelled, while their subsequent ladder

1 position was denoted via the size of their 'point' using the *geom\_label*, and *geom\_point* functions in  
2 the 'ggplot2' package.<sup>25</sup>

3 To determine the combination of performance indicators that provided the greatest competition  
4 classification, a conditional interference (CI) classification tree was grown in the 'party' package.<sup>26</sup>  
5 This type of classification tree was chosen as it estimates a regressive relationship through binary  
6 partitioning by testing the null hypothesis between a set of explanatory variables (team performance  
7 indicators) and a binary response variable (competition).<sup>26</sup> Partitioning ceases when the null  
8 hypothesis cannot be rejected ( $P \geq 0.05$ ). A benefit of this analysis is that its fitting algorithm corrects  
9 for multiple testing, avoiding overfitting, resulting in the growth of an unbiased classification tree  
10 that does not require pruning.<sup>26</sup>

### 11 3. Results

12 Collinearity was noted between 'all runs' and 'all run metres' ( $r > 0.5$ ), with the latter being removed  
13 from further analysis given its dependence on the 'all run' indicator. The descriptive statistics and  
14 between group effects are presented in Table 1. A significant effect of competition was noted ( $V =$   
15  $0.936$ ,  $F = 23.194$ ,  $P < 0.05$ ), with ten of the 11 modelled indicators yielding significance (Table 1).  
16 Further, 'all runs' expressed the largest effect relative to competition ( $d = 1.22$ , Table 1).

17 **\*\*\*\*INSERT TABLE ONE ABOUT HERE\*\*\*\***

18 The dissimilarity matrix solution was reached after 20 iterations (stress = 0.09, rmse =  $3.1 \times 10^{-4}$ ,  
19 maximum residual =  $1.4 \times 10^{-3}$ ). The subsequent two-dimensional ordination showed distinct  
20 competition dissimilarity along dimension one (MDS1, Figure 1). Notably, the profiles of the NRL  
21 teams oriented on the right panelling of the first dimension, while the profiles of the U20 teams  
22 oriented on the left panelling (Figure 1). Despite this multivariate competition dissimilarity, it was of  
23 interest to note the similar positioning of dominant and less dominant teams across both  
24 competitions along the second dimension (MDS2). Notably, the higher ranked teams (i.e., closer to

1 '1' on the ladder, denoted by a smaller 'point') oriented the top half of MDS2 on the ordination  
2 surface, while the lower ranked teams (i.e., closer to '16' on the ladder, denoted by a larger 'point')  
3 generally oriented the lower half of MDS2 on the ordination surface (Figure 1).

4 **\*\*\*\*INSERT FIGURE ONE ABOUT HERE\*\*\*\***

5 The CI classification tree successfully classified 293 of the 372 U20 observations (79%) and 350 of the  
6 378 NRL observations (93%). Of the 11 team performance indicators modelled, five were retained  
7 within the full tree (Figure 2); these being 'all runs' (root node 1), 'tackle breaks', 'tackles', 'missed  
8 tackles', and 'kicks'. Accordingly, 14 terminal nodes were grown from these performance indicator  
9 combinations (Figure 2).

10 **\*\*\*\*INSERT FIGURE TWO ABOUT HERE\*\*\*\***

11 Progressing to the right of the root node ( $>167$  'all runs'), leaf node 19 partitions the data based on  
12 'tackle breaks' at a count of 36 (Figure 2). Progressing to leaf node 20 ( $\leq 36$  'tackle breaks'), the data  
13 was partitioned based on 'tackles' at a count of 288. Of the 144 observations within terminal node  
14 22 ( $>167$  'all runs',  $\leq 36$  'tackle breaks' and  $>288$  'tackles'), 98.6% were classified as NRL observations,  
15 while only 1.4% were classified as U20 observations. This combination provided the most accurate  
16 classification of NRL observations and lowest classification of U20 observations within each terminal  
17 node on the right of the tree.

18 Progressing to the left of the root node ( $\leq 167$  'all runs'), leaf node 2 partitioned the data based on  
19 'tackles' at a count of 314. Progressing to leaf node 3 ( $\leq 314$  'tackles'), the data was partitioned based  
20 on 'tackle breaks' at a count of 30. Of the 177 observations in terminal node 7 ( $\leq 167$  'all runs',  $\leq 314$   
21 'tackles' and  $>30$  'tackle breaks'), 95.5% were classified as U20 observations, while only 4.5% were  
22 NRL games. Although terminal nodes 15 and 18 resolved 100% classification accuracy for U20  
23 observations, it is important to note that these nodes consisted of a small number of observations  
24 (12 and 11, respectively).

#### 1 **4. Discussion**

2 The aim of this study was to compare game-play characteristics between the U20 and NRL  
3 competitions within Australia. As shown in Figure 1, there was a clear dissimilarity in the multivariate  
4 (performance indicator) profiles of U20 and NRL teams. Given this competition dissimilarity, it was  
5 expected to note the high classification accuracy shown by the CI classification tree. A unique  
6 combination of 'all runs', 'tackle breaks' and 'tackles' provided the greatest classification of both the  
7 NRL and U20 observations (Figure 2). These results demonstrated that there were clear differences  
8 in game-play behaviours between competitions, primarily manifested via 'all runs', 'tackle breaks'  
9 and 'tackles'. Coaches at the U20 level could utilise these results to base training interventions to  
10 address the apparent performance gaps in talent development for the NRL.

11 The nMDS analysis revealed apparent dissimilarity between the two competitions, indicating a  
12 difference in multivariate team profiles. These multivariate differences may have arisen from a range  
13 of factors, such as coaching strategies and team tactics implemented across competitions, or the  
14 functional capacities of players across both competitions. Given the U20 competition offers a feeder  
15 of talent for the NRL, it would seemingly be beneficial for coaches at this level to implement tactics  
16 that attempt to enable game-play characteristics that express similarity to the NRL (e.g., minimising  
17 missed tackles and generating greater ball carries), assisting with player development. However, the  
18 dissimilar positioning of U20 and NRL teams from the same club suggests distinctive profiles  
19 generated by teams from the same club. Nonetheless, it is possible that these multivariate  
20 differences stemmed from functional differences between the players in both competitions.  
21 Specifically, given their current stage of development, U20 players may be unable to perform the  
22 same types of actions as frequently as their NRL counterparts.

23 The apparent similarity between higher and lower ranked U20 and NRL teams along MDS2 on Figure  
24 1 was of note. Higher ranked teams (closer to '1' on the ladder) in both the U20 and NRL  
25 competitions generally clustered along the top half of MDS2, while lower ranked teams (closer to



1 '16' on the ladder) generally clustered along the lower half of MDS2. Although speculative, this may  
2 indicate that superior teams across both competitions produce unique multivariate profiles relative  
3 to their respective competitions. This is supported by the recent findings of Woods et al.<sup>13</sup> who  
4 noted that superior NRL teams (defined via grand final representation) generated highly dissimilar  
5 profiles relative to their less superior counterparts. It is, however, important to note that this data  
6 signature was more prominent within the NRL as opposed to the U20 competition (noted in the  
7 positioning of the West Tigers and the Roosters on Figure 1). Subsequently, it is possible that the  
8 focus of the U20 competition is not only to win games, but also to promote player development,  
9 which may not always be synonymous with match success.

10 The results of the CI classification tree are likely to yield practical utility in the development of  
11 prospective NRL players. This analysis indicated that NRL games were classified by a greater number  
12 of 'all runs', 'tackles' and a lower number of 'tackle breaks' relative to the U20 level. Accordingly,  
13 U20 players entering the NRL may not have been exposed to the type of physicality (e.g., tackling  
14 capacity) needed to compete within this elite senior competition.<sup>27</sup> This suggestion is somewhat  
15 supported by the work of Ireton et al.<sup>12</sup> who examined the differences in physical fitness and athletic  
16 movement between elite senior and youth rugby league players. Their results demonstrated  
17 differences between elite senior and youth rugby league players for measures of body mass, lower  
18 body power and athletic movement.<sup>12</sup> Although a multitude of factors could have implicated the  
19 performance indicator characteristics resolved here, when the work of Ireton et al.<sup>12</sup> is coupled with  
20 the current study, the competition differences could be, in part, due to lower body power and  
21 movement quality discrepancies. However, in addition to physical precocity being an important  
22 element in determining tackling efficiency,<sup>28</sup> the differences noted in our study may also be  
23 underpinned by differences in tackling technique.<sup>29</sup> Accordingly, it is recommended that coaches at  
24 the U20 level integrate a holistic approach to the development of tackling derivatives that consists of  
25 both physical and technical elements.<sup>28,29</sup>

1 Additionally, NRL coaches and talent recruitment managers could consider 'bridging' an U20 player's  
2 transition into the NRL by encouraging their participation in the State League, which is a state-based  
3 senior competition. Given that the State League is classified as a senior competition, it is possible  
4 that it offers an environment slightly more conducive to the physicality needed within the NRL.  
5 However, given the paucity of data supporting this recommendation, continued work is required to  
6 compare game-play characteristics between the State League competition and the U20 and NRL  
7 competitions.

8 Despite the practical utility of this work, it is not without limitations. Firstly, it did not investigate the  
9 physical activity profiles of competition levels. Future work may integrate global positioning system  
10 (GPS) analysis with these results to gain a deeper insight into the differences between the U20 and  
11 NRL levels. Despite being the premier youth rugby league competition in Australia, U20 coaches are  
12 likely to have limited access to their players, as they are not full time athletes like their NRL  
13 counterparts. Thus, it is likely that NRL players have a greater potential to develop their performance  
14 qualities relative to their U20 counterparts, potentially exacerbating the observed performance  
15 differences. Notably, a greater number of technical errors in the U20 competition (potentially  
16 underpinned by limited training time in contrast to the NRL) may result in less runs, which slows the  
17 speed of play. Nonetheless, these preliminary results may offer coaches with the capability to  
18 develop targeted training interventions in time-constrained environments.

## 19 **5. Conclusion**

20 This work demonstrates differences in game-play characteristics between the U20 and NRL  
21 competitions, manifested via certain team performance indicators. The multivariate profiles of  
22 teams from both competitions was distinctly dissimilar. Additionally, NRL game-play was  
23 characterised by a greater number of 'all runs', 'tackles' and a lower count of 'tackle breaks' in  
24 comparison to game-play at the U20 level.

## 25 **6. Practical Applications**

- 1 • Coaches at the U20 level should look to integrate training interventions that enable players  
2 to engage in a high number of 'all runs' and 'tackles', while equipping them with the  
3 defensive capabilities to minimise the number of 'missed tackles'.
- 4 • Alternatively, NRL coaches and talent recruitment managers may consider encouraging U20  
5 players to 'bridge' the gap between the U20 and NRL levels by participating in State League  
6 games. Given the State League is a senior competition, it is possible that it will afford an  
7 environment more conducive to that seen within the NRL.
- 8 • Performance analysts working with rugby league teams may consider the analytical  
9 techniques used here to examine performance differences across developmental levels or  
10 competitions given their visualisation capacities and consideration of non-linear phenomena  
11 within datasets.

## 12 **References**

- 13 1. Gulbin J, Weissensteiner J, Oldenzil K, et al. Patterns of performance development in elite  
14 athletes. *Eur J Sport Sci.* 2013; 13(6):605-614
- 15 2. Gagné F. Constructs and models pertaining to exceptional human abilities. In K. A. Heller, F.  
16 J. Monks, F. J. Passow (Eds.), *International handbook of research and development of*  
17 *giftedness and talent* (pp 63-85); 1993. Oxford: Pergamon Press.
- 18 3. Durand-Bush N, Salmela JH. The development of talent in sport. In: R. N. Singer, H. A.  
19 Hausenblas, C. M. Janelle (Eds.), *Handbook of sport psychology* (pp. 269-289); 2001. New  
20 York: Wiley.
- 21 4. Vaeyens R, Lenoir M, Williams AM, et al. Talent identification and development programmes  
22 in sport: current models and future directions. *Sports Med.* 2008; 38(9);703-714
- 23 5. Woods CT, Bruce L, Veale JP, et al., The relationship between game-based performance  
24 indicators and developmental level in junior Australian football: implications for coaching. *J*  
25 *Sports Sci.* 2016; 34(23):2165-2169

- 1 6. Launder A. *Player practice: The games approach to teaching and coaching*. 2001;  
2 Champaign, IL: Human Kinetics.
- 3 7. Gabbett T, Jenkins DG, Abernethy B. Physiological and anthropometric correlates of tackling  
4 ability in junior elite and subelite rugby league players. *J Strength Cond Res*. 2010;  
5 24(11):2989-2995
- 6 8. Till K, Jones B, Geeson-Brown T. Do physical qualities influence the attainment of  
7 professional status within elite 16-19 year old rugby league players? *J Sci Med Sport*. 2016;  
8 19(7):585-589
- 9 9. Till K, Scantlebury S, Jones B. Anthropometric and physical qualities of elite males youth  
10 rugby league players. *Sports Med*. In-press; doi:10.1007/s40279-017-0745-8
- 11 10. Tedrea M, Dascombe B, Sanctuary CE, et al. The role of anthropometric, performance and  
12 psychological attributes in predicting selection into an elite development programme in  
13 older adolescent rugby league players. *J Sports Sci*. 2017; 35(19):1897-1903
- 14 11. Till K, Copley S, O'Hara J, et al. Using anthropometric and performance characteristics to  
15 predict selection in junior UK rugby league players. *J Sci Med Sport*. 2011; 14(3):264-269
- 16 12. Ireton M, Till K, Weaving D, et al. Differences in the movement skills and physical qualities of  
17 elite senior & academy rugby league players. *J Strength Con Res*. In-press; doi:10.1519/JSC
- 18 13. Woods CT, Robertson S, Sinclair WH, et al. Non-metric multidimensional performance  
19 indicator scaling reveals seasonal and team dissimilarity within the national rugby league. *J*  
20 *Sci Med Sport*. In-press; doi: 10.1016/j.jsams.2017.06.014
- 21 14. Dutt-Mazumder A, Button C, Robins A, et al. Neural network modelling and dynamic systems  
22 theory: are they relevant to study governing dynamics of association football players? *Sports*  
23 *Med*. 2011; 41(12):1003-1017
- 24 15. Robertson S, Back N, Bartlett JD. Explaining match outcome in elite Australian rules football  
25 using team performance indicators. *J Sports Sci*. 2016; 34(7):637-644

- 1 16. Morgan S, Williams MD, Barnes C. Applying decision tree induction for identification of  
2 important attributes in one-versus-one player interactions: a hockey exemplar. *J Sports Sci.*  
3 2013; 31(10):1031-1037
- 4 17. Woods CT, Sinclair WH, Robertson S. Explaining match outcome and ladder position in the  
5 national rugby league using team performance indicators. *J Sci Med Sport.* In-press; doi:  
6 10.1016/j.jsams.2017.04.005
- 7 18. James LP, Robertson S, Haff GG, et al. Identifying the performance characteristics of a  
8 winning outcome in elite mixed martial arts competition. *J Sci Med Sport.* 2017; 20(3):296-  
9 301.
- 10 19. R Core Team. *R: a language and environment for statistical computing.* R Foundation for  
11 Statistical Computing, Vienna, Austria
- 12 20. Kenkel NC, Orloci L. Applying metric and nonmetric multidimensional scaling to ecological  
13 studies: some new results. *Ecology.* 1986;67:919-928.
- 14 21. Kelly K. The MBESS R Package. 2016; Available at [https://cran.r-](https://cran.r-project.org/web/packages/MBESS/MBESS.pdf)  
15 [project.org/web/packages/MBESS/MBESS.pdf](https://cran.r-project.org/web/packages/MBESS/MBESS.pdf)
- 16 22. Hopkins WG. A new view of statistics. *Sportscience.* <http://www.sportsci.org/resource/stats>
- 17 23. Hout MC, Goldinger SD, Brady KJ. *MM-MDS: a multidimensional scaling database with*  
18 *similarity ratings for object categories from the massive memory picture database.* *PLoS One.*  
19 et al., 2014; 9(11):1-11
- 20 24. Oksanen J, Blanchet GF, Kindt R, et al. *Vegan: community ecology package.* 2015; Available  
21 at <https://cran.r-project.org/web/packages/vegan/vegan.pdf>
- 22 25. Wickham H. Package 'ggplot2'. 2016. <https://cran.r-project.org/web/packages/ggplot2> of  
23 subordinate document. Accessed 22 Feb 2017.
- 24 26. Hothorn T, Hornik K, Zeileis A. Unbiased recursive partitioning: A conditional inference  
25 framework. *J Comput Graph Stat.* 2006;15(3):651-674

- 1 27. Hausler J, Halaki M, Orr R. Application of global positioning system microsensor technology  
2 in competitive rugby league match-play: a systematic review and meta-analysis. *Sports Med.*  
3 2016; 46(4):559-588.
- 4 28. Speranza MJ, Gabbett TJ, Johnston RD, et al. Relationship between a standardized tackling  
5 proficiency test and match-play tackle performance in semiprofessional rugby league  
6 players. *Int J Sports Physiol Perform.* 2015; 10(6):754-760
- 7 29. Hendricks S, van Niekerk T, Sin DW, et al., Technical determinants of tackle and ruck  
8 performance in international rugby union. *J Sports Sci.* In-press: doi:10.1080/02640414  
9

1 **Figure 1.** The ordination plot using nMDS of a dissimilarity matrix calculated from team performance  
2 indicators of each U20 and NRL team in the 2016 season

3

4 **Figure 2.** The CI classification tree showing the classification of U20 and NRL observations.

5 *Note:* 'n' represents the number of observations in each node (minimum of five observations was  
6 set). The first 'y value' denotes the classification of U20 observations and the second denotes that  
7 classification of NRL observations (e.g., 0.8 = 80%). 'AR' all runs; 'TB' tackle breaks; 'TK' tackles; 'MT'  
8 missed tackles; 'K' kicks. Certain performance indicators appear twice in this tree as the recursive  
9 partitioning performed by the fitting algorithm searches for classification rules between each  
10 variable using a non-linear approach.

1 **Table 1.** Descriptive and between group effects relative to developmental level

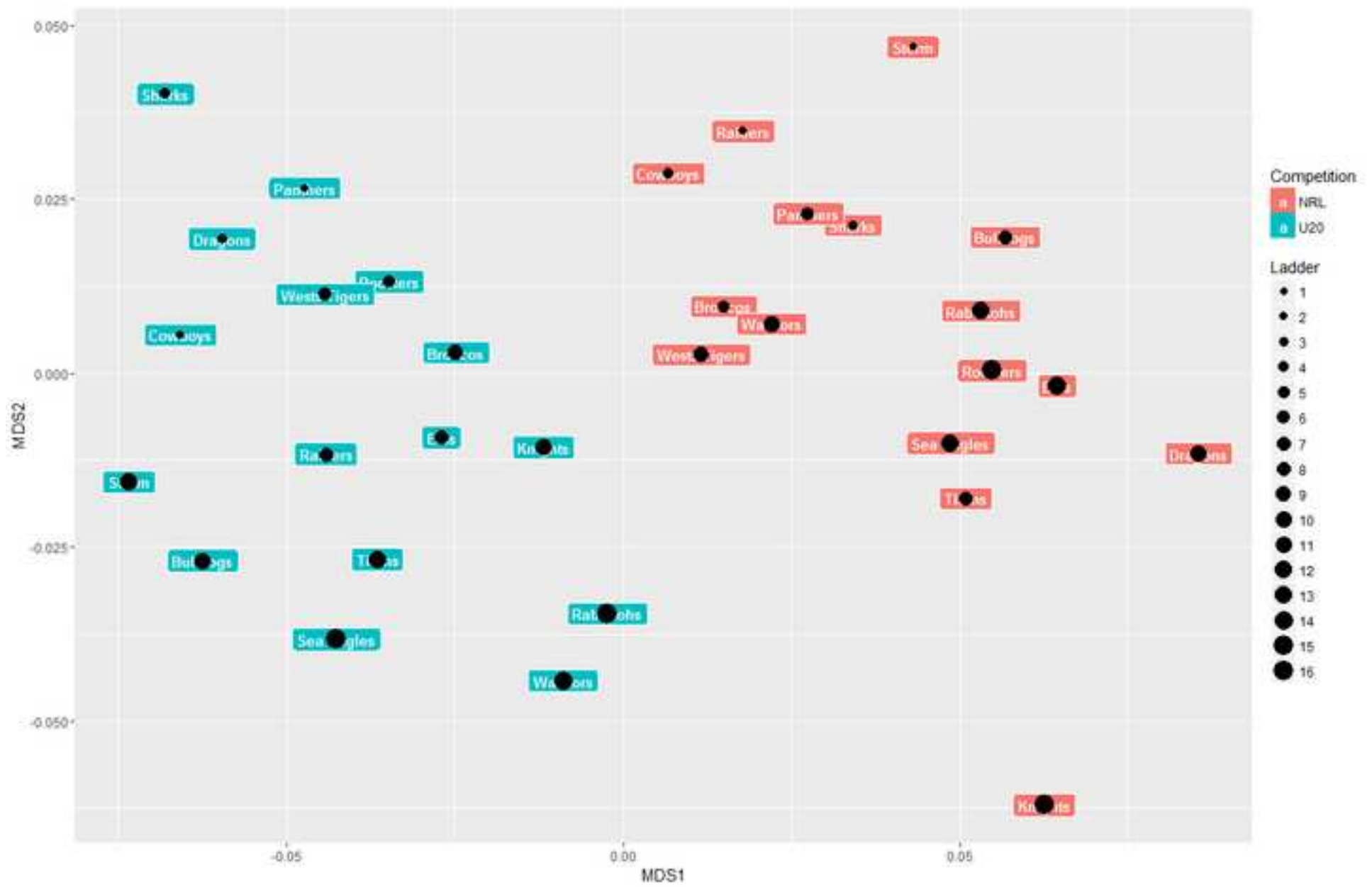
Performance indicator	NRL	U20	<i>d</i> (90% CI)	Size
All runs*	170.2 ± 19.8	147.2 ± 17.4	1.22 (1.09 – 1.35)	'large'
Line breaks*	4.0 ± 2.3	5.6 ± 2.5	0.64 (0.51 – 0.76)	'moderate'
Try assists*	2.8 ± 1.8	3.4 ± 1.9	0.34 (0.22 – 0.46)	'small'
Offloads*	10.3 ± 4.4	7.0 ± 3.3	0.82 (0.69 – 0.95)	'moderate'
Tackles*	325.0 ± 39.7	283.4 ± 35.6	1.10 (0.97 – 1.22)	'moderate'
Missed tackles*	27.6 ± 8.4	35.7 ± 10.9	0.82 (0.70 – 0.95)	'moderate'
Errors*	9.2 ± 2.7	10.4 ± 3.2	0.39 (0.27 – 0.51)	'small'
Total kicks*	19.0 ± 3.8	14.7 ± 3.6	1.13 (1.00 – 1.26)	'moderate'
Line break assists*	3.0 ± 2.0	3.6 ± 2.0	0.30 (0.18 – 0.42)	'small'
Dummy half runs	11.1 ± 4.5	10.3 ± 4.6	0.15 (0.03 – 0.27)	'trivial'
Tackle breaks*	27.6 ± 8.4	35.7 ± 10.9	0.83 (0.70 – 0.95)	'moderate'

2 \* denotes  $P < 0.05$ .

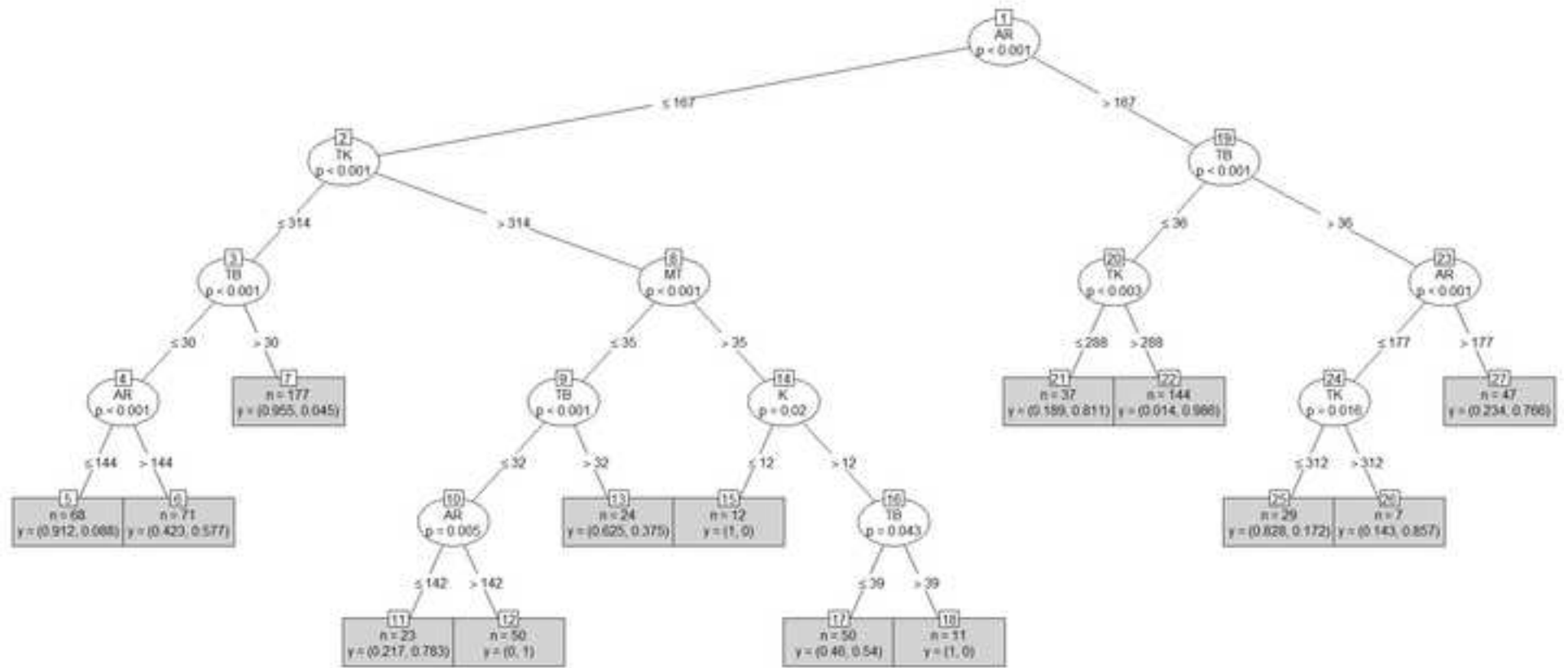
3



Figure 1  
[Click here to download high resolution image](#)



**Figure 2**  
[Click here to download high resolution image](#)



**Supplementary Table 1.** Team performance indicator descriptions

<b>Team performance indicator</b>	<b>Description</b>
All runs	The total number of times a player runs while in possession of the ball. A higher number of 'runs' is likely to indicate an efficient offence
All run metres	The total number of metres accumulated following each run a player attempts while in possession of the ball. A greater accumulation of 'run metres' is likely to indicate an efficient offence
Line breaks	The number of times a player was able to run through (or 'break') an oppositions defensive line while in possession of the ball. A greater number is likely to indicate an efficient offence
Try assists	A pass (via hand or foot) to a teammate who scores a 'try'
Offloads	Passing or 'offloading' the ball to a teammate whilst being tackled
Tackles	The use of physical contact to prevent or hold up an opposition player in possession of the ball
Missed tackles	The number of times an attacking player penetrates a team's defensive line without being tackled or incurring physical contact
Errors	Instances during game-play in which a team loses possession through a dropped ball, high hit, or knock-on
Total kicks	Disposing of the ball with any part of the leg below the knee including kicks off the ground
Line break assists	The number of times an attacking player passed the ball to a teammate who then was able to run through (or 'break') an oppositions defensive line either with or without opposition contact
Dummy half runs	The number of times the acting half collects the ball and runs before passing
Tackle breaks	The action of breaking a team's defence despite incurring physical contact from the opposition defensive

1 **Acknowledgements**

- 2 The authors would like to acknowledge the many analysts who recorded and coded the publicly  
3 available data over the course of the 2016 Holden Cup and NRL seasons.