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Title: Modelling movement energetics using Global Positioning System (GPS) devices in contact team sports: limitations and solutions.

Running Head: Modelling energetics in contact team sports

Key points:

- The approach of energetic modelling denotes a progression in the application of motion-analysis technology to the team sports environment, complementing traditional spatio-temporal information provided by micro-technology;

- A previous attempt to estimate metabolic energy demand (global energy measurement) has been criticised for its inability to fully quantify the energetic costs of team sports, particularly during collisions;

- We propose the adoption of a mechanical modelling approach, with potential to solve some of these problems, whereby the 'work done' can be accurately estimated based on the basic principles of work-energy theorem.

Abstract

Quantifying the training and competition loads of players in contact team sports can be performed in a variety of ways, including: kinematic, perceptual, heart rate or biochemical monitoring methods. Whilst these approaches provide data that are relevant for team sports practitioners and athletes, their application to a contact team sport setting can sometimes be challenging or illogical. Furthermore, these methods can generate large fragmented datasets, do not provide a single global measure of training load and cannot adequately quantify all key elements of performance in contact team sports. A previous attempt to address these limitations via the estimation of metabolic energy demand (global energy measurement) has been criticised for its inability to fully quantify the energetic costs of team sports, particularly during collisions. This is despite the seemingly unintentional misapplication of the models' principles to settings outside of its intended use. There are other hindrances to the application of such models, which are discussed herein, such as the data-handling procedures of global position system manufacturers and the unrealistic expectations of end-users. Nevertheless, we propose an alternative energetic approach, based on GPS-derived data, to improve the assessment of mechanical load in contact team sports. A framework for the estimation of mechanical work done during locomotor and contact events with capacity to globally quantify the work done during training and matches is presented.

1. Introduction

Monitoring the overall demands of contact team sports, such as rugby union, rugby league and Australian football, involves the quantification of training loads imposed on players during training or competition [1]. These parameters can be quantified by a combination of internal and external loads, whereby the internal load represents the psycho-physiological response experienced by players, whilst the external load broadly refers to the gross movement of players [2]. The external load or 'dose' performed ultimately dictates the degree of internal biological strain (e.g. cardiovascular or metabolic) [2]. Whilst monitoring the external load placed on players during contact team sports has become commonplace, less is understood about the associated internal load. This is problematic because both cardiovascular and skeletal muscle adaptations to exercise and the subsequent recovery period depend upon the magnitude of metabolic disturbance [3-6]. Indeed, a reduction in the metabolic cost of exercise, and thus the attenuated homeostatic derangement, for a given external load is a key feature of endurance training adaptation [4-5,7]. Therefore, it is important for team sports practitioners to quantify, and concurrently monitor, external demands and internal responses placed on players during training and competition.

One relatively recent approach has been to estimate the metabolic or 'internal' cost of activities performed during matches based upon players' external movement profiles. This approach has been used to model the metabolic power of elite team sport players during both training [8] and competition [9-15]. However, the efficacy of this approach has not yet been fully elucidated in contact team sports i.e. sports where the laws of the game permit forceful physical contact between opposing players. 'Contact' in this context is a collective term encompassing coached skills/activities such as tackling and scrummaging, as well as natural collisions that occur during contests in play. Such sports require frequent performance of technical match activities that occur with limited displacement, yet are energetically demanding, such as tackling (~0.3-0.8 contacts per min) and scrummaging [16-21]. This has important implications for metabolic estimations which are particularly sensitive to rapid changes in velocity [9]. Moreover, the limitations of modelling metabolic power and energy expenditure based on the data derived from Global Positioning System (GPS) devices, rather than camera tracking systems, have not yet been fully explored. Accordingly, the aims of this review were three-fold: 1) to critique the current approaches of internal and external load measures in contact team sport; 2) review the theories that underpin the estimation of metabolic power and energy cost from human locomotion, highlighting considerations when applying energetic models to contact team sports; 3) discuss the advantages and limitations of using data derived from GPS devices to estimate metabolic power and energy cost and briefly propose alternative approaches.

2. Quantifying Demands in Contact Team Sports

External demands are typically quantified by monitoring the gross movement patterns (i.e. distance, speed and acceleration) of players during matches. This process has been facilitated by the advent of time-motion analysis instruments, such as semi-automated multiple camera systems (MCS) and micro-technology devices (small unit co-housing a GPS receiver and various micro-electrical mechanical systems (MEMS)). Given their good reliability [22-26], portability and low-cost (when viewed relative to the large, rich data sets that are quickly accrued), micro-technology devices are now the preferred method of motion-tracking technology during contact sports matches [10-15, 17, 27-30]. By default, most commercial micro-technology devices use GPS outputs to quantify the external loads experienced by players, by providing the distances covered and the time spent or distance covered in discrete speed zones ranging from 0 to 36 $km \cdot h^{-1}$ [31].

The outputs from MEMS compliment the GPS derived metrics, with most commercial devices featuring triaxial accelerometers sampling at 100 Hz. Such accelerometers measure a composite vector magnitude (expressed as g-force, the acceleration relative to freefall) by recording the sum of proper accelerations measured in three separate orthogonal axes (anterioposterior [x], mediolateral [y] and vertical [z]) [24]. Accelerometer data can be used to quantify the magnitude of change of direction, accelerating and decelerating movements [17, 24, 32-33]. Furthermore, commercial systems offer accelerometer derived indices of external load e.g. 'Player Load' (Catapult Innovations, Melbourne, Australia) and 'Body Load' (GPSports, Canberra, Australia), reported in arbitrary units (AU) [13]. That these accelerometer load scores have been reported to relate (r = 0.45 to 0.63) to session Ratings of Perceived Exertion (session-RPE) during typical rugby league training [34] highlights the importance of incorporating accelerometer data into the assessment of external load. However, it is important to note that accelerometer load scores provide an arbitrary measure of match or training load, which lacks both mechanical and physiological meaning. This limits the application of accelerometer load as a tool to monitor external load and in particular the physiological response, which requires a more direct quantification of the metabolic demands of exercise and, thus, potential challenges to bodily homeostasis.

The combination of body load, heart rate (HR) and distance covered explain some (64.3%), but not all, of the variance in the perceived training load of rugby league players [34]. Indeed, various studies have reported moderate-to-strong relationships between summated-HR scores and session-RPE, explaining approximately 40-70% of the variance in perceptual training load [29, 35-36]. The relationship between RPE and HR has been well-established at sub-maximal steady-state exercise [37], reflecting RPE as the conscious expression of an individual's total physical and psychic reaction to exercise [38]. However, the linearity of this relationship is questionable during activities that require greater anaerobic energy contributions, such as those performed during team sports performance [39-40]. For example, higher RPE values (Borg 6-20 scale) have been reported among subjects performing intermittent protocols compared to steady-state exercise matched for the total work performed [41]. Importantly, differences in RPE were reported without a change in oxygen uptake ($\dot{V}O_2$) or HR between the two exercise conditions [41]. Therefore, while relationships exist between indices of external load and different measurements of internal physiological load [42], they are unlikely to account for all aspects of energy cost during exercise in team sports.

Heart Rate has often been used to directly describe the internal training load in contact sports, and players consistently reach 75-85% of maximum HR values [17,29,43-45]. Owing to HR's well-known linear relationship with oxygen consumption ($\dot{V}O_2$) during steady state submaximal exercise, regression analyses have been used to estimate the energy expenditure of individual players during soccer [46], rugby union [17] and rugby league matches [43]. This approach requires an up-to-date knowledge of each individual's $\dot{V}O_2$-HR relationship (assessed during an incremental test), from which the energy expenditure ($kJ \cdot min^{-1}$) can be estimated, assuming a fixed energy equivalent of oxygen [47]. However, it is problematic to use HR data obtained during laboratory-based steady state submaximal running to estimate energy expenditure during the various movement patterns of contact team sports. This is because the $\dot{V}O_2$-HR relationship is non-linear at very low and very high intensities [47] and HR responses do not appropriately account for the energy cost of high-intensity bouts that actuate non-oxidative energy pathways [9], for example in submaximal running bouts of every-changing speed, resisted movements/static exertions, sprint efforts and stationary recovery periods. The estimation of energy expenditure from HR recordings is further complicated by certain factors, such as dehydration and circadian rhythm, which are impractical to control in a team sport environment [47]. Previous attempts to estimate the contributions of anaerobic metabolism during soccer match-play using blood lactate concentration or creatine phosphate resynthesis have provided approximations of the intermittent physiological loads experienced during matches [39-40]. However, blood lactate concentrations sampled at the capillary poorly reflect those at the muscle, and biopsy techniques are impractical for monitoring training and competition [2,39]. Furthermore, HR monitors and gas analysis instruments are usually not permitted, and are impractical or uncomfortable for players to wear during contact team sports.

The deliberate, frequent physical contact between opposing players in contact sports typically manifests in two phases; an initial collision and subsequent static exertion (likened to wrestling and grappling). Whilst the aforementioned metrics of internal and external load are employed across both contact and non-contact sports, teasing out the loads attributable to colliding and performing static exertions in contact sports has proven challenging. Arguably the locomotor events leading up to the point at which two players collide incurs a metabolic cost as the player's motion is the result of their own muscular effort. The collision itself, needs to be viewed differently as the characteristic rapid deceleration of the players center of mass (somewhat represented in a microtechnology device's velocity-time curve) is not attributable to forces generated by the players own musculature, but rather the sudden application of an opposing force i.e. the opposing player's mass. As such, the internal load or acute energy cost associated with colliding is negligible. In contrast, the external load can be substantial, as during inelastic collisions, the system's kinetic energy is not conserved, meaning during the collision, a proportion of the system's kinetic energy is transformed to other forms e.g. heat and sound and most importantly from a load monitoring perspective absorbed by the player's body tissues. This external mechanical loading and deformation of tissues can result in trauma e.g. contusion [48] and has been implicated in post-match muscle soreness, altered function and biochemical markers of muscle damage [20,48-50]. There are typically between 0.3 and 1.1 impacts (tackling, ball-carrying, rucking, mauling) per minute of match-play during contact team sports [16,18,20-21,51]. Given the mechanical loads imposed on tissues, it seems prudent to monitor these during both training and match-play.
Collisions have been commonly identified from match video footage [20,52]; however, automated tackle and collision detections have also been incorporated into micro-technology in order to quantify the magnitude and frequency of collisions within match-play [50,53].

Through temporal analysis of the on-board data (acceleration magnitude and device orientation), one commercially available micro-technology device (Catapult, Optimeye S5, Melbourne, Australia) was reported to identify 97.6% of collision events within rugby league match-play [54]. This identification technique was not found to be precise when applied in Australian football where it identified 78% of collision events [55], highlighting the variable nature of collisions and the need for sport specific algorithms. Furthermore, collisions are typically preceded by an increase in velocity (up to 7 $m \cdot s^{-1}$) in the 0.5 s prior to contact with the opposing player [56] and can cause significant decelerations in the order of -7 $m \cdot s^{-2}$ throughout match-play (see Figure 2, Panel B). These values are in excess of typical 'high' acceleration and deceleration demarcations in contact team sports, such as rugby sevens (> 4 $m \cdot s^{-2}$; [28]) and Australian football (> 3 $m \cdot s^{-2}$; [32]). How such collisions should be quantified (e.g. as counts in acceleration zones; kinetically- as impulses; or energetically- as lost kinetic energy) remains an open question.

Wrestling or grappling activities also characterise contact team sports and often occur after the initial contact, forming part of the physical contest between players for possession of the ball or to gain line success. Such activities necessitate muscular force generation whilst remaining relatively stationary, which is obviously reliant upon the hydrolysis of adenosine triphosphate (ATP) to support cross-bridge cycling (i.e. an energy cost) [57]. For example, recent studies have documented the external forces [58] and spinal muscle activation patterns [59] during scrums in rugby union players which, given the energy cost associated with whole-body resisted movements are in the order of 10-20 $kcal \cdot min^{-1}$ [60-61], static exertions such as these are likely to incur substantial energetic costs. Notably, whilst muscle tension and perceived effort are high during static exertions, minimal displacement of the trunk (where the micro-technology device is located) typically occurs. This disparity between muscle activity and concomitant motion of the device results in disproportional internal/external load metrics. This is not to say that GPS and/or accelerometer outputs are erroneous during static exertions, rather that they are not an appropriate tool (by virtue of what they measure) to quantify the loads associated with static exertions.

3. Energetic Modelling

3.1 Current Model

A more recent, novel, approach has been to estimate the metabolic or 'internal' cost of activities performed during matches based upon players' external movement profiles [62].

Previous findings suggest that velocity profiles obtained via micro-technology devices can be used to estimate the energetic demands of intermittent running-based activities [8-10]. Such methods offer team sports practitioners a way of quantifying the global training load using a metric (i.e. energy) that more appropriately describes the physiological stimulus of an exercise bout. Estimating energy expenditure based on the movement profiles of team sport players circumvents the issues associated with direct assessment of oxygen uptake during matches, whilst also accounting for the energy cost of high-speed locomotor activities. Given the intermittent nature of team sport running patterns, including rapid accelerations and decelerations often over short distances, such models might more adequately describe the total demand placed on players during field-based training or competition.

Studies in soccer have used energetic modelling (rather than analysis of physiological measures) to estimate the metabolic demands of match-play [8-9]. In these studies, the sprint running model proposed by di Prampero et al. [62] was integrated with motion-analysis systems (MCSs or GPS) to determine the energy costs and metabolic power of soccer players. This approach assumes that accelerations (athlete leaning forward) performed on a flat surface induce an energy cost (EC) equivalent to running uphill at constant speed. In this way, the magnitude of acceleration can be related to the degree of inclination, called the equivalent slope (ES). As shown in Figure 1, the EC of gradient running varies with the slope in a predictable manner [63], as such, one is able to factor the equivalent high-intensity accelerations performed during matches into the energetic estimation of constant speed running at an equivalent slope. Metabolic power ($W \cdot kg^{-1}$) is simply derived as the product of the energy cost ($J \cdot kg^{-1} \cdot m^{-1}$) and velocity ($m \cdot s^{-1}$) of the player at a given instance. This method is advantageous, in that it is non-invasive and allows profiling of the metabolic demand [9] to sustain forward running at an instant in time. Using this technique, Osgnach et al. [9] reported an estimated energy expenditure of 4633 ± 498 kJ in an average soccer player, which is remarkably similar to previous analyses using HR-based methods [40,45].

(Figure 1 near here)

3.2. Validity of Energy Expenditure Estimates

The application of di Prampero's et al. [62] energetic model to intermittent team sports has recently been questioned [66-68] based on observed differences between estimates of energy expenditure and metabolic power modelled from a runner's acceleration profile [62] and those derived from indirect calorimetry (open-circuit spirometry). Using the model of di Prampero et al. [62], systematic underestimations of mean metabolic power between 23% (exercise) and 85% (recovery) were reported during an intermittent soccer-specific circuit [66]. Highton et al. [67] reported similar differences in mean energy expenditure (~45%) for comparisons made during an intermittent collision-based protocol. In contrast, during constant speed, aerobic running (7.5 – 10 $km \cdot h^{-1}$, RER < 1), energy cost modelled using the di Prampero model only slightly overestimates energy cost [69]. Despite some concern over the methodological approaches in these validation studies [65], these findings generally demonstrate the limitations of applying the model to conditions that challenge its underlying assumptions [9,62]. Indeed, when applied to overground activities on a level playing field, the model assumes that the athlete is always running in a forward direction based on the velocity-time curve provided. This assigns an energy cost of ~4 $J.kg.min^{-1}$ (depending on terrain constants) when velocity is constant and proportionally increases the energy cost in accordance with the polynomial equation provided by di Prampero [62] when velocity is changing. Additionally, based on its derivation, the model assumes the runner's limbs move in a direction, rate and amplitude synonymous with uphill/downhill treadmill running. As such, when the athlete changes their gait to accommodate possession of a soccer ball [66], changes direction rapidly [68-69] and/or performs repeated collisions/tackling efforts [67], the model will not accommodate the associated increased energy expenditure attributable to the greater muscular work done in these tasks compared to forward running.

The mismatch between instantaneous metabolic power estimates from velocity-time data and simultaneous recording of respiratory gas exchange during recovery periods [66] is readily explained. It was clearly articulated in original descriptions [9,62] that the metabolic power estimate provided by the model reflects the required rate of ATP hydrolysis to sustain forward running at an instant in time or, alternatively, a thermodynamic expression of ATP utilised to perform the muscular work done during running. This implies that resting metabolism or the resting state is not included (i.e. only the net, instantaneous, metabolic demand of running is determined from the di Prampero [62] model). This is not synonymous with the net, instantaneous, metabolic supply. Rather, this is defined by the summed contributions of the metabolic pathways (the 'three energy systems') in muscle responsible for ATP synthesis, during running, above rest. Whilst it is fair to assume demand and supply are equal at an instant in time, the relative contributions from each energy system in supplying ATP is dependent on the exercise bouts' intensity, duration and number. As such, comparisons between modelled metabolic power (demand) and metabolic power derived from one component of the supply system (e.g. oxygen consumption) at an instant in time will be erroneous. For further detail and examples of modelled metabolic supply and demand, readers are referred to other works that have applied such methods to examine exercise performance [70].

Recently, this energetic model has been applied to contact team sports [10,14-15]. The appropriateness of this application has come into question, given the purported greater contributions of non-locomotor activities to overall energy expenditure during play, particularly contact activities such as tackling and the wrestle phases that follow. In support of this, Docherty et al. [71] found that elite rugby league players reported making or being tackled the most fatiguing aspect of play. More recently, Highton et al. [67] objectively demonstrated significant metabolic (mean blood lactate concentration of 10.5 $mmol \cdot L^{-1}$) and cardiovascular (mean heart rate of 87.4 % of maximum) responses to a tackling based drill, confirming the metabolically taxing nature of contact activities. However, time-motion analyses in rugby league suggest that the proportion of time spent in non-locomotor activities (pooled tackling, being tackled, playing the ball, passing the ball and scrums) is less than 10 % of a match [72-73]. Indeed, contact event (match activities where opposing players make contact through an initial collision) counts by positional group range from 16 (outside backs) to 37 (hit up forwards) per rugby league match [53], and with the average tackle (initial collision and subsequent contact) lasting 3.4 s [74], the time involved in contact activities totals no more than ~3 min across the course of a ~80 min match (<1 %). In contrast, in the majority of rugby league matches, ~60% is spent in locomotor activities (pooled walking, cruising, jogging and sprinting), with ~30% of time spent stationary [72-73]. As such, whilst non-locomotor activities maybe energetically costly, they represent a minor portion of play time, heavily outweighed by locomotor activities and standing. Therefore, analyses in the time domain lend support to the use of a locomotor-based model provided the cost of low intensity activities (walking and standing) are appropriately accounted for. Similar analyses in the energy domain are not available, but they may reveal a different distribution. Whilst the energy cost of discrete contact activities is not well defined in the literature, estimates of peak metabolic power during sprint running and cycling do exist, with values in the order of

80 W·kg^{-1} [70] for sprint-trained athletes. This is thermally equivalent to an oxygen consumption of ~230 ml·kg^{-1}·min^{-1}, a value 4-5 times that of maximal oxygen uptake and ~64 times that of resting metabolic rate. On this understanding, a 2 second effort at peak metabolic power is thermally equivalent to ~45 seconds of walking i.e. with a physiologically plausible oxygen uptake of ~10 ml·kg^{-1}·min^{-1}. Evidently, very little time is needed (i.e. seconds) at supramaximal intensities to impose metabolic demands that outweigh 'minutes' of low intensity locomotor activities. Assuming many non-locomotor activities are supramaximal in nature, analysis in the energy domain highlights the need to establish valid methods of quantifying all forms (locomotor and non-locomotor) of short-duration, high intensity activities.

One final consideration when applying the di Prampero model to contact team sports is how the model quantifies the rapid deceleration of a player's mass when they collide with an opposing player. As discussed earlier, in a contact event (initial collision and subsequent static exertion) the collision will primarily load the body's tissues mechanically, with the metabolic costs incurred more than likely attributable to muscle contractions used to perform any subsequent static exertion and/or repositioning following initial contact. This is problematic for the metabolic power approach because it is theoretically implausible for the model to quantify such an activity. The model assumes the player is continuously running in a forward direction and, as such, a contact event that results in an abrupt deceleration of their mass, is treated as a rapid, voluntary deceleration (quantified accordingly) and any static exertion occurring during contact is not acknowledged. Arguably, alternative methods are needed to account for the contribution of contact events to external and internal load during training and competition.

4. Proprietary Data Processing: Implications for Energetic Analyses

The widespread use of micro-technology in professional team-sports as part of daily monitoring practices suggests a general acceptance, lack of choice and/or a lack of concern for the systems limitations [75]. This is most likely based on the convenience and potential value of the data obtained. Whilst energy-based metrics are arguably the most dimensionally suitable methods to quantify intensity and load [11], modelling energy exchanges from commercially available GPS data introduces new considerations during data processing. A recent consensus statement on monitoring athlete training loads [64] provides recommendations for use and interpretation of GPS derived data. The authors indicated that caution should be exercised when monitoring exercise bouts with rapid accelerations and changes in direction. Furthermore, it was suggested that an understanding of the smoothing and filtering techniques applied by the manufacturer is needed to understand how commercially available metrics are determined. These recommendations are of particular importance when analysing energy-based metrics, especially during contact events. Figure 2 kinematically (panels A and B) and energetically ([62]; panels C, D & E) describes a collision between rugby league players (unpublished data) using a micro-technology device, housing a 5 Hz GPS chip. The rapid deceleration (panel B) results in an ES (panel C) that exceeds the range of human performance for downhill running i.e. less than -0.45. Indeed, the study of Minetti et al. [63], which informs the original model of di Prampero et al. [62] did not exercise participants beyond a slope of +0.45 or -0.45. Because the polynomial function used in this model to determine EC is invalid outside of this range, it quantifies the collision in a manner that is not physiologically possible. The highest accelerations reported in a soccer match infrequently approached 5 $m \cdot s^{-2}$, which equates to an ES of +0.50. As such, it was thought that the typical changes in velocity observed during soccer performance could be tolerated by this energetic model [9,65]. For ES values beyond +0.45 or -0.45, it is the approach of micro-technology manufacturers to linearly extrapolate the data of Minetti et al. [63] (shown in Figure 1) to readily replace negative energy cost predictions at extreme equivalent slopes with physiologically feasible estimates. The validity of this approach to quantify rapid decelerations has not been examined.

(Figure 2 near here)

It is also common for some commercially available programs to apply a zeroing technique to velocity profiles. This technique uses a proprietary algorithm to replace low velocity data-points with zero values, as shown in Figure 3. In this Figure, we have applied linear interpolation (dashed line) to demonstrate the way in which the proprietary algorithms remove critical data points during decelerating and accelerating movements. The accumulation of these zeroed data points over the course of a match would prevent any valid analysis of acceleration profiles and energy expenditure. This is particularly noteworthy for contact team sports, whereby players are frequently engaged in activities that take place at low velocity, yet have a potentially high EC. Importantly, this observation questions the validity of the automated summary values related to metabolic power that are reported in some micro-technology software programs. The data-handling described here exemplifies how models/methods presented in the literature can be modified in the software debugging process to ensure commercial products are robust across multiple applications. Unfortunately, manufacturers' attempts to provide a 'one-size fits all' solution means end-users do not necessarily gain access to appropriately derived metrics for use in their specific application. This extends to the treatment of accelerometer data as well [76]. Practitioners wishing to model metabolic demands based on micro-technology data should be cognisant of each device's limitations and, in particular, any signal manipulation that may occur before using this information to alter training or dietary regimens based on current metabolic models.

(Figure 3 near here)

5. Future Directions for Energetic Analyses

The previous sections in this review have identified a number of limitations when applying energetic modelling in collision sports. Firstly, it is clear that micro-technology manufacturers have incorporated energetic modelling into their products, without making provisions for sport specific applications. In collision sports, game activities (e.g. tackling) are performed after a series of locomotor efforts, both of which make substantial contributions to the load experienced by the player. Evidently, locomotor or running-based models alone are not well- equipped to quantify collisions [67]. Equally, collision-focussed metrics do not appropriately describe locomotor volume. As such, where a more accurate approximation of load is desired, the locomotor and collision components of the signal produced from micro-technology devices during matches need partitioning and subsequent quantification using different, yet complimentary, techniques. This mandates a move toward more sophisticated analytics, such as pattern recognition algorithms and machine learning, to temporally partition datasets into movement categories or types before applying an appropriate model. Notably, many of these techniques require significant data science expertise; as such the onus is, firstly; on applied sport scientists to develop sound models, based on their understanding of human movement for the evaluation of particular movement types; and secondly, on micro-technology manufacturers to work closely with sport scientists to ensure the appropriate integration of models to meet the end-users requirements. This should limit the inappropriate adoption and application of complex models of human movement.

Assuming micro-technology outputs can be accurately classified into movement types/categories, the models applied to each movement category or type must share common dimensionality i.e. the same units, so they may be readily summed to ensure the total load (whether external or internal) can be determined. As proposed by Furlan et al. [11], work and/or energy are the most dimensionally appropriate units for quantifying the volume of an exercise bout. Work-energy theorem uniquely positions the Joule as the only unit that unifies kinematic outputs (distance, velocity, acceleration data) and kinetic outputs (force, torque data) to quantify "how much was done". A convincing argument for continuing to use mechanical work to describe load (irrespective of movement type/category) lies in its inherent ability to appropriately quantify both the velocity of a body in space and its rate of change in velocity (acceleration) in a single value. To illustrate this point, consider the velocity-time curve of an athlete performing a 40 m sprint (Figure 4a). One energetic approach to quantifying the bout is to derive the mechanical work done to move the body's centre of mass horizontally. On the understanding that the change in kinetic energy between one GPS velocity sample and the next is equal to the horizontal work done, the absolute summation (as opposed to algebraic summation to capture both positive and negative work done) yields the horizontal work done on the body's centre of mass. For the sprint shown in Figure 4a, this equates to 4.178 kJ, shown graphically as the area under the curve in Figure 4b. This energy-based model oversimplifies the energy exchanges e.g. the changing kinetic and potential energies of various body segments occurring during human gait; however, additional components could be added to improve the estimate. This may include the work done to raise and lower the centre of mass with each step, to overcome air resistance and to swing the limbs with respect to the centre of mass, as other power-balanced models of running performance [70,77-79] have done. Acknowledging that field-sport specific gait patterns (e.g. sideways shuffling) and match activities (e.g. ball carrying) do limit the validity of directly applying such models to team sport settings, forward running remains the most logical start-point, therefore such a model is conceptualised in Figure 5. Collectively these components may provide a reasonable mechanical-based description of the locomotor work done during a running bout, effectively, summarising the bout in a single parameter. For comparative purposes, Figure 4c shows the metabolic power curve for the same sprint effort based on the Di Prampero method. The area under the curve represents the energy required to perform the bout, which equates to 23.263 kJ, an estimate ~5.5 times the horizontal mechanical work done; appropriate, given the efficiency of positive muscular work (~0.25) and that the remaining components identified in Figure 5 were not accounted for. The traditional metrics of sprint performance e.g. split times and the standard breakdown of distance travelled across speed zones provided by most commercial software packages, fragments data into several values in order to describe exercise bouts. For the 40 m sprint discussed earlier, a speed zone analysis reveals that the player travelled 0.6 m at 0-12 $km \cdot hr^{-1}$, 0.6 m at 12-14 $km \cdot hr^{-1}$, 0.9 m at 14-18 $km \cdot hr^{-1}$, 1 m at 18-20 $km \cdot hr^{-1}$, 2.3 m at 20-24 $km \cdot hr^{-1}$ and 34.6 m at >24 $km \cdot hr^{-1}$. Evidently, approaches that breakdown and fragment the data are limited in their ability to succinctly quantify load; however, analytical methods that identify the frequency of efforts and/or bouts categorised by their spatiotemporal characteristics (e.g. distance travelled, duration, peak speed etc.) are valuable in that they readily inform the design of sport specific conditioning drills, as these parameters are used to deliver field based training sessions. In contrast, energy-based metrics used in isolation are not readily translated to session design and delivery, given these metrics tend to summate rather than fragment. As such, we propose that complete and meaningful interpretation can only be achieved by the collection of complimentary kinematic and energetic metrics, on the understanding that spatiotemporal indices are necessary to describe the movement patterns, collectively quantified by energetic indices.

(Figure 4 & 5 near here)

Describing contact events in terms of the mechanical work done is arguably more challenging. In locomotion, body mechanics change in a consistent manner largely dependent on speed over flat terrain [80]. As such, the components that make up the model in Figure 5 could be readily predicted from accurate velocity and/or acceleration data obtained from micro-technology. In contrast, the nature of contact events in training and match-play is highly variable in terms of players' postures and limb movements e.g. front-on *vs.* side-on, tackler *vs*. ball-carrier, held upright *vs*. taken to ground. This far less predictable situation likely limits energetic modelling of contact events to gross energy gains and losses to/from the player's center of mass. Hendricks et al. [81] applied basic physical principals of collisions (momentum and kinetic energy exchanges) to describe the magnitude of tackles and the interplay between player size, movement velocity at collision onset and the outcome of the tackle (dominant or non-dominant). Whilst Hendricks et al. [81] analysed video footage to determine players' velocities during collisions, these methods and/or similar energetic analyses could be performed on velocity data obtained from micro-technology devices to quantify loads associated with collisions. One caveat of this approach is that in order to get a reasonable description of the event, continuous sampling of both players' velocity is required. Unfortunately, most coaches do not gain access to opposition data sets. Nonetheless, 'collision loads' defined using this type of approach could provide quantitative estimates of loads associated with tissue deformation to be interpreted alongside 'locomotor loads' using the type of approach proposed above. This may provide a more complete description of the total external load of a field-based exercise bout. Whilst theoretically sound, novel approaches such as those proposed herein, require validation prior to routine application.

6. Conclusion

The approach of energetic modelling denotes a progression in the application of motion-analysis technology to the team sports environment, complementing traditional kinematic information provided by micro-technology. Modelling the energetics (metabolic or mechanical) of team sports provides practitioners with a credible global 'estimation' of match or training load but is not without limitations. For example, it is important that potential users of the energetic modelling approach are aware of the data accuracy and handling procedures of micro-technology manufacturers and appreciate how these might confound the estimation of metabolic or mechanical energy demand. Furthermore, the di Prampero model commonly adopted by micro-technology manufacturers faithfully estimates what it claims to (metabolic demand of forward propulsion) but cannot quantify the energetic costs of team sports in their entirety, particularly during contact events. As such, users should appropriately adjust their expectations utilising the outputs of the model in settings that are inconsistent with its intended application. There are potential solutions to many of these problems, some of which require greater transparency from micro-technology manufacturers in regard to data handling procedures and improved communication with sports scientists. In addition, more sophisticated modelling processes are necessary and provide a realistic, yet challenging problem for scientists. We propose that the adoption of a mechanical modelling approach has potential to solve some of these problems, whereby the 'work done' can be accurately estimated based on the basic principles of Work-energy theorem. Its application to training and matches in collision sports will depend upon the reliability of automated systems, with capacity to identify movement types during training or competition. Such an approach has the potential to capture the energetic demands of collisions and locomotor activities, thus progressing the current analysis techniques in sport.

Conflict of Interest

Adrian Gray, Kathleen Shorter, Aron Murphy and Mark Waldron declare that they have no conflict of interest. Cloe Cummins has previously held employment with a micro-technology manufacturer. Cloe Cummins is currently an external consultant to a micro-technology manufacturer in which she produces internal reports on micro-technology device validity and reliability.

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Figure Captions

Figure 1. The relationship between energy cost (EC) and gradient (i) described by the 5th order polynomial, EC = $155.4i^5 - 30.4i^4 – 43.3i^3 + 46.3i^2 + 19.5i + 3.6$ (r^2 = 0.999). The solid line indicates an accepted range of human performance for gradient running, given slopes beyond this range challenge elite mountain racing athletes. The dashed line shows how the polynomial function predicts energy cost beyond the range of human performance. The dotted line predicts energy cost beyond the range of human performance by linear extrapolation of the slope according to EC = $-8.45i + 0.2$ and EC = $51.52i – 4$, for down and up-slopes, respectively. Note: a gradient of 0 is a horizontal running surface and a gradient of +1 or -1 represents a vertical running surface.

Figure 2. A kinematic and energetic description of a collision between rugby league players using a 5 Hz GPS receiver and the original di Prampero [61] model. Panels show changes in a) velocity; b) acceleration; c) equivalent slope; d) energy cost; and e) metabolic power over an 8 s period. The rapid deceleration results in an ES that exceeds the range of human performance for downhill running i.e. less than -0.45. The polynomial function used to determine EC is not valid outside this range and produces erroneous values for energy cost and metabolic power (i.e. values below zero). Systems routinely using this approach must apply relevant filtering/curve fitting treatments to the EC-time curve to correct this effect. Correction of negative EC and MP values using the linear extrapolation shown in Figure 1, is shown by the dashed line in panels d) and e), respectively.

Figure 3. Example of a raw and interpolated velocity profile during a Rugby League match. The raw signal (solid) has been zeroed using proprietary algorithms (Team AMS GPSports systems, Canberra, Australia). The rapid acceleration that results when the zeroing algorithm ceases, amplifies energy based metrics. The dashed line is an example of how end users may have to further process raw data, to permit sound application of energetic models.

Figure 4. Panel A shows a 5 Hz velocity-time curve during a 40 m sprint performed by an elite Australian Football player (87 kg). Panel B shows the horizontal mechanical power of the centre of mass, derived from the change in horizontal kinetic energy between each sample during the sprint. The shaded area under the curve represents the work done (4.178 kJ) to horizontally accelerate the player's centre of mass over the 4.8 s period. Panel C shows the

metabolic power curve associated with the sprint, derived using the Di Prampero method. The shaded area under the curve represents the net energy required (23.263 kJ) to perform the bout.

Figure 5. Theoretical components of a mechanically derived energetic model of running. Total mechanical work done is the absolute sum of external work (work done on the centre of mass i.e. Whor+, Whor-, Wvert+, Wvert-, Wair) and internal work (work done on the body segments with respect to the centre of mass i.e. Wlimbs). Where, Whor+ is the work done when the centre of mass (COM) is accelerated horizontally, Whor- is the work done when the COM is decelerated horizontally, Wvert+ is the work done when the COM is raised with each step, Wvert- is the work done when the COM is lowered with each step, Wair is the work done to overcome air resistance and Wlimbs is the work done to swing the limbs back and forth with each step. How each component is determined e.g. prediction from microtechnology datasets, and the necessity of its inclusion is open to discussion.

Figures

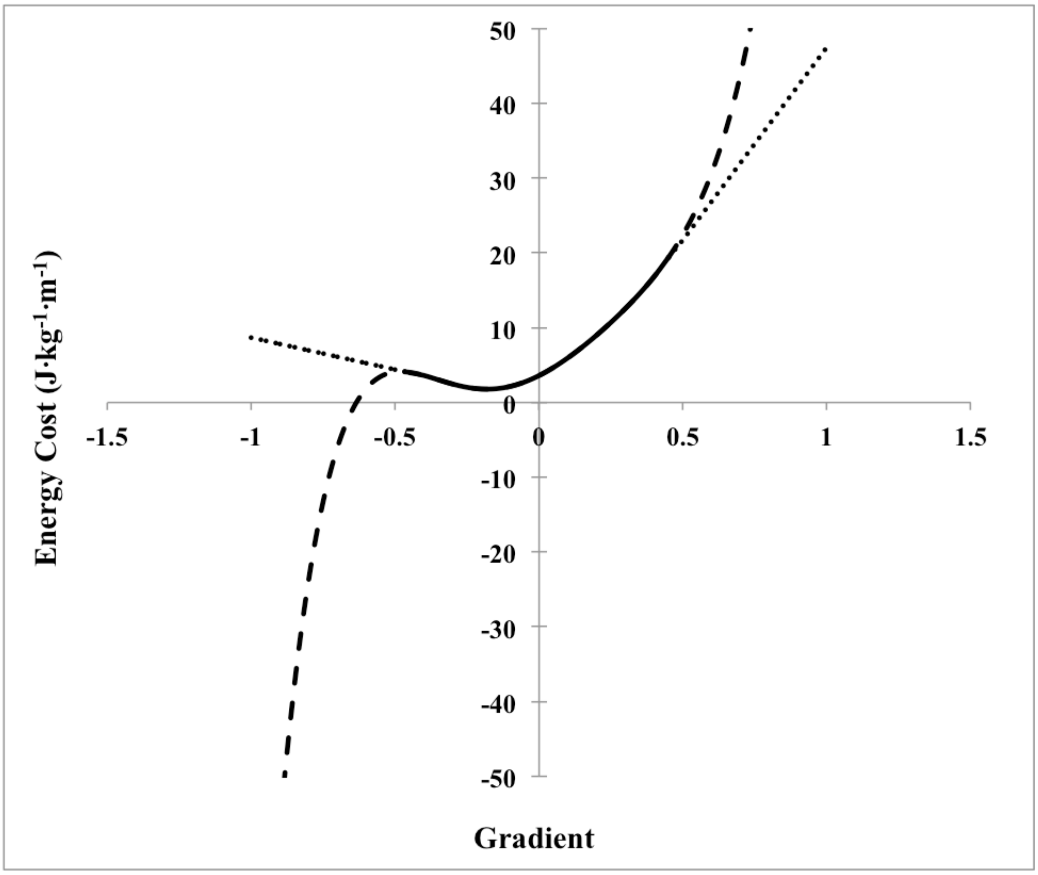

50
40
30
20
10
0
-10
-20
-30
-40
-50
-1.5
-1
-0.5
0
0.5
1
1.5
Energy Cost (J·kg-1·m-1)
Gradient

Figure 1.

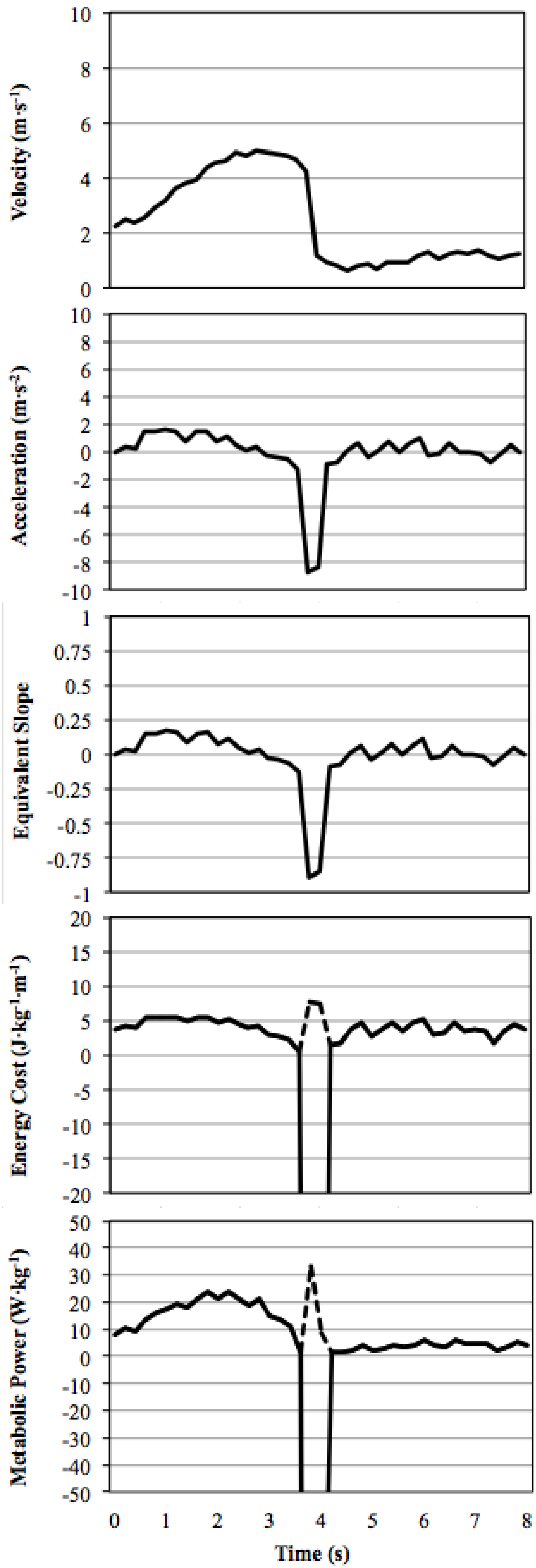
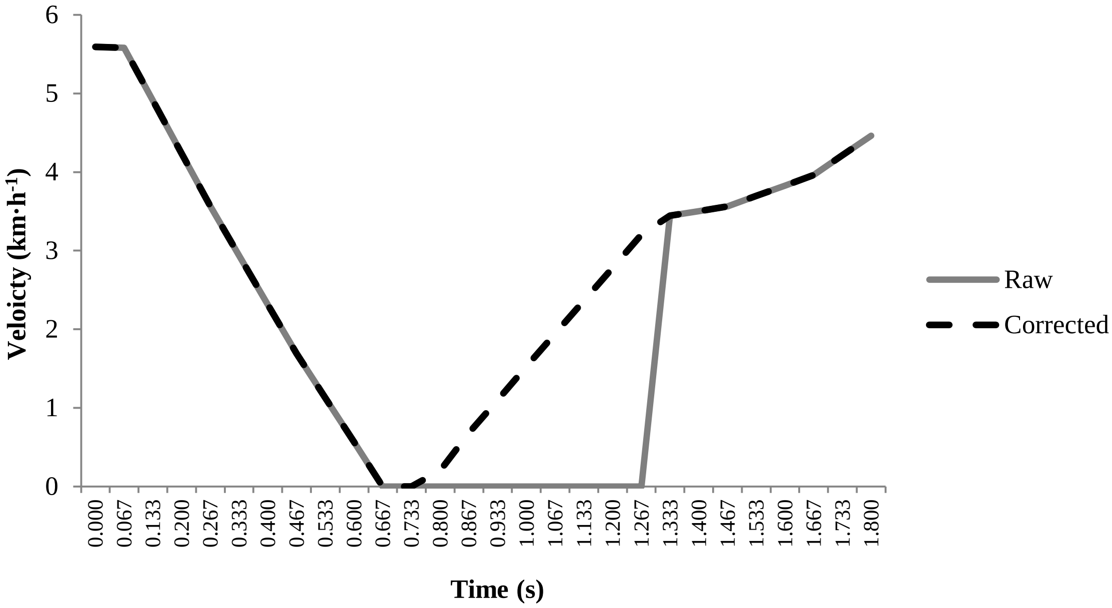

Velocity (m·s⁻¹)
Acceleration (m·s⁻²)
Equivalent Slope
Energy Cost (J·kg⁻¹·m⁻¹)
Metabolic Power (W·kg⁻¹)
Time (s)

Figure 2.



Veloicty (km·h-1)
Time (s)
0
1
2
3
4
5
6
0.000
0.067
0.133
0.200
0.267
0.333
0.400
0.467
0.533
0.600
0.667
0.733
0.800
0.867
0.933
1.000
1.067
1.133
1.200
1.267
1.333
1.400
1.467
1.533
1.600
1.667
1.733
1.800
Raw
Corrected

Figure 3.

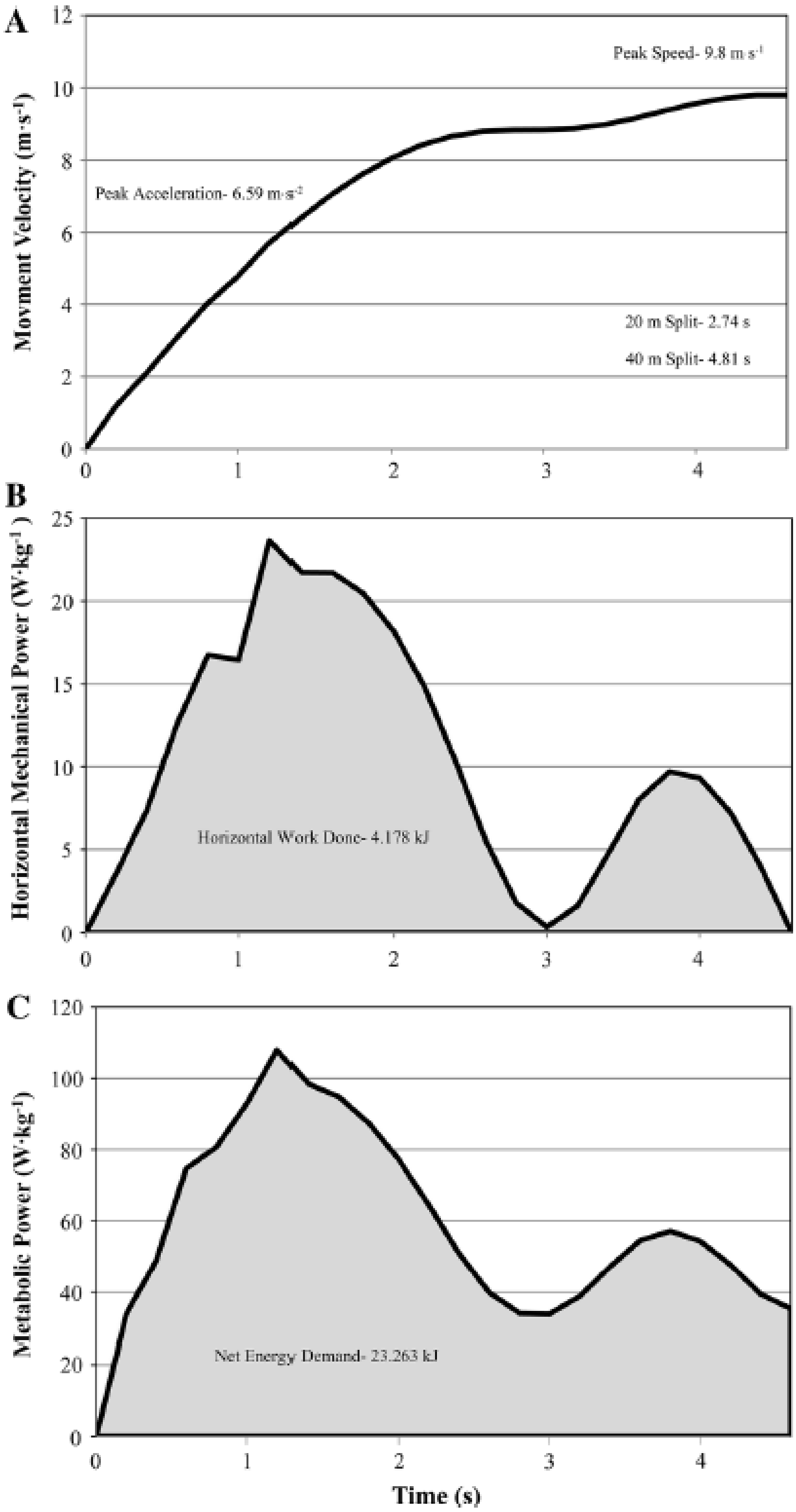
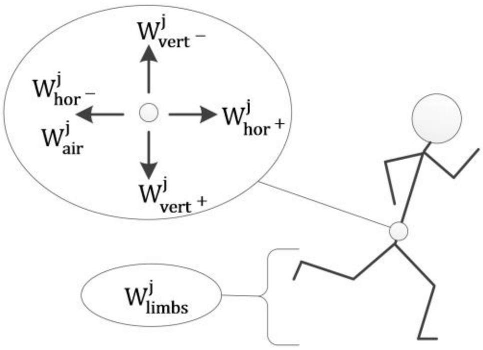

A
Peak Speed- 9.8 m·s⁻¹
Movment Velocity (m·s⁻¹)
Peak Acceleration- 6.59 m·s⁻²
20 m Split- 2.74 s
40 m Split- 4.81 s
B
Horizontal Mechanical Power (W·kg⁻¹)
Horizontal Work Done- 4.178 kJ
C
Metabolic Power (W·kg⁻¹)
Net Energy Demand- 23.263 kJ
Time (s)

Figure 4



$$C_j^{+} = \frac{W^{j}_{hor^+} + W^{j}_{vert^+} + W^{j}_{air} + W^{j}_{limbs}}{{}^{+ve}\eta_j}$$

$$C_j^{-} = \frac{W^{j}_{hor^-} + W^{j}_{vert^-}}{{}^{-ve}\eta_j}$$

Figure 5